IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received July 8, 2021, accepted August 17, 2021, date of publication August 24, 2021, date of current version September 1, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3107237

A Semantic Conceptualization Using Tagged Bag-of-Concepts for Sentiment Analysis

YASSIN S. MEHANNA, (Member, IEEE), AND MASSUDI BIN MAHMUDDIN, (Member, IEEE)
Internetworks Research Laboratory, School of Computing, Universiti Utara Malaysia, Sintok 06010, Malaysia

Corresponding author: Yassin S. Mehanna (yassin.mehanna@gmail.com)

ABSTRACT Sentiment could be expressed implicitly or explicitly in the text. Hence, it is the main challenge for current sentiment analysis (SA) approaches to identify hidden sentiments, other common challenges include false classification of opinion words, ignoring context information, and bad handling of a short text that arise from the bad interpretation of the text and lack of enough data required for analysis tasks. In this study, a semantic conceptualization method using tagged bag-of-concepts for SA is proposed to detect the correct sentiment towards the actual target entity that considers all affective and conceptual information conveyed in the text with a special focus on the short text. Tagged bag-of-concepts (TBoC) is a novel approach to analyze and decompose text to uncover latent sentiments while preserving all relations and vital information to boost the accuracy of SA. This study answers questions: Does the information provided via TBoC enhance sentiment classification results on different analysis levels? Is building a structure of concepts increases the accuracy of overall sentiment towards specific opinion target? Does TBoC approach enhance SA results for short text messages? The proposed solution has been applied on two datasets from the restaurant domain, sentiment analysis is performed using the TBoCs structure on multiple levels including document, aspect, aspect-category, and topic levels. TBoC method with domain-specific sentiment lexicon showed exceptional performance and outperformed other state-of-the-art NB, SVM, and NN methods, especially for aspect-level SA. The use of TBoC within the semantic conceptualization model that leverages NLP tasks, Ontology, and semantic methods proved its high capabilities for concept extraction while preserving the information about the context, interrelations, and latent feelings.

INDEX TERMS Concept extraction, semantic sentiment, sentiment lexicon, natural language processing, sentiment analysis, text processing.

I. INTRODUCTION

Sentiment Analysis (SA) is the examination of the polarity of emotions and opinions expressed in the text by using computational methods [1]. The objectives of SA can be grouped into finding opinions, identifying their sentiments, and classify them into positive and negative opinions [2], however, detecting feelings and grouping them into positive and negative feelings is also one of SA objectives.

Hence, as a field of study SA is concerned about the analysis of expressed attitudes, opinions, emotions, and assessments towards an entity and its attributes in textual data. The entity could be anything that worth interest, it can be something physical like an individual, organization, or product or even nonphysical like a topic, event or issue. SA is a wide research field and rich in research topics. Opinion mining is used often to refer to SA, examples of other related research fields are emotion analysis, subjectivity analysis, and review mining.

Starting from 1990 many published studies have discussed related work, they addressed the analysis of subjectivity and extraction of sentiment adjectives [3], Research on SA started in 2000 [4], but Elkan was the first to address text classification with a special focus on sentiments on 2001 [5]. Nasukawa and Yi were the first to stamp the term sentiment analysis [6] and Dave *et al.* were the first to use the term opinion mining [7].

The evolution of SA as a research area is not limited to computer science only but advances in other fields concerned with people's opinions such as social science, management science, economics, and political science.

Research in SA covers almost entire natural language processing (NLP) research areas, it covers lexical semantics, semantic analysis, information extraction,

The associate editor coordinating the review of this manuscript and approving it for publication was Chang Choi.

discourse analysis... etc., that is why many researchers see SA as a subarea of NLP. Problems in NLP affect SA and the other way round, actually, SA as a new research field introduced many new problems and challenges to the NLP research field. A noticeable difference between research in NLP and SA is the corpus, which should be opinion corpus for SA research.

In addition, SA can be seen as a confined semantic analysis problem. SA focuses on the orientation of the word or document; it does not have to understand the exact meaning of each word because it will not add any value to the key objective to study opinions toward entities. Semantics is mostly ignored in SA approaches and instead, statistical methods are used that handle text as bag-of-words, which results in a low interpretation quality. The main reason is that short text does not have enough words required by statistical methods to provide good results [8].

The main component of SA is the classification process of opinions based on their polarity. The classification can be done on different levels including document-level, sentence-level, phrase-level, or aspect-level, in which each level is considered as the information unit for the classification task [9]. In all types SA consists of two steps, the first step is to differentiate between subjective and objective units and the second step is to classify subjective units into positive and negative opinions [10].

The sentiment is not always expressed in a direct way and words are not always reflecting clear emotions. A lot of information could be hidden in the text and analyzing words alone will not help to extract this information. In SA, many words are classified as objective although they hold a strong sentiment that needs a good understanding of the text in order to be detected. This sentence is a good example of this problem "My brother is going to the war and I may not see him again". The sentence does not contain opinion words that hold direct sentiment but it has a very strong negative feeling. This specific example is a real challenge to all current SA methods.

Many studies have been conducted in recent years to address the sentiment analysis problem. Although these studies contributed to many enhancements in SA methods, still more research and efforts are required to improve SA processes and techniques to reach an acceptable level of accuracy necessary for real-world applications. Most of the current SA approaches rely on machine learning (ML) methods that require massive datasets for training and learning tasks, which is not always applicable especially in short text analysis. Another deficiency in current methods is the common approach used that relies on global classification rather than classifying individual aspects [11].

Hence, the motivation for this work was the need to adopt a comprehensive SA method to detect the correct sentiment towards the actual target entity that considers all affective and conceptual information conveyed in the text with a special focus on the short text.

To achieve this goal, we introduce a semantic conceptualization method using tagged bag-of-concepts (TBoC) for sentiment analysis. TBoC is designed to overcome the limitations of bag-of-words (BoW) and bag-of-concepts (BoC). While BoW is just a representation of text as vectors of words, all text properties, interlinks, attributes and sequence of words are lost. BoW treats each word separately and introduces a superficial understanding that overlooks the semantics and conceptual details embedded in the text which limits the capabilities of any further text analysis. Although BoC overcomes the BoW limitation of isolated words and ambiguous interpretation, it couldn't overcome major limitations such as missing context information and the inability of detecting implicit relations, values, and feelings. Hence, the objective of tagging "bag-of-concepts" is to preserve the information about the context, interrelations, latent feelings, and other important information. TBoC is a comprehensive structure that stores important explicit and implicit information in a context-aware form that can be used to generate conceptual semantic networks and boost the accuracy of sentiment analysis.

The main contributions of the research presented in this paper are:

- We propose a novel method to handle text as a bag of related context-aware concepts to overcome the issue of limited understanding of the text when dealing with it as separate terms. Even if relations between words are considered, most existing analysis methods cannot extract many of the embedded meanings and accordingly cannot obtain the right sentiment.
- We integrate lexical methods with supervised approaches as supporting methods to empower the introduced model and enhance results.
- We utilize TBoC within the semantic conceptualization model that leverages NLP tasks, Ontology, and semantic methods to exploit its high capabilities for concept extraction while preserving the information about the context, interrelations, and latent feelings. NLP important features are utilized as follows 1) context-aware (topic spotting), 2) ability to consider all opinion terms (subjectivity detection) and 3) ability to specify the exact target for each sentiment (aspect and category extraction).
- We introduce a rule-based method for aspect-category extraction using a semantic knowledge base

In addition, TBoC provides deep insights into the underlying text to data scientists, researchers, and software engineers and saves time and computational cost for many text analysis tasks. Using TBoC method, all embedded concepts are extracted along with their contextual and key information and stored in JSON format to be used for different text analysis tasks.

The rest of this document is organized as follows. Section II provides a deep overview of the state-of-the-art work and major applications of semantic methods, NLP approaches, and aspect-level sentiment analysis. Section III illustrates our proposed solution and the implementation process. Section IV explains the evaluation process, datasets used, and sentiment classification methods that were utilized in our experiment. Section V discusses the experimental results. Finally, Section VI concludes our work and presents potential extensions for future research.

II. RELATED WORK

This section studies related work of semantic methods, and focus on short text techniques and aspect-level sentiment analysis. Then, we discuss existing work and studies of the methods used in the proposed model including, subjectivity detection, topic spotting, polarity detection, and concept extraction.

A. SEMANTIC SENTIMENT ANALYSIS

Semantic sentiment analysis is divided into two methods, contextual semantic method and conceptual semantic method; both methods determine semantics for SA.

The contextual semantic method is also called statistical semantics because it determines the sentiment orientation from the statistical correlation between the word and a set of predefined words [12]. A study was done by Turney and Littman who used point-wise mutual information (PMI) to calculate the co-occurrence patterns of given words with a set of words of a known polarity of which the positive and negative sentiments are balanced. The word is assigned a positive orientation if it is more associated with positive words from the given list than negative words and assigned a negative orientation if has a stronger degree of association to negative words than to positive ones [13].

The limitation of this method comes from its dependency on web search engines to get the comparative co-occurrence frequencies of terms. It uses the web as its corpus instead of using one of the commonly used lexicons. The usage of the web as a corpus affects the performance of the SA process. In addition, it restricts its capability of assigning the right sentiment to domain-specific orientation words [14]. Words "Heavy" and "Light" are good examples where the contextual semantic sentiment approach cannot assign the proper sentiment because it does not consider the domain; correct sentiment for IT domain is different from manufacturing domain.

The conceptual semantic method is powerful for implicit sentiment representation of words. It uses natural language processing techniques on semantic knowledge bases such as semantic networks and ontologies to obtain the conceptual representation of words with an implicit sentiment.

Authors in [15] proved that the accuracy of SA has been improved after using general conceptual semantics with supervised classifiers. Cambria *et al.* introduced SenticNet, which is a concept-based lexicon to overcome the performance problem and expand the semantic knowledge base. Open Mind corpus was used as the main resource of concepts, then associated with their sentiment orientations [16]. SenticNet is not limited to micro-blogs only like similar lexicons such as SentiStrength. Conceptual semantic methods are more effective when compared to syntactical approaches [17], but their weakness is the restriction to their limited knowledge bases, which is a real problem in social media with the quick semiotic evolution and language distortions.

Concept-level SA targets the semantic analysis of text [17]. Semantic parsing is an NLP task that interprets the text of natural language into concepts. The gathering of conceptual and emotive information that is associated with natural language opinions is carried out through using semantic networks or web ontologies. The utilization of extensive semantic knowledge bases directs these approaches away from indiscriminate use of keywords and co-occurrence count and depends on features implied by natural language concepts. Concept-based approaches can find sentiments that are expressed indirectly, while syntactical techniques do not have this ability.

Semantics related to natural language are represented more accurately using the bag-of-concepts model rather than using the bag-of-words [18]. In the bag-of-words model semantics of the input, a sentence could be disrupted when a concept is divided into separate words and dealing with them individually. For example, Apple's iPhone is a concept if dealt with as separate words, the word Apple would be interpreted as a fruit-related concept, which is misleading. One of the most important phases of automatic concept-level text analysis is the extraction of the concept. Cao *et al.* used domain-specific ontologies to collect knowledge from the text, then they utilized these ontologies and were able to find 1.1 million common-sense knowledge assertions [19].

Many tasks could be carried out using concept mining including text classification and information retrieval. Most recent approaches to collect concepts from text-focused particularly on term extraction methods. These methods either belong to the category of linguistic rules or statistical approaches. Zheng and Lu calculated term weighting using a non-linear function through the employment of word location and term frequency [20]. Agirre *et al.* created topic signatures of concepts through the mining of concepts from the web and accordingly building a hierarchical cluster of these concepts, which put words in the related lexicon [21]. Du *et al.* used a mix between linguistic rules and statistical approaches to improve the process of concept extraction [22].

Some related research in the concept mining field targeted the extraction of concepts from documents. Gelfand *et al.* built a method using the semantic relation graph to extract concepts from a complete document. Therefore, to extract a concept they employed the relationship between words, which is driven from a lexical database [23]. Another prominent technique to extract concepts is lexico-syntactic pattern matching, Hearst had a theory that researched a new direction in concept mining, which presumed that new lexical syntactic patterns can be extracted using existing hyponymy relations [24].

Many applications have been introduced that utilize semantic knowledge for sentiment analysis. Ali *et al.* used ontology and latent Dirichlet allocation (OLDA) for topic modeling to label sentences automatically and extract only traffic events from traffic-related data, the authors used bidirectional long short-term memory (Bi-LSTM) to detect traffic accidents and sentiment analysis to identify exact conditions of traffic events. Their proposed social network-based, real-time monitoring framework outperformed existing systems based on sensors and social networking platforms [25]. Ontologies are utilized within a big data analytics engine and based on the cloud environment to build an intelligent monitoring model. Ontologies are used to provide semantic information about entities and their interrelations to enhance classification accuracy using Bi-LSTM. The proposed model was also capable of handling diversified data [26].

Semantic knowledge is utilized in a new framework to overcome the limitations in existing transportation systems [27]. The authors developed fuzzy ontology-based semantic knowledge to extract opinion terms. They utilized fuzzy ontology-based sentiment analysis of transportation activities and city feature reviews, also used semantic web rule language (SWRL) rule-based decision-making to monitor transportation activities and to develop a polarity map for city features. They extracted related sentiments using an unsupervised linear method on consumer reviews and tweets. Their technique showed good results for categorizing uncertain reviews and detecting polarities for city and transportation features. A topic modeling using OLDA along with a word embedding technique is proposed for sentiment analysis. The proposed system was capable of retrieving transportation data from social networks, extract useful information and determine features and topics. The authors used lexicon-based techniques to improve the word embedding model for document representation. Also, they employed ontology-based semantic knowledge to empower the LDA model, this approach showed enhanced results for a topic generation. Also, the system was able to represent each word semantically with a low-dimensional vector [28].

Ali *et al.* introduced semantic knowledge to extract important and hidden information and features from social network data. They developed a fuzzy ontology to store semantic information and relations of entities and features. The ontology and Word2vec model are utilized to enhance features extraction and text classification tasks using the Bi-LSTM method. Their model overcomes the limitation of the LDA method that ignores important features with small datasets and the general limitation of ML methods that miss the semantic meaning of words. The proposed system was able to extract features from unstructured data and consider semantic meaning with text representation to enhance the efficiency of text mining and sentiment analysis.

However, the authors faced new challenges with respect to the complexity of classification methods as a result of the huge knowledge extracted from the fuzzy ontology that includes a massive number of concepts and their related information [29].

B. SENTIMENT ANALYSIS TECHNIQUES FOR SHORT TEXT

Handling short-length textual data in social media is a big challenge, techniques using semantic analysis and ontology-based approaches have proven success for micro-blogs.

1) CONTEXT-BASED MODEL AND SEMANTIC ANALYSIS

Sentiment detection in tweets was usually considered like other text classification tasks; this has been proven by most papers that took part in the SA in the Twitter task in SemEval-2013 challenge [30] a computational analysis for a received instance is produced for one tweet at a time. This task is very complicated and has critical limitations because messages are short in length and this causes the semantics to be ambiguous.

The context of the 'Conversation' is what makes it possible to distinguish messages even if they are very short, and accordingly being able to classify them depending on the time it was posted and its author.

We can benefit from these observations (considering the whole conversation) and define a context-sensitive SA model through two main tracks: First, incorporating the conversation information in the tweet representation to improve it. Second, presenting a sophisticated classification model, which processes a complete tweet sequence and not just one tweet at a time. On a computational level, detecting the polarity of a tweet in its context is considered a sequential classification task. That is, the conversation and topic-based context are promptly a sequence of many messages that are organized based on the time it was sent putting the target tweet at the end of the sequence. Support vector machine (SVM) learning algorithm was used, for its ability to classify a tweet considering the entire sequence [31]. SVM classifiers make it possible to identify the sentiments of each tweet independently, Altun *et al.* proposed a new technique that employed Hidden Markov SVM (HM-SVM) learning algorithm to label all tweets as a whole in a sequence. Accordingly, it is expected to detect patterns in a conversation and use them in a new sequence by using a standard decoding task [32].

2) ONTOLOGY-BASED SENTIMENT ANALYSIS

Studer *et al.* defined ontology as ''explicit, machine-readable specification of a shared conceptualization'' [33]. Ontologies can be used to organize the terms of a certain domain, also to build the relations between these terms. Currently, it is used in many different fields like e-commerce platforms. Natural language generation is one of the applications of ontology, also semantic-based access to the internet, and the ability to gain information from texts. Another application is intelligent information integration. Above all the most important contribution of ontologies remains the important part it plays in developing the field of semantic web [34].

The semantic web is considered as an elaboration of the existing web because the information is tagged with a well-defined meaning, which facilitates the collaboration between human users and computers [35]. More reasons that motivate favoring the use of ontologies in applications include 1) Being able to analyze domain knowledge and distinguishing the recent knowledge from the operational knowledge. 2) Allowing the use of domain knowledge over and over again. 3) Helping domain assumptions to be more specific, and 4) Building a common understanding of the structure of information and communicating it between people and/or software agents.

The work done by [36] is considered the most remarkable work concerning the use of ontologies in the micro-blogging domain. In their work, they offered a methodology for spreading actual earthquake evacuation ontology with instances depending on tweets. Other possible fields of research might cover developing ontologies to represent micro-blog posts and the links between social-network users such as FOAF, SIOC, OPO, SMOB2 [37], or ontologies that describe different levels of emotions [38].

C. ASPECT-LEVEL SENTIMENT ANALYSIS

Many studies and research papers addressed the problem of aspect extraction using different approaches and techniques. Nazir *et al.* presented an overview of existing surveys that addressed aspect-based sentiment analysis. They focused on the challenges and issues in aspect extraction subtasks including the discovering of contextual-semantic relationships [39]. Schouten and Frasincar summarized known techniques in their survey; they mentioned that aspect-level sentiment analysis can be achieved through three consecutive steps starting from aspect identification then classification and aggregation [40]. While Rana *et al.* mentioned slightly different subtasks of aspect and opinion extraction, then sentiment lexicon analysis, and finally opinion summarization [41]. They all agreed that the first task to identify and extract aspects is the most significant and challenging task in the entire analysis process. Hu and Liu distinguished between implicit and explicit aspects [42], however, the majority of studies focused only on explicit aspects. Based on [40] and [41] surveys and several research papers we categorized aspect extraction methods into six categories; Frequency-Based Methods, Syntax-Based/relation-based Methods, Supervised machine learning, Unsupervised machine learning, Semi-supervised machine learning, and Hybrid approaches.

1) FREQUENCY-BASED METHODS

It may also be called statistical methods. These methods are based on the idea that if certain terms are repeated more than others in a text, then they are strong aspect candidates. Usually, these frequent terms are nouns and noun phrases. Adopting this basic idea is not sufficient to provide good results because it will miss many actual aspects that are less mentioned in the text, also it will consider many repeated terms that are not actual aspects. Hu and Liu proposed a method to enhance results by adding a set of rules to consider specific types of terms only such as nouns and compound nouns [42]. Further improvements using grammatical relations have been introduced by Long *et al.* [43]. However, Bafna and Toshniwal investigated implicit aspects using frequency-based methods with association rule mining [44]. Another approach carried out by Scaffidi *et al.* is to extract only actual aspects through statistical methods by mapping the frequency of candidate aspects to a benchmark derived from a large corpus contains millions of English conversation words [45]. Hu and Liu suggested multiple analysis steps, first to extract frequent terms as potential aspects, and then extract closest adjectives as opinions associated with them [42].

2) SYNTAX-BASED METHODS

Syntax-based or rule-based methods utilize syntactical relations in the text to identify aspects and related concepts. Adjectives and nouns represent a basic relation that could denote an opinion target (aspect) and related opinion. The more syntactical rules are defined, the higher performance is achieved. Zhao *et al.* proposed a tree kernel to generalize syntactic patterns to enhance the process of aspect extraction [46]. While Qiu *et al.* used a dependency parser to build a set of syntactical rules derived from grammatical relations; they introduced a double propagation algorithm to solve the problems of aspect extraction and expanding domain sentiment lexicon. The double propagation technique is built on a smart idea of using the relations between aspects and opinions to identify all implicit and explicit aspects and opinion words in the text. It starts with a small set of seed words to identify opinion words then uses these opinions to extract target aspects. The next step is to iterate with extracted aspects and opinion words going through the entire text to find new opinions and aspects using their relations and predefined set of rules until all aspects and opinions are discovered [47].

Many models and algorithms were introduced to identify aspects and opinions based on syntactical relations such as the word-based translation model (WTM) that was introduced by Liu *et al.*, which is a monolingual word alignment model [50]. Bancken *et al.* introduced ASPECTATOR, an algorithm to identify and evaluate product aspects using syntactic dependency paths [49]. The Translation-Based Language Model (TrLM) was introduced by Du *et al.* to extract aspects from product reviews through examining the structure of the reviews at sentence-level [50].

3) SUPERVISED MACHINE LEARNING METHODS

Usually, when applying supervised methods for the task of aspect extraction, they have to be supported with other methods, or more precisely, they are used as supporting methods for other techniques. To obtain good results, supervised methods should be feed with high influential and expressive features, approaches vary in methods used to extract features, and the way supervised techniques are employed.

Jin and Ho integrated linguistic features like POS and lexical patterns into Hidden Markov Models HMMs to extract aspects and opinion words from review documents [51]. Jiang *et al.* introduced tree kernels to encode syntactic structure and sentiment-related information, their goal was to generate effectual features required for opinion mining. Using a kernel-based approach, they were able to investigate similarities between two trees rather than dealing separately with each tree [52]. Jiang *et al.* used pointwise mutual information (PMI) to identify relations between aspects and opinions. Their results show good improvement of aspect extraction and sentiment classification performance.

Many approaches used conditional random field (CRF) such as the approach introduced by Jakob and Gurevych who used a linear chain CRF, they dealt with the aspect extraction task as a labeling problem that could be solved by processing the entire string of words to consider the context of each labeled word [53]. Skip-chain CRFs and Tree CRFs approaches were introduced by Li *et al.* [54] to extract aspects and opinion words, while Yang and Cardie [55] utilized direct relations between terms to identify related opinion words after extracting implicit and explicit aspects using CRF.

The semantic-based approach is also investigated under supervised methods by Li *et al.* [56], they addressed the aspect extraction task as a shallow semantic parsing problem, considering opinion terms and expressions as predicates, and related opinion targets as their arguments. Li *et al.* represented each sentence by a parse tree rather than using a sequence of words, also they used constituent rather than words to identify aspects through defined heuristic rules.

Peng *et al.* introduced a two-stage framework for aspect-based sentiment analysis using Bi-LSTM and a Graph Convolutional Network (GCN). In the first phase, they generate candidate aspects and candidate opinions along with sentiment polarities. In the second phase, they generate a candidate pair pool of all possible aspect-opinion pairs and classify the validity of each pair [57].

4) UNSUPERVISED MACHINE LEARNING METHODS

Latent Dirichlet Allocation (LDA) is one of the popular unsupervised methods used for aspect-level sentiment analysis. However, this approach is not very successful when dealing with aspect extraction, but it gives good results for topic modeling tasks [58]. The reason is that LDA design is to work on document-level; working on aspect-level does not suit its original design. Applying LDA on document-level returns generic results while applying on a narrower level such as sentence-level will lead to inadequate results due to the small number of input terms [59]. Many solutions were introduced to enhance the performance of LDA for aspect extraction such as supporting the method with dictionaries and use syntactical relations to extract opinion targets [60].

Bootstrapping is another unsupervised method that is introduced by Zhu *et al.* [61]. In their work, they introduced multi-aspect bootstrapping (MAB) to extract aspects on sentence-level. Bagheri *et al.* [62] used a set of seeds and POS patterns then applied bootstrapping method for aspect extraction. Authors in [63] defined a different set of rules based on sentence structure to identify relations between opinion targets and opinion words. They applied bootstrapping on identified patterns to extract aspects and opinions. Popescu and Etzioni introduced a technique using PMI to improve rule-based methods through evaluating prospective aspects; they excluded all aspects with low PMI. Results showed an improvement in precision after utilizing the PMI method [64].

5) SEMI-SUPERVISED METHODS

Wang and Wang introduced bootstrapping in a Semi-supervised approach, they used a context-based method to identify opinion words and targets. To extract frequent aspects, they used bootstrapping that utilizes seeded opinion words, while linguistic rules are employed to extract infrequent aspects [65]. Zhao *et al.* tried to enhance bootstrapping method results by supporting it with a refinement process to exclude false aspects [66]. Hai *et al.* introduced other methods to improve results, they used likelihood ratio set (LRTBOOT) and latent semantic analysis (LSABOOT) bootstrapping methods [67].

Wu *et al.* constructed a tree from sentences that represent relations between distinct phrases. They used a dependency parser and utilized relations between terms to generate the tree, noun and verb phrases are then extracted as candidate aspects, and opinion words are extracted using a dictionary-based approach. Wu *et al.* used dependency parser and the rule stating that opinion words usually exist close to opinion targets, they constructed a tree kernel and combined it with SVM to identify the relations between aspects and opinion words [68]. Liu *et al.* introduced a different method to identify the correlation between opinion targets and opinion words; they combined word alignment with syntactic rules in the Partially-Supervised Word Alignment Model (PSWAM). As in many other studies, they considered nouns and noun phrases as prospect aspects [69].

Xu *et al.* introduced a Walk and Learn approach to extract aspects and opinion words. First, they discovered patterns of aspects and opinion words using a sentiment graph walking algorithm, the objective of this task is to extract potential aspects and related opinions. Then true aspects were extracted using the self-Learning semi-supervised approach, they mentioned that considering pattern confidence in the graph made a noticeable difference in results [70].

6) HYBRID METHODS

Schouten and Frasincar classified hybrid methods into serial hybridization where different methods are used in consecutive phases and parallel hybridization where more than one method is used simultaneously in the same task [40]. Approaches belong to serial type are utilized by Popescu and Etzioni who used PMI to identify potential aspects, then utilized Naïve Bayes to extract explicit aspects [64]. Also, Raju *et al.* used dice similarity measure for noun phrases clustering to identify prospect aspects, then they used SVM to evaluate them and extract actual aspects only [71]. Work done in [72] can be considered of the parallel type where they used

MaxEnt classifier to find frequent aspects and rule-based methods are used to find infrequent aspects.

Kobayashi *et al.* carried out another hybrid approach. They adopted a dictionary-based method to extract opinion words and use them to extract concepts by utilizing syntactic patterns. They used a corpus to train a classifier after that to test the relations between opinion words and related aspects [73]. Ma *et al.* introduced another hybrid approach combining unsupervised LDA and lexicon-based approaches for aspect extraction from reviews. Their approach was to construct a set of potential aspects using LDA then expand the list using the lexicon [74].

D. SUBJECTIVITY DETECTION

The target of subjectivity detection is to automatically divide the text into either subjective (opinionated) or objective (neutral). Subjectivity detection is of great benefit in finding the response of people towards different events, which is useful to analysts in the fields of politics, commerce, and government [75]. Linguistic pre-processing could be utilized to determine emphatic sentences and exclude sentences that are just thoughts and accordingly do not have any sentiments [76]. This could be notably useful in systems that should sum up disparate opinions to produce multiple answers to users depending on opinions extracted from various sources (Question-Answering summarization systems).

Earlier methods employed general subjectivity clues to producing training data from un-annotated text [77]. Furthermore, some features like adverbs, modals, and pronouns, proved to be useful in subjectivity classification. Many currently existing resources have lists of subjective words, and some NLP empirical methods automatically determined adjectives, verbs, and N-grams that are correlated with subjective language.

Two problems associated with this method are: 1) Many subjective words rarely occur such as ‘outwardly’ which means that a huge training dataset is needed to produce an extensive and comprehensive subjectivity detection system. 2) Short comments generated in micro-blogging require a better way to capture sentiments from them. To this end, Wiebe and Riloff employed extraction pattern learning to produce linguistic structures automatically that represent subjective expressions. The features obtained were utilized to train the most recent classifiers such as SVM which consider that each feature’s class is independent of the class of other features [78].

E. TOPIC SPOTTING

Topic spotting objective is to put opinions into the context of a specific topic. Topic spotting is the process of tagging some text with category labels, it is also known as auto-categorization. Topic spotting when handling a large corpus, it does not target clustering words into a group of topics, it rather aims to give the input text a context. It is more like short text conceptualization. For example, this statement ‘‘Red Devils rule’’ when taken as a whole after a football match, obviously means that a certain football team has won, but taken as separate words would give unrelated results. Similarly, in a bag-of-words model, the word ‘‘cooked’’ in a political context would not give the meaning of some sort of cheat and negative sentiment.

Certainly, the ability to put words into the right concept is a purely human trait. The focus here is how to guess concepts from texts or words. As an example, the word ‘‘Egypt’’ would invoke in a person’s mind the concept of a country. Given two words, ‘‘Egypt’’ and ‘‘Sudan’’ the main concepts might alter to African countries or River Nile. Adding another word, ‘‘Somalia’’, the top concept might change to Arabic Countries or East Africa, and so on. Other than generalizing from a term to a concept, humans also build concepts from descriptions. For example, ‘Blackberry’ and ‘mobile’’ would be conceptualized to a company, but ‘Blackberry’, ‘cupcake’ and ‘taste’ conceptualized to a fruit.

The problem is whether machines can do this or not. A lot of research has been dedicated to the discovery of topics from text. Many approaches have been produced but they were only able to classify short text through several limited, predefined, and general topics. To correctly find topics from short text, a concept-based approach must be utilized. Lately, Wang *et al.* produced a framework that can classify short text into general categories. Their method depends on a bag-of-concept model and a wide range of taxonomy. It first detects the concept model for each category and then assigns short text to a number of related concepts [79].

F. POLARITY DETECTION

The most famous task of SA is polarity detection. The terms ‘‘polarity detection’’ and ‘‘sentiment analysis’’ are used interchangeably in several research papers. This has resulted from the definition of sentiment analysis as the NLP process of deciding the polarity of text is positive or negative [80]. This process encompasses many other tasks that should be considered to correctly determine the polarity of an opinion target -or even several opinion targets- in an informal text. The current approaches to detect the polarity of text can be classified into four leading approaches: keyword spotting, lexical affinity, statistical methods, and concept-level approaches [81].

Concept-based approaches use web ontologies or semantic networks to perform semantic analysis of text, which enables the acquisition of the conceptual and effective information that is included in natural language opinions. Through using large semantic knowledge bases, these approaches depend on the latent meaning or features included in natural language concepts and are far from blindly using keywords and word co-occurrence count.

G. CONCEPT EXTRACTION

Many papers tackled the problem of concept extraction using different methods and a variety of semantic commonsense knowledge bases.

Mouriño-García *et al.* [82] mentioned three approaches for extracting concepts and build bag-of-concepts text representation. The first approach uses Latent Semantic Analysis (LSA) to define each concept as a vector denoting the frequency of each term in the context. Although this approach is capable to handle synonymy, it cannot address polysemy. The second approach uses Explicit Semantic Analysis (ESA), external knowledge bases are utilized to annotate documents and map concepts. A clear weakness of this approach is the generation of outliers, which are irrelevant concepts. Mouriño-García *et al.* used a third approach that employs Support Vector Machines (SVM).

The main idea of this approach is to use a semantic annotator to extract concepts from a text document and map them to an external knowledge base, assign weights, and handle disambiguation. According to Mouriño-García *et al.*, their approach was able to handle synonymy and polysemy but the quality of results is dependent on the features of the corpora that determine the performance of the semantic annotator [82].

Cambria and Hussain [83] introduced an algorithm to extract concepts through splitting text into clauses, apply linguistic rules, then extract concepts and construct bags of concepts. They considered verb chunks and noun chunks and used the POS bigram algorithm to extract object concepts and event concepts. They utilized external knowledge bases as a source for multi-word expressions to find event concepts.

Rajagopal *et al.* used a similar approach to [83] except in some details such as using a stemming algorithm to normalize verb chunks instead of lemmatization. They were able to extract concepts not included in knowledge bases through exploiting semantic similarity detection techniques [84].

Kim *et al.* proposed a method to create a bag of concepts representation through clustering semantically similar words generated from word2vec. They applied concept frequency-inverse document frequency to get relative weight for extracted concepts and create document vectors [85].

Agarwal *et al.* considered concepts as semantic features; they introduced a concept extraction algorithm that utilizes semantic relationships between terms in a text document to extract complex concepts as semantic features. Then, they retrieved additional related semantic information from the ConceptNet lexicon. Important concepts are selected and redundant concepts are eliminated using the feature selection technique Minimum Redundancy and Maximum Relevance (mRMR). They used the machine-learning method for sentiment classification, utilizing extracted concepts for the training model [86].

Chung *et al.* [87] followed a graph-based approach to extract concepts from a text document and represent it with bags of concepts. They used the SentiConceptNet dictionary to extract sentimental concepts. SentiConceptNet is a concept-based dictionary with embedded sentiments. It is built through utilizing ConceptNet5, ANEW, and SenticNet to extract concepts and assign sentiment values; they adopted a basic rule stating that concepts with related semantics share similar sentiments. At the time of writing their paper, SentiConceptNet was incorporating around 265 thousand concepts with their assigned sentiments.

Poria *et al.* tried to utilize more than a research field and resource to overcome the limitations of the bag-of-concepts model. Limitations include the high dependency on the quality and quantity of knowledge bases content, in addition to losing information structure, which is important to understand the sentiments conveyed in the text document. The authors utilized machine learning, linguistics, and common-sense computing to understand the dependency relations between concepts that provide a better understanding of the contextual role of each concept [88].

Wang *et al.* introduced a novel framework; they called it bag-of-concepts for lightweight short-text oriented classification applications. The framework builds a concept model per class. They used the Probase knowledge base to map terms and expressions from the text document to relevant concepts. They used their framework for short text classification and ranking that is fit to be used with small online applications [79].

Song *et al.* introduced a probabilistic method composed of knowledge base layer and inferencing techniques layer using Bayesian mechanism on top of it to extract concepts from the text. They found that their method outperforms statistical methods and other methods that utilize knowledge bases only in extracting concepts from a short text. They used the Probase knowledge base because it provides instances and attributes related to each concept, also it contains weights for all nodes and their relationships, these weights are important for hired inferencing techniques. Song *et al.* developed a model to cluster short pieces of text using K-means and extract the most probable concepts based on identified related instances or attributes from the underlying text. They faced many challenges such as when instances and attributes cannot be separated, they handled this problem using generative and discriminative models with different assumptions about the term being an instance and attribute of the same concept or the term is an instance or an attribute of the target concept. Another challenge, when a collection of terms represents different classes of unconnected concepts, this problem has been addressed using a bipartite graph, they conduct a co-clustering of concepts and terms to identify candidate classes based on heuristic rules to rank the concepts [8].

This study introduces a solution to overcome the limitations in existing SA frameworks which would lead to a noticeable enhancement in sentiment analysis results. The proposed TBoC method is designed in a way to overcome existing limitations in SA frameworks, it encompasses a transformation process that reforms imperfect text to achieve a good understanding of all messages conveyed in the text. TBoC method analyze and decompose text to uncover latent sentiments while preserving all relations and vital information to boost the accuracy of SA. The text is split into small groups of BoCs, each group contains an opinion target, opinion words, assigned categories, and other important information. These context-aware BoCs can be used efficiently to identify the sentiment at different levels.

III. SEMANTIC CONCEPTUALIZATION MODEL USING TAGGED BAG OF CONCEPTS

Tagged BoCs is a way to identify all concepts along with their important information, store them in a form of small groups, and feed each group to a polarity detection task. Tagged BoCs support the identification of opinion targets, related aspects, opinion concepts, and assign categories for processing on different SA levels. Sentiment Classification would give results that are more accurate because the inputs are comprehensive, clear, and specific. TBoC is designed to solve the issue of extracting concepts from the underlying text while preserving all relations and information to achieve accurate SA results.

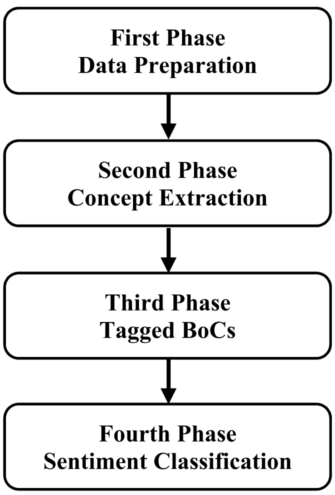

FIGURE 1. The proposed semantic conceptualization model using tagged bag-of-concepts for sentiment analysis. The model comprises four phases, the first phase is for data collection and pre-processing, concepts are extracted using semantic knowledgebase in the second phase, text documents are deconstructed into TBoC using NLP and supervised techniques in the third phase, and the last phase contains sentiment classification on multiple levels.

The proposed semantic conceptualization model using tagged bag-of-concepts for sentiment analysis comprises four phases as shown in Fig. 1. The first phase is for data collection and pre-processing tasks. In the second phase, concepts are extracted from the entire text without split the text into chunks; an algorithm has been developed to perform this step using a semantic knowledge base to retain all direct and indirect, apparent, and hidden relations between concepts.

NLP and supervised techniques are utilized in the third phase to deconstruct documents into tagged bag-of-concepts by applying aspect and category extraction, topic spotting, and subjectivity detection techniques. The approach used to group related concepts in detached bag-of-concepts is to process the constructed concept structure. The process searches the concepts structure to identify aspects (opinion targets). Each aspect represents the core of one bag-of-concepts. Then, related concepts are discovered and associated with the identified aspect in detached bag-of-concepts under one topic. The fourth phase encompasses sentiment classification tasks.

Fig. 2 shows the implementation and evaluation process of the semantic conceptualization model using the TBoC method for sentiment analysis. The process starts with the data pre-processing step, in which data cleansing and text transformation tasks are performed. Concept extraction and aspect extraction functions are then applied to the text data.

A customized algorithm is used to extract concepts from a semantic knowledge base and construct bag-of-concepts, while the supervised BiLSTM-CNNs-CRF method is used for aspect extraction. An aspect list is then created by mapping the extracted aspects to the bag-of-concepts, a filtering process is carried out using a semantic knowledge base to build the aspect list. After identifying aspects from the bag-of-concepts, the remaining concepts are classified into subjective and objective concepts. Sentiment lexicon is used for subjectivity detection task to perform this step. The next step is to assign opinionated concepts to related aspects using the sentence tokenization method, objective concepts are assigned in the TBoC implementation process to related concepts as well to support various text analysis methods. Next, aspect-categories are extracted using a rule-based model that utilizes a semantic knowledge base and employs concept interrelations.

The last step of building the TBoC structure is topic spotting which is carried out using the LDA method. As the process of building TBoC is completed, a JSON file is created to hold the new structure that guarantees human-readable and efficient media for further text processing tasks. Sentiment classification using TBoC is examined on four levels; document-level, aspect-level, category-level, and topic-level.

The process of constructing tagged BoCs from text data can be illustrated in the following steps:

1. Prepare Input data for processing
2. Extract Concepts
3. Deconstruct the text into bag-of-concepts
4. Build a structure of interlinked concepts
5. Identify opinion targets (aspects) from the structured BoCs
6. Associate concepts to related opinion targets
7. Group each opinion target and related concepts in an independent bag-of-concept
8. Identify opinions (subjective concepts) that reflect implicit or explicit sentiment towards opinion targets in each BoC
9. Tag each BoC with proper topic and category
10. Group tagged BoCs in a multi-level structure based on their categories
11. Group tagged BoCs under same topics for further analysis

The details of each task are explained in the following subsections.

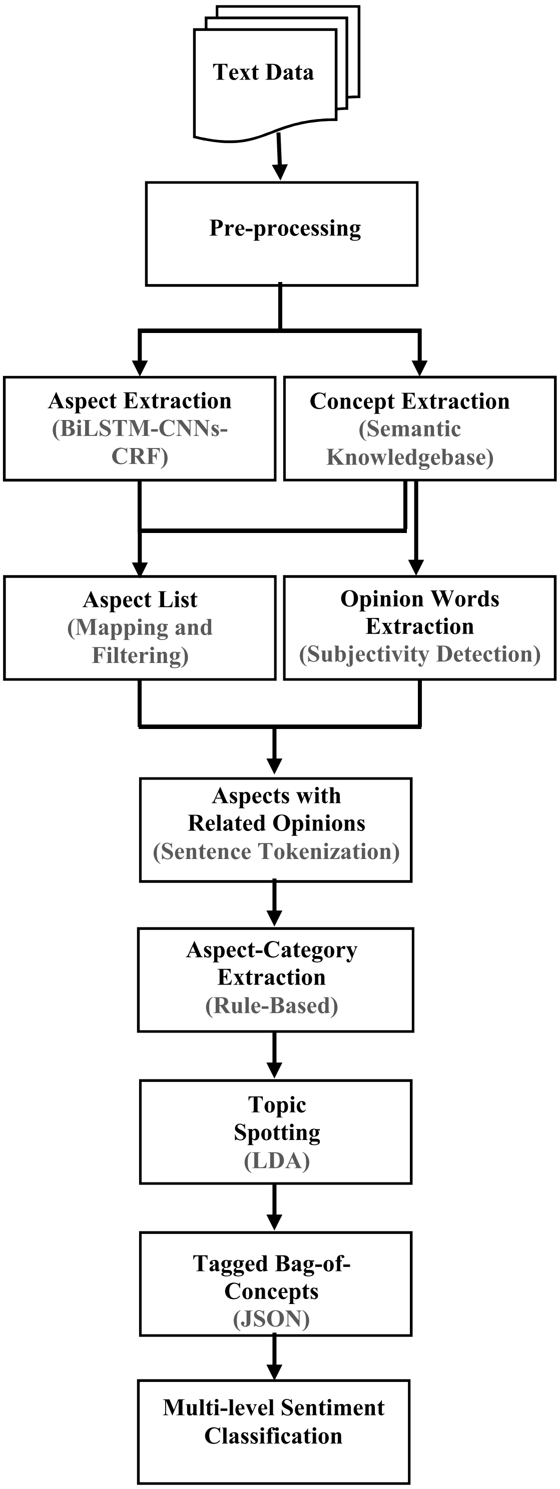

FIGURE 2. The implementation process of semantic conceptualization model using TBoC method for sentiment analysis. The implementation and testing process includes data pre-processing, extract concepts, discover interrelations, decompose data into its basic components, identify opinion targets and opinion concepts, and then restructure them into bags-of-concepts form, finally tagging the bags with important information; these tags are very efficient generally in text analysis and specifically in sentiment analysis. Testing is done on four levels including document-level, aspect-level, category-level, and topic-level.

A. DATA PRE-PROCESSING

Following commonly used pre-processing techniques for sentiment analysis are utilized:

- Basic data cleaning (remove non-ascii chars, remove break-line, remove duplicated white spaces)
- Remove URLs & user mention
- Remove punctuation
- Remove numbers
- Spelling correction
- Replace abbreviations & acronyms
- Negation handling
- Handle repetitions of punctuation
- Handle capitalized words
- Replace elongated words
- Remove stop-words

B. CONCEPT EXTRACTION

A customized algorithm was developed to extract concepts from ConceptNet. The unit of processing for the algorithm is the entire document in which it is handled as an array of words [89]. The method uses the graph-structured knowledge in ConceptNet to extract concepts. Fig. 3 shows the pseudo-code of the concept extraction algorithm. Starting with the first three words, they are checked to find the valiant concept in ConceptNet. If found, it is added to an array of concepts, and then the next three words are checked. If not found, then the first two words are checked in ConceptNet. If found, the concept is added to the array of concepts, and three words starting from the third word are checked in ConceptNet. If not found, then the only first word is checked.

The concept is added to the array of concepts if found, otherwise, it is ignored and three words starting from the second

```
Input Data: Restaurant Review Documents
Result: Valid Concepts
For each document do
  Initialize ConceptArray as array
  Initialize b as length of document
  Initial i = 1
  While i less than b
    Check b[i-1] and b[i] in ConceptNet
    If found
     Increase i with two
     Append in ConceptArray
    Else
      Check b[i-1] in ConceptNet
      If found
        Increase i with one
        Append in ConceptArray
      Else
        Increase i with one
      End if
    End if
  End
End for
```

FIGURE 3. Pseudo-Code of algorithm 1: Concept extraction from short text using the graph-structured knowledge of ConceptNet knowledge base.

word are checked in ConceptNet. The loop continues until all words in the document are processed.

However, it has been found that it is more practical to start the initial check with only two words because it is very rare to find a three-words-concept, also computational wise it is more cost-effective to check two times from ConceptNet instead of three times. Hence, the final version of our algorithm is checking only for the two-words-concept and the one-word-concept.

C. ASPECT EXTRACTION

According to Yadav and Vishwakarma, the LSTM model provides better results when applied to sentiment analysis subtasks compared to other models [90]. The BiLSTM-CNNs-CRF method is used for aspect extraction. This method is based on aspect extraction methods introduced by Poria *et al.* [91] and Ma and Hovy [92]. Authors in [91] used a window of five words consists of a target word plus two pre words and two post words. They used this window for each word in a sentence to build its feature vector and fed it to CNN. Network architecture had one input layer, first convolution layer comprised of hundred feature maps with filter size two, second convolution layer comprised of 50 feature maps with filter size 3, and max-pool layers with pool size two after each convolution layer. The non-linear hyperbolic tangent function was used to compute the output of convolution layers. Whereas Ma *et al.* built their NN model by providing output vectors of bi-directional long-short term memory (BiLSTM) to a conditional random fields (CRF) layer to decode the best label sequence. CNN was used to compute the character representation for each word, and then concatenate it with word embedding and fed them into the BiLSTM network [92].

```
Input Data: Restaurant Review Documents, List of aspects and bag-of-
concepts
Result: Dictionary of aspects with their related subjective and
objective concepts
Split the document into sentences
For each sentence
      Extract all aspects using List of aspects and bag-of-concepts
      If aspect exists
            If more than one aspect exist
                  Split sentence into multiple sentences based on
                  number of aspects and conjunctions
            End if
            Extract existing concepts from sentence using bag-of-
            concepts
            For each extracted concept
                  Detect polarity and weight using sentiment lexicon
            End for
            Add aspects with their related subjective and objective
            concepts into dictionary
      End if
End for
```

FIGURE 4. Pseudo-Code of algorithm 2: Assigning subjective and objective concepts to aspects using sentence tokenization technique. Each sentence is split into multiple sentences based on the number of aspects and conjunctions.

D. OPINION WORDS EXTRACTION AND ASSIGNING TO ASPECTS (OPINION TARGETS)

After completing the aspect extraction step, a mapping task is performed to match extracted aspects with bag-of-concepts that have been constructed using ConceptNet.

Each document is split into sentences using the NLTK sentence tokenization library. Each sentence must have only one aspect, if a sentence contained more than one aspect then the sentence is split into multiple sentences based on the number of aspects and conjunctions. Finally, sentiment lexicons are used for subjectivity detection before assigning subjective and objective concepts to each aspect. Fig. 4 presents the pseudocode of assigning subjective and objective concepts to each aspect.

E. RULE-BASED METHOD FOR ASPECT-CATEGORY EXTRACTION USING SEMANTIC KNOWLEDGE BASE

The method consists of two phases. The first phase uses the graph-structured knowledge in ConceptNet to extract concepts, extracts fine-grained aspects by utilizing the supervised BiLSTM-CNNs-CRF based approach, and map identified aspects to extracted concepts. Then in the second phase, aspect-categories are identified using a customized algorithm. The algorithm mine a semantic knowledge base to generate association rules and use them to group similar aspects and assign them to their categories. It also exploits ConceptNet labeled edges heavily and employs specific relations to extract aspect categories using a rule-based model. The pseudo-code of the aspect-category extraction algorithm is shown in Fig. 5.

Relation types "IsA" and "PartOf" are employed with their assigned weights. The first step is searching all existing categories using the "IsA" relation and sort them by weights. If the aspect does not have an "IsA" relation then all existing categories are retrieved using the "PartOf" relation and sort them by weights.

If the aspect does not have neither "IsA" nor "PartOf" relations then the aspect itself is considered as the category.

For Aspects that share the same categories, below heuristic rules are used:

Rule#1: Only categories with the highest number of aspects are considered, i.e. if two categories contain the same aspects and one of them contains additional aspects then the category with the least number of aspects is ignored.

Rule#2: If an aspect is shared between two categories with different aspects, then both categories are considered.

Example:

- Animal (Cat, Dog, Elephant, Lion)
- Pet (Cat, Dog)
- Carnivore (Lion, Puma)
- Insect (Ant)

Only categories (Animal, Carnivore, and Insect) are considered and category (Pet) is eliminated. It is important to mention that in that case the sentiment of Lion is considered two times for both (Animal) and (Carnivore) categories.

```
Input Data: List of aspects
Result: List of aspect categories
Initialize b as length of aspects list
Initial i = 1
 While i less than b
  Check aspect[i-1] in ConceptNet
  If aspect has "is a" category
   Return selected aspect and its categories
    For each other aspect in aspects list
     Compare "is a" categories of aspect[i-1] to "is a" categories
     of other aspect
    If match found
     Add aspect[i-1] and category to IsAList
     Increase i with one
    Else if match not found
     Compare "is a" categories of aspect[i-1] to "part of"
     categories of other aspect
     If match found
      Add aspect[i-1] and category to IsAList
      Increase i with one
     Else if match not found
     Compare "part of" categories of aspect[i-1] to "is a"
     categories of other aspect
      If match found
       Add aspect[i-1] and category to PartOfList
       Increase i with one
      Else if match not found
       Compare "part of" categories of aspect[i-1] to "part of"
       categories of other aspect
       If match found
        Add aspect[i-1] and category to PartOfList
        Increase i with one
```

```
       Else if match not found
        Add aspect[i-1] and category with highest weight to
        IsAList
        Increase i with one
       End if
      End if
     End if
    End if
   End for
  Else if aspect does not has "is a" category
   Check "Part of" category
   If found
   Return selected aspect and its categories
    For each other aspect in aspects list
     Compare "part of" categories of aspect[i-1] to "is a"
     categories of other aspect
     If match found
      Add aspect[i-1] and category to PartOfList
      Increase i with one
     Else if match not found
      Compare "part of" categories of aspect[i-1] to "part of"
      categories of other aspect
      If match found
       Add aspect[i-1] and category to PartOfList
       Increase i with one
      Else if match not found
       Add aspect[i-1] and category with highest weight to
       PartOfList
       Increase i with one
      End if
     End if
    End for
   Else if not found
    Add aspect[i-1] as category to IsAList
    Increase i with one
   End if
 End
```

FIGURE 5. **Pseudo-Code of algorithm 3: Aspect-category extraction using ConceptNet semantic knowledge base. The algorithm generates association rules to identify categories of similar groups of aspects.**

Rule#3: If category C1 contains category C2, then it should contain all aspects included in C2.

Example:

- Man (Man, Woman, Boy, Father)
- Person (Man, Woman, Person, Sister)

Since (Person) category includes (Man) category, then (Person) Category only is considered and (Man) category is ignored, (Person) category is amended to contain all aspects in both categories:

- Person (Man, Woman, Person, Sister, Boy, Father)

Rule#4: If an aspect does not have any shared category with other aspects, then return the ''IsA'' relation with the highest weight. If the ''IsA'' relation does not exist, then return the ''PartOf'' relation with the highest weight. If the ''PartOf'' relation does not exist, return aspect as the category.

F. IDENTIFY ASPECT-RELATED TOPICS

We employed Latent Dirichlet Allocation (LDA) to identify aspect-related topics. LDA is a known and simple unsupervised method for topic modeling that can identify the latent topics [93]. However, LDA has many limitations such as, it cannot learn the semantic structure of the documents and generate noisy topics when applied to short text. Ali *et al.* employed ontology-based semantic knowledge to overcome the limitations of LDA and obtains proper topics [28].

G. TAGGED BAG-OF-CONCEPTS JSON FILE

The JSON file is the primary and most important product that is showing the tagged bag-of-concepts details. The JSON file contains processed and organized data in the TBoC format to perform sentiment analysis on multiple levels and make statistical analysis on the underlying dataset.

The structure is organized as follows:

{
''Aspect'': {
''Polarity'': P1,
''Topic'': ''T1'',
''Objective concept'': [
''O1'', ''O2'' . . . Om],
''Subjective concept'': [
''S1'': Polarity, ''S2'': Polarity . . . Sn],
''Category'': ''C1'', ''C2'' . . . Ct}
}

H. DOMAIN-SPECIFIC SENTIMENT LEXICON

A subjectivity lexicon has been built to overcome the weaknesses of SentiWordNet:

- SentiWordNet is a general-purpose lexicon; it cannot detect domain-related sentiments.
- It links emotions to words rather than concepts and consequently not providing the ability to differentiate between different meanings of the same word.
- It cannot discover the implicit sentiment that is associated with the semantics and context of words.

Domain-specific sentiment lexicon was built using the corpus-based approach. Semantic methods along with the statistical methods were used to assign polarities to extracted concepts. SentiWordNet was utilized to obtain a list of subjective terms and provide similar sentiment polarities to semantically close concepts. Lexical rules were also applied such as negation and intensifiers in the calculation of the average polarity strength.

I. FEATURE SELECTION

The objective of feature selection is to discover and select influential features and exclude irrelevant words or terms. Following feature selection methods are employed in the model:

- Finding Opinion words and phrases
- Negation handling
- Stop-words removal
- Concept extraction (Conceptualization)

IV. EXPERIMENT

The objective of the experiment is to investigate the efficiency of semantic conceptualization using the tagged BoC method and its effect on the performance of sentiment analysis.

A comparative study was conducted with the state-of-the-art SA framework to analyze results, and come out with improvement rates and answer research questions.

Two datasets from SemEval have been utilized for the experiment. A concept extraction algorithm has been applied using ConceptNet5 to extract concepts from the text. SentiWordNet generic sentiment lexicon and domain-specific sentiment lexicon were used for polarity detection. Different methods with customized algorithms were applied to extract aspects, related opinions, identify aspect categories, and assign aspects to proper topics. Aspects were extracted by utilizing a supervised BiLSTM-CNNs-CRF based approach. A developed algorithm is used to mine a semantic knowledge base to generate association rules and use them to group similar aspects and assign them to their categories, it exploited ConceptNet labeled edges heavily and employed specific relations to extract aspect categories using a rule-based model. Another method has been implemented to extract concepts and map them to identified aspects using the graph-structured knowledge in ConceptNet. Topics were identified using the LDA method. The text was reconstructed in small bags-of-concepts and tags were applied to them. The new structure of TBoCs was generated in JSON form. Sentiment classification using the TBoC method was examined on document-level, aspect-level, category-level, and topic-level. Sentiment analysis was done for aspects and aspect categories on the entire dataset as well.

A. DATASET

The experiment was conducted on two datasets from SemEval 2014 and SemEval 2016. Both datasets are from the restaurant domain, they have been restructured and consolidated in a unified dataset. The employed dataset from SemEval 2014 is a modified version by Tang et al, they worked on the dataset to keep it balanced and removed conflict category, where the same sentence contains both negative and positive opinions towards the same aspect [94].

Dataset from subtask 2 of SemEval 2016 is for text-level aspect-based sentiment analysis (ABSA). This task was introduced for the first time in SemEval 2016. The dataset was organized in the following format {Category: ''Entity#Attribute'', Polarity} [95]. The details of the consolidated dataset are depicted in Table 1.

B. SEMANTIC KNOWLEDGE BASES

ConceptNet5 was used for concept extraction and SentiWordNet 3.0 was used in this experiment for polarity extraction. ConceptNet5 knowledge base contains a considerable semantic graph, which depicts human knowledge representation in natural language. ConceptNet comprises many human languages. It provides rich information about embedded words and phrases including definition, lexical relationships, and common-sense associations [96].

SentiWordNet 3.0 was made specifically for research purposes and to support sentiment classification and opinion mining tasks, it was developed by automatically annotating all WordNet 3.0 Synsets based on their level of positivity, negativity, and neutrality. A semi-supervised learning algorithm is used for automatically annotating WordNet with a random-walk task for refining the scores [97].

C. SENTIMENT CLASSIFICATION METHODS

Sentiment classification was done using state-of-the-art methods NB, SVM, and NN. Results were compared against the TBoC method and their efficiency has been evaluated using evaluation metrics.

TBoC method has been implemented using two approaches. First approach TBoC (SWN) utilized generic sentiment lexicon SentiWordNet for polarity detection and second approach TBoC (DSL) utilized domain-specific sentiment lexicon for polarity detection.

1) NEURAL NETWORK (NN)

The method consists of a simple neural network model, which has an input layer that gets numerical representation of words, a hidden layer with 100 nodes, and an output layer. Most of the calculations happen in the hidden layer, every node of the hidden layer has a rectified linear unit (ReLU) activation function that takes an input from the input layer, makes some calculations, and based on the threshold, it passes a value to the output layer. The activation function of the output layer is the sigmoid function, which produces output values between zero and one, based on hidden layer output. Following hyper parameters were used in the experiment:

- Cost function: Cross-entropy
- Optimization function: Adam
- Epochs: 4 (tried to train it on 20 and 12 epochs but got a lower accuracy)
- Metrics: accuracy

2) SUPPORT VECTOR MACHINES (SVM)

SVM is one of the best learning methods that usually shows good results with sentiment classification. SVM is suitable for short-text analysis and its performance increases with concept-based SA. Following parameters were used in the experiment:

- Gamma: 0.01
- Regularization parameter C:100
- kernel: 'linear'

3) NAIVE BAYES (NB)

NB is one of the probabilistic classifiers' family. NB's main advantage is that it does not require a big amount of training data to provide proper estimates. It can be tremendously fast compared to other sophisticated classification methods. Default parameters from the Scikit-learn library were used in the experiment.

D. EVALUATION

Four evaluation metrics were used in this experiment, recall, precision, F-measure, and accuracy. Recall and precision rates are the standard and popular evaluation methods that are used with SA models to measure the quality of the classification process. Using the recall and precision rates, we can assert that a classification method is more accurate than another classification method if it proves to have recall and precision rates, which are notably higher. Therefore, to compare two classification methods we need to calculate these rates. The recall rate defines if the retrieval is complete. It is defined as the number of true positives (TPs) i.e. terms that the process has classified correctly against the number of the positive examples encompassing the false negatives (FNs) that the process did not retrieve i.e. the terms that have been classified in the negative classes falsely.

On the other hand, precision rate defines the definite accuracy of the classification, and it could be defined as the number of the true positives (TPs) available against the number of true positives (TPs) and false positives (FPs) i.e. the terms that are classified wrongly in the positive class. F-measure uses both the recall and precision rates in one equation, $\propto$ defines the way precision and recall are weighted. $\propto = 1$ in the case recall and precision are evenly distributed. However, in this experiment precision rates, recall rates, and F-measure values were calculated with respect to both positive and negative classes in addition to average accuracy for each method. The following equations (1 - 7) show the calculation of each evaluation metric.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

Positive Class:

$$Recall\ Rate\ (Sensitivity) = \left(\frac{TP}{TP + FN}\right) \times 100\% \tag{2}$$

$$Precision\ Rate = \left(\frac{TP}{TP + FP}\right) \times 100\% \tag{3}$$

$$\mathrm{F} = (1 + \propto) \times \frac{PrecisionPos * RecallPos}{\propto *PrecitionPos + RecallPos} \tag{4}$$

Negative Class:

$$Recall\ Rate\ (Specificity) = \left(\frac{TN}{TN + FP}\right) \times 100\% \tag{5}$$

$$Precision\ Rate = \left(\frac{TN}{TN + FN}\right) \times 100\% \tag{6}$$

$$\mathrm{F} = (1 + \propto) \times \frac{PrecisionNeg * RecallNeg}{\propto *PrecitionNeg + RecallNeg} \tag{7}$$

V. RESULTS AND DISCUSSION

Table 1 shows important counts of the dataset that help in the investigation of the intercorrelations between data components and explanations of experiment results:

- Number of train documents used in the experiment
- Number of test documents
- Number of words in test documents before pre-processing
- Number of words after pre-processing
- Number of concepts
- Number of aspects
- Number of opinions (subjective concepts)
- Number of categories

While train documents were used with machine learning methods only, test documents were used with both machine learning and lexicon-based methods. Train documents were split into 677 negative and 1223 positive. Test documents were split into 172 negative and 256 positive.

The number of concepts represents the count of unique concepts after removing all duplicates, since the same concepts may appear many times in different documents or in the same document.

As shown in the table, one document may contain more than one aspect. The number of categories is greater than the number of aspects because the count here represents unique aspects and the same aspect can have more than one category in different documents. For example, aspect chicken may have category soup in one document if accompanied with aspects tomato and lentil, while it has category salad if accompanied with green salad, and category meal if accompanied with meat and fish in another document. The number of opinions is the number of subjective concepts that hold a sentiment towards a specific opinion target (aspect).

As illustrated in Fig. 6 the first primary product of the experiment is the JSON file that includes a complete structure of tagged bag-of-concepts for the underlying datasets. This structure was the base for all successive steps of sentiment analysis on multi-levels including document, aspect, topic, and category levels.

TABLE 1. Counts of dataset documents, words, concepts, aspects, opinions, and categories.

Input Text	Count
Number of train documents	1,900
Number of test documents	428
Number of words in test documents	13,511
Number of words after pre-processing	13,200
Number of concepts	6,428
Number of aspects	736
Number of opinions	1,117
Number of categories	951

Fig. 6 shows JSON file structure with multiple layers of TBoC and two examples of the output.

Each tagged bag-of-concept has one aspect, one topic, and one category on document-level. However, on the dataset-level, it may contain multiple topics and categories as illustrated in the second example. Aspect "sauce" has two categories "food" and "condiment" since it appeared in more than one document with other aspects that belong to these two categories.

Following are experiment results and a discussion about each result. The semantic conceptualization model using the TBoC method has been evaluated against state-of-the-art machine learning and deep learning methods NB, SVM, and NN. Weighted average rates were used to consider the ratio of positive and negative values in the dataset. TBoC is represented in result tables in two records, first record TBoC (SWN) refers to the lexicon-based approach using generic sentiment lexicon SentiWordNet for polarity detection and the second record TBoC (DSL) refers to lexicon-based approach using domain-specific sentiment lexicon for polarity detection. Table 2 presents the confusion matrix for document-level sentiment analysis using lexicon-based TBoC (SWN), TBoC (DSL), NB, SVM, and NN methods.

TBoC performed comparably to state-of-the-art NN and ML methods. However, NB performed slightly better, and SVM was slightly worse than other methods. While NB's ability to predict positive documents was the best, TBoC (DSL) was the best in detecting negative documents. TBoC (DSL) performed substantially better than TBoC (SWN), which indicates that the efficiency of lexicons used for concept and polarity extraction is a key performance factor. The higher the efficiency of the lexicons, the more competitive is TBoC compared to state-of-the-art methods. The evaluation of classification methods is shown in Table 3 for document-level sentiment analysis.

NB and NN produced the best accuracy results; however, TBoC (DSL) showed close results to them. SVM performance was the worst among all methods. The recall rate for NB and NN only exceeds 75% and NB showed the best precision rate of 77%. Prediction of negative documents was a challenge for all methods, yet it showed the strength of TBoC (DSL). F-measure of positive documents was much better

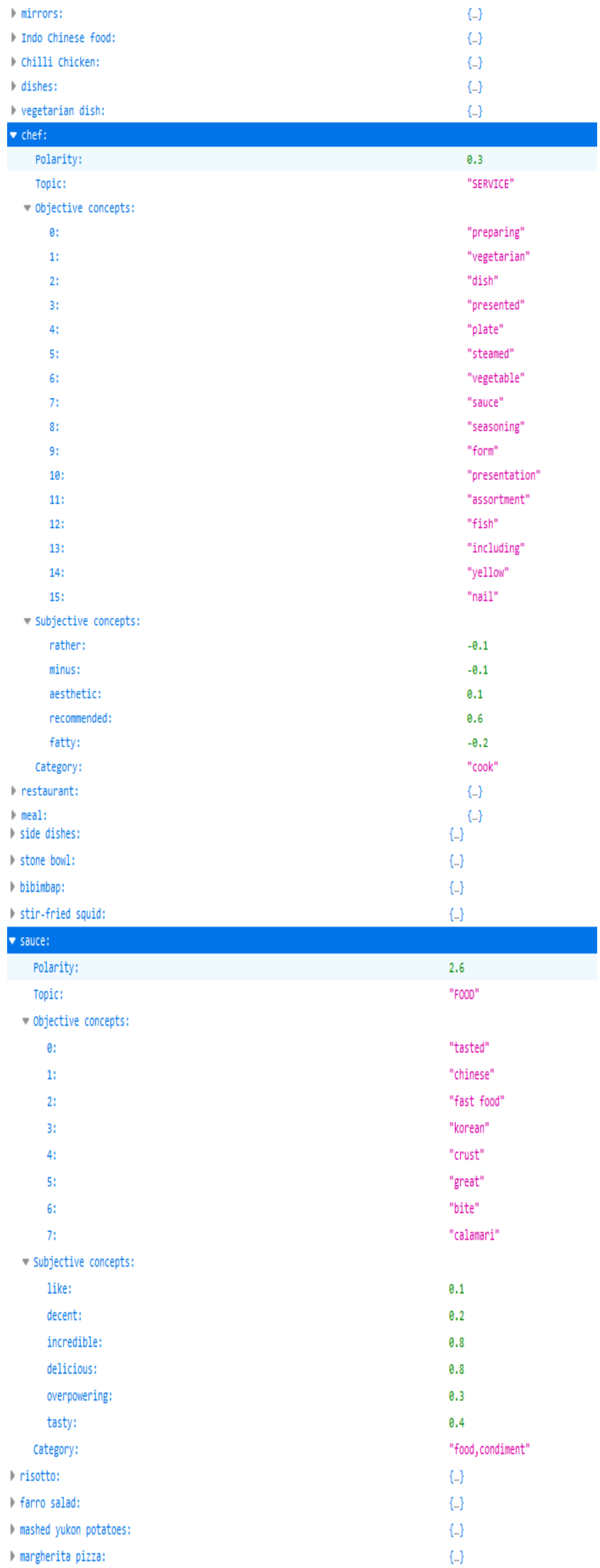

FIGURE 6. Two examples of the output in JSON format. The examples show the interlinked structure that consists of multiple layers of TBoC. This form can be used for efficient multi-level sentiment analysis and various text analysis tasks.

TABLE 2. Confusion matrix for document-level SA.

	TP	FP	TN	FN
NB	230	76	96	26
SVM	205	79	93	51
NN	209	56	116	47
TBoC (SWN)	205	75	97	51
TBoC (DSL)	197	54	118	59

than F-measure of negative documents for all classification methods. F-measure is a good general measure because it combines both recall and precision rates. This means that the ability of all methods to predict positive reviews is much better than their ability to predict negative reviews. Many reasons could cause this problem including the excess use of irony and comparisons.

Table 4 presents the confusion matrix for aspect-level sentiment analysis using lexicon-based TBoC (SWN), TBoC (DSL), NB, SVM, and NN methods.

Obviously, TBoC outperformed other state-of-the-art methods and showed its capability with aspect-level sentiment classification. While deep learning and machine learning methods were suffering from a lack of sufficient data for proper training, TBoC was able to achieve good results with relatively small sets of data. This was always a major challenge with short text micro-blogging analysis. State-of-the-art ML methods may be able to overcome the problem of limited data on document-level SA because there is quite an adequate number of subjective concepts included in each document but they are having limited capabilities when it comes to a very limited number of opinions associated with each aspect. Both approaches of TBoC using SentiWordNet generic sentiment lexicon and domain-specific sentiment lexicon performed much better than other methods with respect to predicting positive aspects, while NB and NN performed better than TBoC in predicting negative aspects.

TABLE 3. Evaluation report for document-level classification methods.

		NB	SVM	NN	TBoC (SWN)	TBoC (DSL)
Precision	Pos	0.75	0.72	0.79	0.73	0.78
	Neg	0.79	0.65	0.71	0.66	0.67
	Avg	0.77	0.69	0.76	0.70	0.74
Recall	Pos	0.90	0.80	0.82	0.80	0.77
	Neg	0.56	0.54	0.67	0.56	0.69
	Avg	0.76	0.70	0.76	0.71	0.74
F-measure	Pos	0.82	0.76	0.80	0.76	0.78
	Neg	0.65	0.59	0.69	0.61	0.68
	Avg	0.75	0.69	0.76	0.70	0.74
Accuracy	Avg	0.76	0.70	0.76	0.71	0.74

The evaluation of classification methods is shown in Table 5 for aspect-level sentiment analysis.

TABLE 4. Confusion matrix for aspect-level SA.

	TP	FP	TN	FN
NB	314	136	196	74
SVM	327	180	152	61
NN	297	127	205	91
TBoC (SWN)	483	244	92	24
TBoC (DSL)	463	196	164	38

All methods provided bad results for recall rates of negative aspects; their ability to predict negative aspects was very limited, this could be an interesting point for further research. Accuracy results of TBoC (DSL) and NB only have exceeded 70%. TBoC (DSL) was the best in all evaluation metrics. It was the only method, which exceeded 75% for average precision rate and exceeded 73% for average recall rate. TBoC (SWN) results were close to other state-of-the-art methods. These results confirmed again the good performance of the TBoC method, and that the efficiency of the utilized lexicons is a key factor in the performance of the TBoC method.

A. TOPIC DISCUSSION

We utilized six labels mentioned in the SEMEVAL dataset:

- Food, this topic is used for reviews that discuss food or aspects related to food such as menu items.
- Drinks, used for reviews expressing opinions on drinks or items related to drinks.
- Service, for reviews focusing on all aspects of staff, kitchen, reception, delivery, counter, and offers.
- Ambience, this topic was assigned to the opinions discussing the interiors or exteriors of the restaurant and the general feeling of the atmosphere.
- Location, used for any expressed opinions towards the place, the view, or the surrounding of the restaurant.
- Restaurant, this is a general topic used if the review is not addressing a specific aspect but expressing opinions on the restaurant as a whole.

TABLE 5. Evaluation report for aspect-level classification methods.

		NB	SVM	NN	TBoC (SWN)	TBoC (DSL)
Precision	Pos	0.70	0.64	0.70	0.66	0.70
	Neg	0.73	0.71	0.69	0.79	0.81
	Avg	0.71	0.68	0.70	0.72	0.75
Recall	Pos	0.81	0.84	0.77	0.95	0.92
	Neg	0.59	0.46	0.62	0.27	0.46
	Avg	0.71	0.67	0.70	0.68	0.73
F-measure	Pos	0.75	0.73	0.73	0.78	0.80
	Neg	0.65	0.56	0.65	0.41	0.58
	Avg	0.70	0.65	0.70	0.63	0.71
Accuracy	Avg	0.71	0.67	0.70	0.68	0.73

Table 6 lists the number of aspects per each topic, and the number of times each topic appeared in the dataset. Food and service topics were the most mentioned topics in the dataset, the location was the least mentioned topic. This, in turn, affected number of aspects under each topic where the highest number of aspects belong to food and service topics and only eight aspects have location topic.

TABLE 6. Counts of each topic in the dataset and aspects per each topic at dataset-level.

Topic	Topic / Dataset	Aspects / Topic
Service	121	161
Food	279	462
Drinks	40	46
Ambiance	76	97
Location	8	8
Restaurant	75	86

Table 7 presents the confusion matrix for topics on document-level sentiment classification using lexicon-based TBoC (SWN) and TBoC (DSL) methods. The polarity for each topic was aggregated by adding up aspect polarities under the same topic. Positive sentiment was assigned to the topic if positive value dominates, while negative value was assigned to the topic if negative value dominates.

TBoC (SWN) outperforms TBoC (DSL) for the prediction of positive topics, while TBoC (DSL) provides better results for predicting negative topics. The difference between the results of both methods was not that big in aspects-level sentiment classification, this difference happened mainly because of weight values of aspect polarities. Keeping in mind that the only difference between the two methods is the sentiment lexicon used for polarity detection, refining polarity weights can play a major role in enhancing the efficiency of the employed lexicon. The evaluation of topic classification is shown in Table 8 for document-level sentiment analysis.

TABLE 7. Confusion matrix for topics on document-level SC.

	TP	FP	TN	FN
TBoC (SWN)	345	167	67	12
TBoC (DSL)	243	58	189	109

Results were very interesting for TBoC (SWN), the precision rate for negative topics was 85% and the recall rate for positive topics was 97%, these results are outstanding. However, the recall rate for negative topics was 29%, which is very bad. This means that TBoC (SWN) could not predict most negative topics but it had a good ability to distinguish between topics. An important reason for these odd results is imprecise polarity values for negative subjective concepts in the generic sentiment lexicon SentiWordNet. Deep investigation in SentiWordNet showed many negative concepts that hold neutral or positive polarities in the lexicon. This drawback was rectified - to an extent - in the domain-specific sentiment lexicon. The average F-measure of TBoC (DSL) was much better than TBoC (SWN) and average accuracy was better as well.

TABLE 8. Evaluation report for topics on document-level SA.

		TBoC (SWN)	TBoC (DSL)
Precision	Pos	0.67	0.81
	Neg	0.85	0.63
	Avg	0.74	0.74
Recall	Pos	0.97	0.69
	Neg	0.29	0.77
	Avg	0.70	0.72
F-measure	Pos	0.79	0.74
	Neg	0.43	0.69
	Avg	0.65	0.72
Accuracy	Avg	0.70	0.72

Table 9 shows how easily the TBoC method can be used to evaluate the sentiment towards important topics in business or news or any domain, know what people like and dislike. Simply, JSON files have been utilized to add up polarities of all aspects on dataset-level for the entire set of reviews and categorized them by assigned topics. The same method was applied to aspects and categories to – instantly - predict their sentiment on the dataset-level.

B. CATEGORY DISCUSSION

Utilizing the same method used for document and topic polarity detection, the polarity for each aspect-category is calculated by adding up all aspect polarities under the same category. Positive sentiment is assigned to the category if positive value dominates, while a negative value is assigned to the category if negative value dominates. Table 10 presents the confusion matrix for aspect-categories on document-level sentiment analysis using the lexicon-based TBoC method.

TABLE 9. Counts of positive and negative sentiments for each topic in the dataset.

Topic	Positive	Negative
Service	83	38
Food	229	50
Drinks	31	9
Ambiance	61	15
Location	7	1
Restaurant	57	18

TBoC (SWN) produced slightly better results than TBoC (DSL) with respect to predicting positive aspect categories; however, TBoC (DSL) was much better in predicting negative aspect categories. TBoC (SWN) provided much higher false positives predictions, as explained earlier the main reason is the false assigning of positive polarities to negative and neutral terms in the generic sentiment lexicon.

The evaluation of category classification is shown in Table 11 for document-level sentiment analysis.

TABLE 10. Confusion matrix for aspect categories on document-level SA.

	TP	FP	TN	FN
TBoC (SWN)	511	304	110	22
TBoC (DSL)	493	206	215	37

TBoC (DSL) was the best by far for all metrics evaluation results except for the recall rate of positive aspect categories where TBoC (SWN) was slightly better. Both methods performed badly for recall rates of negative aspect categories. The average F-measure and average accuracy of the TBoC (DSL) method were much better than TBoC (SWN).

Interesting observations are, although the prediction of sentiments on the aspect, topic, and category levels depend on the polarities of subjective concepts assigned to each aspect, their performance is not consistent. TBoC (SWN) performed better at the topic-level than aspect-level and worst at category-level sentiment analysis, while TBoC (DSL) performed worse at the topic-level than aspect-level and best at category-level sentiment analysis. These were surprising results since all these levels are interrelated to each other. A possible reason could be because polarity weights are considered in the prediction not only numbers of positive and negative values. Hence, big and small weights could influence the overall results.

TABLE 11. Evaluation report for aspect-categories on document-level SA.

		TBoC (SWN)	TBoC (DSL)
Precision	Pos	0.63	0.71
	Neg	0.83	0.85
	Avg	0.72	0.77
Recall	Pos	0.96	0.93
	Neg	0.27	0.51
	Avg	0.66	0.74
F-measure	Pos	0.76	0.80
	Neg	0.40	0.64
	Avg	0.60	0.73
Accuracy	Avg	0.66	0.74

C. SENTIMENT ANALYSIS ON DATASET-LEVEL

Using the TBoC Json file, sentiment analysis was performed for aspects on the dataset-level. This means that sentiment prediction for aspects, aspect-categories, and topics can be performed on both levels, the document or review level and the entire dataset-level.

One aspect like ''salad'' could have negative sentiment in one review document but the overall sentiment of all customers is positive towards ''salad''. The same concept is applied on topics such as service or location, the sentiment of one topic could be positive in one review document but negative or neutral when calculated for all reviews.

VI. CONCLUSION AND FUTURE WORK

In this paper, the authors have proposed a comprehensive SA method to detect the correct sentiment towards the actual target entity that considers all affective and conceptual information conveyed in the text with a special focus on the short text. Tagged bag-of-concepts is a novel approach to analyze and decompose text to uncover latent sentiments while preserving all relations and vital information to boost the accuracy of SA. It encompasses a transformation process that reforms imperfect text to achieve a good understanding of all messages conveyed in the text.

The study has presented the implementation and evaluation of the suggested semantic conceptualization model for sentiment analysis using tagged bag-of-concepts. Two datasets from SemEval have been utilized for the experiment. A concept extraction algorithm has been developed and applied using ConceptNet5 to extract concepts from the text. SentiWordNet generic sentiment lexicon and domain-specific sentiment lexicon were used for polarity detection. Different methods with customized algorithms were applied to extract aspects, related opinions, identify aspect categories, and assign aspects to proper topics. The text was reconstructed in small bags-of-concepts and tags were applied to them. The new structure of TBoCs was generated in JSON form. Sentiment analysis was performed using the new TBoCs structure on multiple levels including document, aspect, aspect-category, and topic levels. Sentiment analysis was done for aspects, aspect-categories, and topics on the entire dataset as well. TBoC method with domain-specific sentiment lexicon showed exceptional performance and outperformed other state-of-the-art NB, SVM, and NN methods, especially for aspect-level SA. The results answered research questions and confirmed that the tagged bag-of-concepts approach enhanced SA results compared to state-of-the-art methods.

This concludes the discussion of the research objective of investigating the efficiency of TBoCs that contain information about the context, interrelations, latent feelings. In addition to the utilization of TBoC within semantic conceptualization model that leverage NLP tasks, Ontology and semantic methods, and the evaluation of the model against state-of-the-art SA methods.

However, there are many potential extensions for future research that arose from the study to enhance the functionality of the proposed model and general sentiment analysis process. Directions for future research can be grouped in the following categories:

A. ENHANCE SENTIMENT LEXICONS FOR POLARITY DETECTION

In future work, there is a large space for enhancing polarity detection using lexicons, different known lexicons were utilized in the study to retrieve the polarity of concepts but generally, results were unsatisfactory. Most of the lexical resources that were developed to perform opinion mining tasks are incomplete and noisy. It was a big challenge to retrieve accurate polarity values for many concepts. General-purpose lexicons cannot detect domain-related sentiments. They link emotions to words rather than concepts and consequently are not able to differentiate between the different meanings of the same word. In addition, they cannot discover the implicit sentiment that is associated with the semantics and context of words.

Sentiment lexicons assign fixed polarities to terms, they ignore the fact that the polarity of most of the terms and expressions is affected by the context and properties of the domain. Their performance is inconsistent across different domains. Thus, the key to building efficient sentiment lexicons is to consider analyzing the term in its context and take into account neighboring words. A recent study was done by Mowlaei *et al.* to address this problem; they introduced a combination of static and dynamic lexicons that were built using statistical methods and genetic algorithms. Their method showed good results with aspect-based polarity classification; however, improvements are still required to consider POS-tags and to locate the implicit aspects in a sentence [98].

Another direction for future research would be utilizing semantic methods along with the statistical methods and applying lexical rules such as negation and intensifiers to develop concept-based domain-specific sentiment lexicons.

There is a big chance that enhancing polarity detection using sentiment lexicons would lead to a leap in sentiment analysis using the lexicon-based approach.

B. ENHANCE SEMANTIC KNOWLEDGE BASES FOR CONCEPT MINING

Although ConceptNet5 is considered as one of the most comprehensive semantic knowledge bases that contain over 21 million edges and over 8 million nodes, its English vocabulary contains approximately 1,500,000 nodes. ConceptNet is still lacking a lot of concepts and missing important relations. In addition, existing relations still need more purification. In this study, concept extraction and aspect-category extraction challenges aroused the need for more research efforts to enhance semantic knowledge bases.

The dimensions of the employed knowledge bases affect greatly the validity of the concept-based approaches. The domain name is one of the important dimensions that is missing and should be considered and influence all edges, weights, and relations.

Another research need is to discover better dependency relationships to mine the concepts, various ontologies could be utilized to enrich the process of concept mining and enhance the process of categorizing concepts semantically. In addition, there is an obvious need to employ more semantic resources to increase the number of available common-sense concepts.

C. ENHANCE THE ABILITY TO PREDICT NEGATIVE SENTIMENTS

In the tagged bag-of-concepts experiment, results showed that the ability of all methods to predict positive sentiments is much better than their ability to predict negative sentiments. Many reasons could cause this problem including the excess use of irony and comparisons. A major challenge is how to identify the contextual polarity correctly, the challenge here is what dimensions should be used to define the contextual polarity. Using an insufficient number of dimensions will lead to inefficient results. Many problems persist such as polysemy, synonymy, entity duplication, and inconsistencies that arise from the lack of good understanding of the text. A good potential extension for future research to solve these problems could be in the area of enhancing the syntactical analysis of the text.

REFERENCES

[1] I. Maks and P. Vossen, "A lexicon model for deep sentiment analysis and opinion mining applications," *Decis. Support Syst.*, vol. 53, no. 4, pp. 680–688, Nov. 2012.
[2] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams Eng. J.*, vol. 5, no. 4, pp. 1093–1113, 2014.
[3] J. M. Wiebe, "Identifying subjective characters in narrative," in *Proc. 13th Conf. Comput. Linguistics*, 1990, pp. 401–406.
[4] S. Das and M. Chen, "Yahoo! for Amazon: Extracting market sentiment from stock message boards," in *Proc. APFA*, 2001, pp. 35–43.
[5] C. Elkan, "Method and system for selecting documents by measuring document quality," U.S. Patent 7 200 606 B2, Apr. 3, 2001.
[6] T. Nasukawa and J. Yi, "Sentiment analysis: Capturing favorability using natural language processing," in *Proc. Int. Conf. Knowl. Capture (K-CAP)*, 2003, pp. 70–77.
[7] K. Dave, S. Lawrence, and D. M. Pennock, "Mining the peanut gallery: Opinion extraction and semantic classification of product reviews," in *Proc. 12th Int. Conf. World Wide Web (WWW)*, 2003, pp. 519–528.
[8] Y. Song, H. Wang, Z. Wang, H. Li, and W. Chen, "Short text conceptualization using a probabilistic knowledgebase," in *Proc. Int. Joint Conf. Artif. Intell.*, 2011, pp. 2330–2336.
[9] B. Liu, *Sentiment Analysis and Opinion Mining*. Toronto, ON, Canada: Morgan & Claypool, 2012.
[10] T. Wilson, J. Wiebe, and P. Hoffmann, "Recognizing contextual polarity in phrase-level sentiment analysis," in *Proc. Conf. Hum. Lang. Technol. Empirical Methods Natural Lang. Process. (HLT)*, 2005, pp. 347–354.
[11] H. Saif, M. Bashevoy, S. Taylor, M. Fernandez, and H. Alani, "SentiCircles: A platform for contextual and conceptual sentiment analysis," in *Proc. Int. Semantic Web Conf.*, 2016, pp. 140–145.
[12] H. Takamura, T. Inui, and M. Okumura, "Extracting semantic orientations of words using spin model," in *Proc. 43rd Annu. Meeting Assoc. Comput. Linguistics (ACL)*, 2005, pp. 133–140.
[13] P. D. Turney and M. L. Littman, "Measuring praise and criticism: Inference of semantic orientation from association," *ACM Trans. Inf. Syst.*, vol. 21, no. 4, pp. 315–346, Oct. 2003.
[14] T. Xu, Q. Peng, and Y. Cheng, "Identifying the semantic orientation of terms using S-HAL for sentiment analysis," *Knowl.-Based Syst.*, vol. 35, pp. 279–289, Nov. 2012.
[15] H. Saif, Y. He, and H. Alani, "Semantic sentiment analysis of Twitter," in *Proc. 11th Int. Conf. Semantic Web*, Boston, MA, USA, 2012, pp. 508–524.
[16] E. Cambria, C. Havasi, and A. Hussain, "SenticNet 2: A semantic and affective resource for opinion mining and sentiment analysis," in *Proc. FLAIRS*, 2012, pp. 202–207.
[17] E. Cambria, "An introduction to concept-level sentiment analysis," in *Proc. MICAI*, 2013, pp. 478–483.
[18] E. Cambria, B. Schuller, B. Liu, H. Wang, and C. Havasi, "Knowledge-based approaches to concept-level sentiment analysis," *IEEE Intell. Syst.*, vol. 28, no. 2, pp. 12–14, Mar. 2013.
[19] C. Cao, Q. Feng, Y. Gao, F. Gu, J. Si, Y. Sui, W. Tian, H. Wang, L. Wang, and Q. Zeng, "Progress in the development of national knowledge infrastructure," *J. Comput. Sci. Technol.*, vol. 17, no. 5, pp. 523–534, 2002.
[20] J. H. Zheng and J. L. Lu, "Study of an improved keywords distillation method," *Comput. Eng.*, vol. 31, no. 18, pp. 194–196, 2005.

[21] E. Agirre, O. Ansa, E. Hovy, and D. Martínez, "Enriching very large ontologies using the WWW," 2000, *arXiv:cs/0010026*. [Online]. Available: https://arxiv.org/abs/cs/0010026

[22] B. Du, H. Tian, L. Wang, and R. Lu, "Design of domain-specific term extractor based on multi-strategy," *Comput. Eng.*, vol. 31, no. 14, pp. 159–160, 2005.

[23] B. Gelfand, M. Wulfekuler, and W. F. Punch, "Automated concept extraction from plain text," in *Proc. AAAI Workshop Text Categorization*, 1998, pp. 13–17.

[24] M. A. Hearst, "Automatic acquisition of hyponyms from large text corpora," in *Proc. 14th Conf. Comput. Linguistics*, Stroudsburg, PA, USA, 1992, pp. 539–545.

[25] F. Ali, A. Ali, M. Imran, R. A. Naqvi, M. H. Siddiqi, and K.-S. Kwak, "Traffic accident detection and condition analysis based on social networking data," *Accident Anal. Prevention*, vol. 151, Mar. 2021, Art. no. 105973.

[26] F. Ali, S. El-Sappagh, S. M. R. Islam, A. Ali, M. Attique, M. Imran, and K.-S. Kwak, "An intelligent healthcare monitoring framework using wearable sensors and social networking data," *Future Gener. Comput. Syst.*, vol. 114, pp. 23–43, Jan. 2021.

[27] F. Ali, D. Kwak, P. Khan, S. M. R. Islam, K. H. Kim, and K. S. Kwak, "Fuzzy ontology-based sentiment analysis of transportation and city feature reviews for safe traveling," *Transp. Res. C, Emerg. Technol.*, vol. 77, pp. 33–48, Apr. 2017.

[28] F. Ali, D. Kwak, P. Khan, S. El-Sappagh, A. Ali, S. Ullah, K. H. Kim, and K.-S. Kwak, "Transportation sentiment analysis using word embedding and ontology-based topic modeling," *Knowl.-Based Syst.*, vol. 174, pp. 27–42, Jun. 2019.

[29] F. Ali, S. El-Sappagh, and D. Kwak, "Fuzzy ontology and LSTM-based text mining: A transportation network monitoring system for assisting travel," *Sensors*, vol. 19, no. 2, p. 234, 2019.

[30] P. Nakov, S. Rosenthal, Z. Kozareva, V. Stoyanov, A. Ritter, and T. Wilson, "SemEval-2013 task 2: Sentiment analysis in Twitter," in *Proc. 7th Int. Workshop Semantic Eval.*, Atlanta, GA, USA, 2013, pp. 380–383.

[31] Y. Altun, I. Tsochantaridis, and T. Hofmann, "Hidden Markov support vector machines," in *Proc. Int. Conf. Mach. Learn.*, 2003, pp. 3–10.

[32] A. Vanzo, D. Croce, and R. Basili, "A context-based model for sentiment analysis in Twitter," in *Proc. 25th Int. Conf. Comput. Linguistics*, Dublin, Republic of Ireland, 2014, pp. 2345–2354.

[33] R. Studer, V. R. Benjamins, and D. Fensel, "Knowledge engineering: Principles and methods," *Data Knowl. Eng.*, vol. 25, nos. 1–2, pp. 161–197, Mar. 1998.

[34] E. Kontopoulos, C. Berberidis, T. Dergiades, and N. Bassiliades, "Ontology-based sentiment analysis of Twitter posts," *Expert Syst. Appl.*, vol. 40, no. 10, pp. 4065–4074, Aug. 2013.

[35] T. Berners-Lee, J. Hendler, and O. Lassila, "The semantic web," *Sci. Amer.*, vol 284, no. 5, pp. 34–43, 2001.

[36] I. S. M. Iwanaga, T.-M. Nguyen, T. Kawamura, H. Nakagawa, Y. Tahara, and A. Ohsuga, "Building an earthquake evacuation ontology from Twitter," in *Proc. IEEE Int. Conf. Granular Comput.*, Nov. 2011, pp. 306–311.

[37] A. Passant, U. Bojars, J. G. Breslin, T. Hastrup, M. Stankovic, and P. Laublet, "An overview of SMOB 2: Open, semantic and distributed microblogging," in *Proc. 4th Int. Conf. Weblogs Social Media*, 2010, pp. 303–306.

[38] M. Baldoni, C. Baroglio, V. Patti, and P. Rena, "From tags to emotions: Ontology-driven sentiment analysis in the social semantic web," *Intelligenza Artificiale*, vol. 6, no. 1, pp. 41–54, 2012.

[39] A. Nazir, Y. Rao, L. Wu, and L. Sun, "Issues and challenges of aspect-based sentiment analysis: A comprehensive survey," *IEEE Trans. Affect. Comput.*, early access, Jan. 30, 2020, doi: 10.1109/TAFFC.2020.2970399.

[40] K. Schouten and F. Frasincar, "Survey on aspect-level sentiment analysis," *IEEE Trans. Knowl. Data Eng.*, vol. 28, no. 3, pp. 813–830, Mar. 2016.

[41] T. A. Rana and Y.-N. Cheah, "Aspect extraction in sentiment analysis: Comparative analysis and survey," *Artif. Intell. Rev.*, vol. 46, no. 4, pp. 459–483, Dec. 2016.

[42] M. Hu and B. Liu, "Mining opinion features in customer reviews," in *Proc. 19th Nat. Conf. Artif. Intell. (AAAI)*, 2004, pp. 755–760.

[43] C. Long, J. Zhang, and X. Zhu, "A review selection approach for accurate feature rating estimation," in *Proc. COLING (Posters)*, 2010.

[44] K. Bafna and D. Toshniwal, "Feature based summarization of customers' reviews of online products," in *Proc. KES*, 2013, pp. 142–151.

[45] C. Scaffidi, K. Bierhoff, E. Chang, M. Felker, H. Ng, and C. Jin, "Red opal: Product-feature scoring from reviews," in *Proc. 8th ACM Conf. Electron. Commerce (EC)*, 2007, pp. 182–191.

[46] Y. Zhao, B. Qin, S. Hu, and T. Liu, "Generalizing syntactic structures for product attribute candidate extraction," in *Proc. HLT-NAACL*, 2010, pp. 377–380.

[47] G. Qiu, B. Liu, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation," *Comput. Linguistics*, vol. 37, no. 1, pp. 9–27, 2011.

[48] K. Liu, L. Xu, and J. Zhao, "Opinion target extraction using word-based translation model," in *Proc. EMNLP-CoNLL*, 2012, pp. 1346–1356.

[49] W. Bancken, D. Alfarone, and J. Davis, "Automatically detecting and rating product aspects from textual customer reviews," in *Proc. DMNLP PKDD/ECML*, 2014, pp. 1–16.

[50] J. Du, W. Chan, and X. Zhou, "A product aspects identification method by using translation-based language model," in *Proc. 22nd Int. Conf. Pattern Recognit.*, Aug. 2014, pp. 2790–2795.

[51] W. Jin and H. H. Ho, "A novel lexicalized HMM-based learning framework for web opinion mining," in *Proc. 26th Annu. Int. Conf. Mach. Learn. (ICML)*, Montreal, QC, Canada, 2009, pp. 465–472.

[52] P. Jiang, C. Zhang, H. Fu, Z. Niu, and Q. Yang, "An approach based on tree kernels for opinion mining of online product reviews," in *Proc. IEEE Int. Conf. Data Mining*, Dec. 2010, pp. 256–265.

[53] N. Jakob and I. Gurevych, "Extracting opinion targets in a single and cross-domain setting with conditional random fields," in *Proc. EMNLP*, 2010, pp. 1035–1045.

[54] F. Li, C. Han, M. Huang, X. Zhu, Y. Xia, S. Zhang, and H. Yu, "Structure-aware review mining and summarization," in *Proc. COLING*, 2010, pp. 653–661.

[55] B. Yang and C. Cardie, "Joint inference for fine-grained opinion extraction," in *Proc. ACL*, 2013, pp. 1640–1649.

[56] S. Li, R. Wang, and G. Zhou, "Opinion target extraction using a shallow semantic parsing framework," in *Proc. AAAI*, 2012, pp. 1671–1677.

[57] H. Peng, L. Xu, L. Bing, F. Huang, W. Lu, and L. Si, "Knowing what, how and why: A near complete solution for aspect-based sentiment analysis," in *Proc. AAAI Conf. Artif. Intell.*, 2020, pp. 8600–8607.

[58] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Mar. 2003.

[59] O. Jin, N. N. Liu, K. Zhao, Y. Yu, and Q. Yang, "Transferring topical knowledge from auxiliary long texts for short text clustering," in *Proc. 20th ACM Int. Conf. Inf. Knowl. Manage. (CIKM)*, 2011, pp. 775–784.

[60] T.-J. Zhan and C. H. Li, "Semantic dependent word pairs generative model for fine-grained product feature mining," in *Proc. PAKDD*, 2011, pp. 460–475.

[61] J. Zhu, H. Wang, M. Zhu, B. K. Tsou, and M. Ma, "Aspect-based opinion polling from customer reviews," *IEEE Trans. Affect. Comput.*, vol. 2, no. 1, pp. 37–49, Jan. 2011.

[62] A. Bagheri, M. Saraee, and F. de Jong, "An unsupervised aspect detection model for sentiment analysis of reviews," in *Proc. NLDB*, 2013, pp. 140–151.

[63] Y. Li, Z. Qin, W. Xu, and J. Guo, "A holistic model of mining product aspects and associated sentiments from online reviews," *Multimedia Tools Appl.*, vol. 74, no. 23, pp. 10177–10194, Dec. 2015.

[64] A.-M. Popescu and O. Etzioni, "Extracting product features and opinions from reviews," in *Natural Language Processing and Text Mining*. London, U.K.: Springer, 2007, pp. 9–28.

[65] B. Wang and H. Wang, "Bootstrapping both product properties and opinion words from Chinese reviews with cross-training," in *Proc. IEEE/WIC/ACM Int. Conf. Web Intell. (WI)*, Nov. 2007, pp. 289–295.

[66] Q. Zhao, H. Wang, P. Lv, and C. Zhang, "A bootstrapping based refinement framework for mining opinion words and targets," in *Proc. 23rd ACM Int. Conf. Conf. Inf. Knowl. Manage.*, Nov. 2014, pp. 1995–1998.

[67] Z. Hai, K. Chang, and G. Cong, "One seed to find them all: Mining opinion features via association," in *Proc. 21st ACM Int. Conf. Inf. Knowl. Manage. (CIKM)*, 2012, pp. 255–264.

[68] Y. Wu, Q. Zhang, X. Huang, and L. Wu, "Phrase dependency parsing for opinion mining," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, 2009, pp. 1533–1541.

[69] K. Liu, H. L. Xu, Y. Liu, and J. Zhao, "Opinion target extraction using partially-supervised word alignment model," in *Proc. IJCAI*, 2013, pp. 2134–2140.

[70] L. Xu, K. Liu, S. Lai, Y. Chen, and J. Zhao, "Walk and learn: A two-stage approach for opinion words and opinion targets co-extraction," in *Proc. 22nd Int. Conf. World Wide Web (WWW Companion)*, 2013, pp. 95–96.

[71] S. Raju, P. Pingali, and V. Varma, "An unsupervised approach to product attribute extraction," in *Proc. ECIR*, 2009, pp. 796–800.

[72] S. Blair-Goldensohn, K. Hannan, R. McDonald, T. Neylon, G. Reis, and J. Reynar, ''Building a sentiment summarizer for local service reviews,'' in *Proc. NLPIX*, 2008.
[73] N. Kobayashi, K. Inui, and Y. Matsumoto, ''Extracting aspect-evaluation and aspect-of relations in opinion mining,'' in *Proc. EMNLP-CoNLL*, 2007, pp. 1065–1074.
[74] B. Ma, D. Zhang, Z. Yan, and T. Kim, ''An LDA and synonym lexicon based approach to product feature extraction from online consumer product reviews,'' *J. Electron. Commerce Res.*, vol. 14, pp. 304–314, Nov. 2013.
[75] M. Bonzanini, M. Martinez-Alvarez, and T. Roelleke, ''Opinion summarisation through sentence extraction: An investigation with movie reviews,'' in *Proc. 35th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr. (SIGIR)*, 2012, pp. 1121–1122.
[76] G. Murray and G. Carenini, ''Subjectivity detection in spoken and written conversations,'' *Natural Lang. Eng.*, vol. 17, no. 3, pp. 397–418, Jul. 2011.
[77] E. Riloff and J. Wiebe, ''Learning extraction patterns for subjective expressions,'' in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2003, pp. 105–112.
[78] J. Wiebe and E. Riloff, ''Creating subjective and objective sentence classifiers from unannotated texts,'' in *Proc. 6th Int. Conf. Comput. Linguistics Intell. Text Process.*, 2005, pp. 486–497.
[79] F. Wang, Z. Wang, Z. Li, and J.-R. Wen, ''Concept-based short text classification and ranking,'' in *Proc. 23rd ACM Int. Conf. Conf. Inf. Knowl. Manage.*, Nov. 2014, pp. 1069–1078.
[80] N. M. Shelke, S. Deshpande, and V. Thakre, ''Survey of techniques for opinion mining,'' *Int. J. Comput. Appl.*, vol. 57, no. 13, pp. 1–6, 2012.
[81] E. Cambria, S. Poria, F. Bisio, R. Bajpai, and I. Chaturvedi, ''The CLSA model: A novel framework for concept-level sentiment analysis,'' in *Computational Linguistics and Intelligent Text Processing*. Cham, Switzerland: Springer, 2015, pp. 3–22.
[82] M. Mouriño-García, R. Pérez-Rodríguez, and L. E. Anido-Rifón, ''Bag-of-concepts document representation for textual news classification,'' *Int. J. Comput. Linguistics Appl.*, vol. 6, no. 1, pp. 173–188, 2015.
[83] E. Cambria and A. Hussain, ''Sentic computing,'' *Cognit. Comput.*, vol. 7, no. 2, pp. 183–185, Apr. 2015.
[84] D. Rajagopal, E. Cambria, D. Olsher, and K. Kwok, ''A graph-based approach to commonsense concept extraction and semantic similarity detection,'' in *Proc. 22nd Int. Conf. World Wide Web (WWW Companion)*, 2013, pp. 565–570.
[85] H. K. Kim, H. Kim, and S. Cho, ''Bag-of-concepts: Comprehending document representation through clustering words in distributed representation,'' *Neurocomputing*, vol. 266, pp. 336–352, Nov. 2017.
[86] B. Agarwal, S. Poria, N. Mittal, A. Gelbukh, and A. Hussain, ''Concept-level sentiment analysis with dependency-based semantic parsing: A novel approach,'' *Cognit. Comput.*, vol. 7, no. 4, pp. 487–499, Aug. 2015.
[87] J. K.-C. Chung, C.-E. Wu, and R. T.-H. Tsai, ''Improve polarity detection of online reviews with bag-of-sentimental-concepts,'' in *Proc. 11th Semantic Web Eval. Challenge (ESWC)*. Crete, Greece: Springer, 2014, pp. 379–420.
[88] S. Poria, E. Cambria, G. Winterstein, and G.-B. Huang, ''Sentic patterns: Dependency-based rules for concept-level sentiment analysis,'' *Knowl.-Based Syst.*, vol. 69, pp. 45–63, Oct. 2014.
[89] Y. S. Mehanna and M. Mahmuddin, ''The effect of pre-processing techniques on the accuracy of sentiment analysis using bag-of-concepts text representation,'' *Social Netw. Comput. Sci.*, vol. 2, no. 4, pp. 1–13, Jul. 2021.
[90] A. Yadav and D. K. Vishwakarma, ''Sentiment analysis using deep learning architectures: A review,'' *Artif. Intell. Rev.*, vol. 53, no. 6, pp. 4335–4385, Aug. 2020.
[91] S. Poria, E. Cambria, and A. Gelbukh, ''Aspect extraction for opinion mining with a deep convolutional neural network,'' *Knowl.-Based Syst.*, vol. 108, pp. 42–49, Sep. 2016.
[92] X. Ma and E. H. Hovy, ''End-to-end sequence labeling via bi-directional LSTM-CNNs-CRF,'' *CoRR*, vol. abs/1603.01354, pp. 1–12, Mar. 2016.
[93] E. Ekinci and S. Omurca, ''Extracting implicit aspects based on latent Dirichlet allocation,'' in *Doctoral Consortium on Agents and Artificial Intelligence*. Porto, Portugal: SciTePress, 2017.
[94] D. Tang, B. Qin, and T. Liu, ''Aspect level sentiment classification with deep memory network,'' *CoRR*, vol. abs/1605.08900, pp. 1–11, May 2016.
[95] M. Pontiki, D. Galanis, H. Papageorgiou, I. Androutsopoulos, S. Manandhar, M. Al-Smadi, M. Al-Ayyoub, Y. Zhao, B. Qin, O. D. Clercq, V. Hoste, M. Apidianaki, X. Tannier, and N. Loukachevitch, ''SemEval-2016 task 5: Aspect based sentiment analysis,'' in *Proc. SemEval NAACL-HLT*, San Diego, CA, USA, 2016, pp. 19–30.
[96] R. Speer and C. Havasi, ''Representing general relational knowledge in ConceptNet 5,'' in *Proc. LREC*, 2012, pp. 3679–3686.
[97] S. Baccianella, A. Esuli, and F. Sebastiani, ''SentiWordNet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining,'' in *Proc. 7th Conf. Int. Lang. Resour. Eval.*, Valletta, Malta, 2010, pp. 2200–2204.
[98] M. E. Mowlaei, M. S. Abadeh, and H. Keshavarz, ''Aspect-based sentiment analysis using adaptive aspect-based lexicons,'' *Expert Syst. Appl.*, vol. 148, Jun. 2020, Art. no. 113234.

YASSIN S. MEHANNA (Member, IEEE) received the B.S. degree in agricultural engineering from Ain-Shams University, Cairo, Egypt, in 2000, and the M.S. degree in information technology from the School of Computer Science and Information Technology, The University of Nottingham, U.K., in 2007. He is currently pursuing the Ph.D. degree in computer science with the College of Arts and Sciences, Universiti Utara Malaysia (UUM), Kedah, Malaysia.

His research interests include artificial intelligence, data science, database, and integrated systems.

MASSUDI BIN MAHMUDDIN (Member, IEEE) received the Ph.D. degree in system engineering from Cardiff University, U.K., in 2008. He is currently a Senior Lecturer and the Dean of Student Development and an Alumni with the College of Arts and Sciences, Universiti Utara Malaysia (UUM). During last ten years of his services at the school, teaching, research and development interests have been in the areas of technical and social aspect of network computing, computational intelligent, and expert systems.