I.J. Modern Education and Computer Science, **2024, 4, 1-16**
Published Online on August 8, 2024 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijmecs.2024.04.01

A Hybrid Method based on Rules and Deep Learning for Enhancing Single-Word and Multi-Word Aspects Extraction from French Reviews

Hammi Sarsabene*
ANLP Research Group, MIRACL Lab, FSEGS, University of Sfax, Sfax, Tunisia
Email: hsarsabene@gmail.com
ORCID iD: https://orcid.org/0000-0001-6148-9127
*Corresponding Author

Hammami M. Souha
ANLP Research Group, MIRACL Lab, FSEGS, University of Sfax, Sfax, Tunisia
Email: souha.hammami@ihecs.usf.tn
ORCID iD: https://orcid.org/0009-0003-9191-5934

Belguith H. Lamia
ANLP Research Group, MIRACL Lab, FSEGS, University of Sfax, Sfax, Tunisia
Email: lamia.belguith@fsegs.usf.tn
ORCID iD: https://orcid.org/0000-0002-5063-9246

Received: 06 January, 2024; Revised: 28 February, 2024; Accepted: 27 March, 2024; Published: 08 August, 2024

Abstract: In recent years, Aspect Based Sentiment Analysis (ABSA) has gained significant importance, particularly for enterprises operating in the commercial domain. These enterprises tend to analyze the customers' opinions concerning the different aspects of their products. The primary objective of ABSA is to first identify the aspects (such as battery) associated with a given product (such as a smartphone) and then assign a sentiment polarity to each aspect. In this paper, we focus on the Aspects Extraction (AE) task, specifically for the French language. Previous research studies have mainly focused on the extraction of single-word aspects without giving significant attention to the multi-word aspects. To address this issue, we propose a hybrid method that combines linguistic knowledge-based methods with deep learning-based methods to identify both single-word aspects and multi-word aspects. Firstly, we combined a set of rules with a deep learning-based model to extract the candidate aspects. Subsequently, we introduced a new filtering algorithm to detect the single-word aspect terms. Finally, we created a set of 52 patterns to extract the multi-word aspect terms. To evaluate the performance of the proposed hybrid method, we collected a dataset of 2400 French mobile phone comments from the Amazon website. The final outcome proves the encouraging results of the proposed hybrid method for both mobile phones (F-measure value: 87.27% for single-word aspects and 82.38% for multi-word aspects) and restaurants (F-measure value: 78.79% for single-word aspects and 76.04% for multi-word aspects) domains. By highlighting the practical implications of these results, our hybrid method offers a promising outlook for Aspect Based Sentiment Analysis task, opening new avenues for businesses and future research.

Index Terms: aspect extraction, single-word aspect, multi-word aspect, hybrid method, filtering algorithm

1. Introduction

The sentiment analysis task has been of a considerable importance in the last few years, especially in the commercial domain. Companies examine the customers' opinions about a given product to improve its quality by focusing on the characteristics approved by the clients and trying to enhance the disliked ones. Understanding what customers think about business, products or services is one of the most important aspects of business strategic management, particularly in the business decision-making process. As customers look for online advice and recommendations on products and services, companies need tools that can transform customers' thoughts and conversations into insights for managing production and business. However, this is not possible with the document and sentence levels of analysis. Therefore, to add more accuracy to the analysis process, a new task, called Aspect-Based Sentiment Analysis (ABSA), should be conducted. In contrast to document and sentence sentiment analysis, ABSA offers a more fine-grained result concerning the customer's opinions. It is generally divided into two steps: Aspect Extraction (AE) and Sentiment Analysis (SA). In this study, we focus on AE as it is the most difficult and most important. Previous research works classified the aspects into two types: "explicit aspects" and "implicit aspects". We consider the two following examples:

The phone battery can last for a long time.
This cell phone is fast and nice.

In the first example, the customer expresses his/her opinion in an explicit way about the aspect **"battery".** Thus, the aspect **"battery"** is called an explicit aspect. However, in the second example, the client implicitly mentions the aspects **"rapidity"** and **"appearance"** by expressing his/her opinion by using the words **"fast"** and **"nice"**.

Explicit aspects are also divided into two types: single-word aspects, like **quality**, **screen**, etc., and multi-word aspect terms composed of more than a single word such as **screen quality**, **fingerprint recognition**, etc.

Despite significant advancements in Aspect Extraction filed, current research still exhibits two key limitations. Firstly, previous research studies have mainly focused on the extraction of single-word aspects without giving significant importance to the multi-word aspects, leading to an incomplete understanding of whole user opinions. This is mainly due to the difficulty of detecting multi-word aspects, which often consist of complex phrases or combinations of words. Secondly, the focus on languages like English and Chinese has caused a difficult understanding of diverse perspectives from multilingual sources, including French reviews. To address these limitations, we focus in this study on the extraction of single-word aspects and multi-word aspects from French reviews. To accomplish this, we propose a new hybrid method that combines the strengths of linguistic knowledge-based methods and deep learning-based methods. By exploiting the advantages of both methods, we aim to overcome their limitations and enhance the accuracy and robustness of the AE task. The main contributions of the study are described below:

- Collecting a new French mobile phone dataset containing 2400 reviews annotated through two annotators. Among these reviews, 2000 were utilized for validating our method, including rules and support values, while the remaining 400 reviews were employed for evaluating its performance.
- Proposing an enhanced hybrid method that makes use of the strengths of both linguistic knowledge-based approaches and deep learning-based approaches and thus to effectively address the Aspect Extraction (AE) task. This method incorporates a three-step process. Firstly, a set of rules is combined with the deep learning-based model Word2Vec to identify the potential aspect candidates. Subsequently, a new filtering algorithm is introduced to extract single-word aspect terms from the identified candidates. This algorithm uses a set of measures and conditions to eliminate a specific category of words that cannot be considered as single-word aspects but rather as integral parts of multi-word aspect terms. Finally, a set of 52 patterns is made to detect the multi-word aspect terms.

The remainder of the paper is organized as follows. Section 2 discusses the works related to aspect extraction methods. Section 3 presents the different steps of the proposed aspects' extraction method. Section 4 describes the used dataset and illustrates the obtained experimental results. Finally, Section 5 provides a conclusion.

2. Related Works

The aspect extraction task has been noticeably addressed in the literature due to its importance and the challenges it presents in the ABSA domain. Previous studies have employed four main approaches to manage this task, which are the linguistic knowledge-based approach [1-8], machine learning-based approach [10-14], deep learning-based approach [18-24] and hybrid approach [25-29]. Table 1 provides an overview of the AE-related studies and their reported results.

2.1 Linguistic knowledge-based approach

The linguistic knowledge-based approach is a widely employed approach in aspect extraction tasks. It employs a predefined set of linguistic knowledge (constraints, linguistic rules and grammar) to identify aspect terms. This approach offers several advantages. It provides effective linguistic control, allowing for precise detection of specific syntactic structures and achieving a high level of extraction precision. Additionally, unlike learning-based approaches, the linguistic knowledge-based approach does not rely much on large amounts of annotated data, which makes it useful when labeled training data is limited or expensive to obtain. Many studies have utilized the linguistic knowledge-based approach in their works. Among them, we cite the study of [1] which applied a rule-based method to extract all frequent explicit aspects using the association rule method (employed to collect the different correlated words) and the infrequent ones using the distance between infrequent nouns and opinion words. On the other hand, [2] employed the correlation between aspect terms and opinion words to detect aspect terms. Besides, [3] ameliorated the methods proposed in [1,2] and used the dependency relations to create a set of rules in order to extract both single-word aspect terms and the multi-word aspect terms. They also proposed a new pruning method to remove the incorrect aspect terms. Tubishat et al. [5] improved the previous studies by increasing the number of employed rules, where 126 rules were constructed to extract aspect terms. These rules vary between dependency-based rules and pattern-based rules. Afterward, to ensure the selection of highly effective rules for the AE task, they introduced an Improved Whale Optimization Pruning (IWOA) algorithm. This algorithm effectively identifies and retains rules that yield optimal performance in AE. Furthermore, they suggested a new pruning algorithm (PA) to eliminate the non-aspect terms. This pruning algorithm plays a crucial role in ameliorating the results by selectively removing irrelevant terms, thus improving the precision and accuracy of the aspect term extraction process. Banjar et al. [6] leveraged the semantic similarity among words within a given sentence to identify aspects. In the first step, the authors extracted the nouns existing in the dataset as potential aspects. Then, they measure the semantic similarity among these potential aspects using a co-occurrence-based method. Only the candidates having semantic similarity scores surpassing the predefined threshold were selected as final aspect terms. Ayub et al. [7] constructed a set of rules to address the aspect extraction task. At first, the authors pretreated the dataset to remove noise and irrelevant information. Subsequently, they employed the TF-IDF method to extract relevant keywords that serve as indicators of aspects. These identified keywords were then combined with a set of patterns to create useful rules for the aspect extraction task. Mishra and Panda [8] constructed a set of 31 dependency structure-based rules to extract explicit aspect terms from online reviews. These rules were created based on the spaCy dependency parser, which aims to identify various grammatical elements such as nouns, noun phrases, verbs, and verb phrases within the reviews. Additionally, they proposed a lexicon-based pruning method to eliminate non-aspect terms and enhance the precision of the extracted aspects.

2.2 Machine learning-based approach

The machine learning based-approach is one of the most employed approaches in NLP (Natural Language Processing) tasks. Recently, it has been intensively applied in the aspect extraction task. Unlike the linguistic knowledge-based approach, it is not based on constraints and rules, but it rather relies on algorithms defined to solve classification tasks [9]. This approach first trains algorithms on a labeled dataset to learn patterns and features, and then uses these trained algorithms to make predictions on the test dataset. By using large annotated datasets, machine learning algorithms can generalize well to new datasets and increase flexibility in handling various linguistic patterns and contexts. Furthermore, the machine learning-based approach can adapt to different domains by retraining the models or adjusting the model's parameters. Despite its effectiveness, this approach may require significant quantities of labeled training data and computational resources for both training and inference processes. Additionally, the performance of the machine learning approach heavily relies on the quality and representativeness of the training data, as well as the choice of appropriate features and algorithms. Previous researches concentrated mainly on two algorithms LDA (Latent Dirichlet Allocation) and CRF (Conditional Random Field) to solve the aspect extraction task. Amidst the works that adopted these algorithms, we mention that of [10] who suggested an Interdependent Latent Dirichlet Allocation (ILDA) model based on the assumption of interdependency between aspects and sentiment terms. In the study of [11] a CRF algorithm was used instead of LDA to identify the aspects of products. Moreover, many features, such as POS (part of speech) and the distance between words, were integrated into the CRF to ameliorate the aspect extraction task. Anoop and Asharaf [12] utilized the machine learning model LDA for aspect identification. To achieve this work, the authors pretreated first the dataset by removing irrelevant information like punctuation, URLs, etc. Subsequently, they generated the LDA model to detect aspects and their corresponding terms. Finally, a meticulous matching process was carried out to establish a direct correspondence between the aspects identified by LDA and the topics that existed in the product descriptions. Heinrich and Marchi [14] combined the CRF model with the POS tag to identify the aspect terms. To conduct this study, they first pretreated the dataset by removing stop words and unnecessary information. Then, they used the POS tag to select relevant features for the classification. Finally, the CRF model used these newly produced features to identify the aspect terms accurately.

2.3 Deep learning-based approach

The deep learning-based approach is a subfield of the traditional machine learning-based approach [15-17]. Recently, this approach has demonstrated remarkable success in various fields, including computer vision, speech recognition, and aspect extraction. This success can be attributed to the neural network-based architecture employed in deep learning models. By employing multiple hidden layers, deep learning models can automatically learn hierarchical representations of input data. This hierarchical representation allows the model to capture intricate patterns and extract increasingly abstract features from the input. Moreover, the deep learning-based approach characterizes by its ability to handle large and complex datasets. Deep learning models can process vast amounts of data efficiently, which is especially valuable in domains where data size and complexity are significant factors. Additionally, deep learning models offer great flexibility and adaptability. They can learn directly from raw data without relying heavily on manual feature engineering. However, deep learning-based approaches have certain limitations. One major limitation is their reliance on large amounts of labeled training data. Furthermore, deep learning models often require substantial computational power, memory, and time to train effectively, especially when dealing with complex architectures and large datasets. Many deep learning models, such as LSTM (Long Short Term Memory) and CNN (Convolutional

Neural Network), have been utilized in the aspect good results and often outperform traditional machine learning models, hence they have been widely adopted by researchers.

For instance, [18] utilized the CNN model in aspect identification to output a probability distribution over each aspect term to output a probability distribution over each aspect term in the sentences. The experimental results demonstrated that the CNN model outperformed the baselines and achieved competitive performance across multiple languages. Moreover, [19] incorporated important information about both words and clauses in the Bi-LSTM (Bidirectional Long S-hort Term Memory) model to enhance the aspect extraction task. In this study, [19] combined word-level and clause-level attention networks for aspect extraction. The word-level attention network focuses on relevant words within a sentence, while the clause-level attention network emphasizes larger syntactic units like clauses. By integrating both levels of attention, the Bi-LSTM model achieved a more comprehensive understanding of the text, enabling it to effectively identify different aspects mentioned in the text. This proposed model achieved encouraging results reaching up to 68.50% of the F-measure. Besides, [20] improved the results obtained by previous studies [18,19] by employing a Bi-LSTM-CNN architecture with a self-attention mechanism to perform the aspect identification task. This architecture exploits the sentence-level knowledge transferred through CNN layers to extract the aspect terms. Sharbatian and Moattar [22] proposed an improved CNN-LSTM architecture for AE task. To implement this architecture, the authors pretreated first the dataset, removing noise and irrelevant information. Then, the CNN model was employed to extract local features from the comments. These extracted features were subsequently fed into the LSTM model, which captures long-term dependencies between words. Finally, the LSTM output was integrated into a fully connected neural network to detect the presence of an aspect in a comment. Liu and Shen [23] proposed a new model known as the Information-Augmented Neural Network (IAAN) for aspect term identification. The primary objective of this model was to extract dynamic word senses by integrating informative details regarding the aspect terms. To implement this model, contextualized word embeddings were generated using BERT, which contains contextual information concerning the aspect terms. Subsequently, a Multi-Level Contextualized Representation Network (MCRN) served as an encoder, to detect bidirectional long-distance dependencies and generate meaningful feature vectors. Finally, the GRU (Gated recurrent unit) model was employed as a decoder to interpret the encoding vectors and identify the aspects. Hammi et al. [24] proposed a new architecture named CBCF (CNN-Bi-LSTM-CRF) for the AE task. This architecture combines deep learning models, specifically Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM), with a machine learning model called Conditional Random Field (CRF). To implement this architecture, [24] employed first the Word2Vec model to capture the contextual information of words. This model was trained on a dataset consisting of 20,000 mobile phone reviews. The generated word embedding vectors were then incorporated into the CNN layer to produce new vectors that capture meaningful local features. Afterward, the Bi-LSTM model was employed to capture long-term dependencies between words. This model took the vectors produced by the CNN layer as input and generated new vectors that incorporated both contextual information and local features. Finally, the CRF model was utilized to detect the aspect terms. This model took into account adjacent labels to determine the label of the current word.

2.4 Hybrid approach

The hybrid approach combines the strengths of both linguistic knowledge-based and learning-based approaches (ma- chine learning or deep learning) to execute more efficiently the aspect identification task. This approach combines the interpretability and precision of the linguistic knowledge-based approach with the adaptability and generalization offered by the learning-based approach. For instance, [25] employed the CNN model among a set of linguistic patterns to detect the aspects. To begin, a feature list was created by using word embeddings and multiple linguistic patterns. Subsequently, the CNN model used these features to accurately identify aspect terms. Experimental results showed that the integration of linguistic features into the CNN model helped improving the aspect identification task. Laddha and Mukherjee [26] proposed a hybrid method combining rules, attention-based Bi-LSTM, and CRF for aspect identification. In the first step, the authors created a set of rules by utilizing the opinion lexicon and the POS tagger to annotate the learning dataset. This annotated dataset was then utilized to train a Bi-LSTM-CRF model, enabling the identification of aspects. In this study, the attention-based Bi-LSTM layer was integrated to capture the contextual information of each word in the dataset, while the CRF layer was employed to model the sequential dependencies between words and assign labels to each word in the dataset. The authors evaluated their method using benchmark datasets and compared it against existing methods. The experimental results demonstrated that the attention-based Bi-LSTM-CRF network outperformed other models in terms of precision (88.80%), recall (75.86%), and F-measure (81.82%), showcasing its effectiveness in aspect extraction. Ansari et al. [27] combined the machine learning model K-Nearest Neighbor (KNN) with a set of rules to identify aspects. Initially, a set of rules was developed to identify aspect candidates. Subsequently, an efficient pruning algorithm was introduced to eliminate irrelevant candidates. The resulting list of aspect terms was then used to train the KNN model, which was then applied to annotate the remaining unannotated words. This introduced method achieved encouraging results. Ozyurt and Akcayol [28] prefer to use the machine learning algorithm LDA (Latent Dirichlet Allocation) with the association rules and frequency to create a new method for aspect identification task called SS-LDA (Sentence Segment LDA). This method exploits the aspect terms extracted through the association rules method and frequency and feeds them into the LDA algorithm to extract the rest of the aspect terms. Ray and Chakrabarti [29] introduced a hybrid method to address the AE task. Firstly, the authors constructed a set of rules to annotate the training dataset. These rules were built based on the SentiWordNet lexical resource and took into account intensifiers, negation words, and contextual information. Subsequently, they used the annotated dataset as an input to a CNN model to identify the aspect terms. The authors chose the CNN model for its ability to understand complex patterns in the dataset. The experimental results highlighted the remarkable performance of the proposed hybrid method, surpassing that of existing methods.

Table 1. Overview of the AE studies.

Study	Language	Domain	Method	Results
[1]	English	Products	Rules	F-measure: 72.00%
[2]	English	Products	Rules	-
[3]	English	Restaurants Laptops	Rules	F-measure: 81.90% F-measure: 68.70%
[5]	English	Products	Rules	F-measure: 90.00%
[6]	English	Books	Rules	F-measure: 90.00%
[7]	English	Products	Rules	F-measure: 76.00%
[8]	English	Products	Rules	F-measure: 91.00%
[10]	English	Products	ILDA	F-measure: 83.35%
[11]	English	Products	CRF	F-measure: 83.20%
[12]	English	Products	LDA	F-measure: 83.82%
[14]	Portuguese	Hotels	CRF	-
[18]	multi-language	multi-domains	CNN	F-measure: 54.48%
[19]	English	Restaurants Laptops	Bi-LSTM	F-measure: 68.50% F-measure: 66.70%
[20]	English	multi-domains	CNN	F-measure: 62.57%
[22]	Iranian	Products	CNN-LSTM	Accuracy: 70.00%
[23]	English	Restaurants Laptops	GRU	F-measure: 88.40% F-measure: 87.49%
[24]	French	Smartphone	Bi-LSTM-CNN-CRF	F-measure: 83.49%
[25]	English	multi-domains	CNN Rules	F-measure: 82.83%
[27]	English	Restaurants Laptops	KNN Rules	-
[28]	Turkish	Smartphone	LDA Rules	F-measure: 82.39%
[29]	English	Restaurants	CNN Rules	F-measure: 83.34%

3. Methodology

In this study, we proposed a hybrid method that combines the advantages of linguistic knowledge-based methods and deep-learning-based methods. On one hand, the linguistic knowledge-based methods use a predefined set of rules to identify aspects in text, which can lead to high recall. On the other hand, deep learning-based methods utilize deep learning models and learning techniques to achieve high precision [30]. By proposing a hybrid method, our aim is to extract a list of aspects characterized by both high precision and high recall.

Previous studies often extract the list of aspect terms directly without referring to an intermediary list that contains potential candidate aspects. However, this method may not be very efficient as not all the extracted aspects are guaranteed to be correct. Therefore, constructing a preliminary list from which we can select single-word aspects and multi-word aspects can significantly enhance the aspect extraction process.

In this section, we present a description of the proposed hybrid method for aspect term extraction. Firstly, we utilize a combination of rules and the Word2Vec model to identify potential candidates for aspect terms. The constructed rules demonstrate a strong capability to capture domain-specific knowledge and linguistic nuances, allowing them to extract a significant number of aspects, both frequent and infrequent. However, it is important to note that these rules may also generate a considerable number of incorrect aspects. To address this issue, we incorporate a deep learning model to refine the list of candidate aspects obtained using the rule-based method. Given the hypothesis that aspect terms often occur within similar contexts, we employ the Word2Vec model to identify potential aspect candidates based on such contextual similarity. By training this model on a large labeled dataset, it can effectively learn from the data and discern complex patterns and variations that may not have been explicitly captured by the rules. Subsequently, a new filtering algorithm is applied to identify the single-word aspect terms. This algorithm uses a set of measures and conditions to eliminate a specific category of words that cannot be considered as single-word aspects but rather as integral parts of multi-word aspect terms. Despite the importance of these words in identifying both single-word aspect terms and multi-word aspect terms, previous studies have not incorporated their identification into the AE task. Finally, a set of patterns is used to extract the multi-word aspect terms. As mentioned earlier, the identification of multi-word aspect terms has not received sufficient attention from the scientific community. To address this issue, we have constructed a set of 52 patterns specifi-cally designed for multi-word aspect terms identification. This number is significant and often exceeds that of existing studies. Fig.1 shows the different steps of the developed method used to extract French aspect terms.

3.1 Different types of aspect terms

Previous research has categorized aspects [31,3] into two types: single-word aspects and multi-word aspects.

Single-word aspect terms. These terms refer to those consisting each of a single word. For example, in the domain of mobile phones, we can consider the words **“quality”** and **“design”** as single-word aspects.

Multi-word aspect terms. These terms are composed of more than one word (such as **capacité de stockage**/*storage capacity*, **qualité d’écran**/*screen quality*, etc.). By the end of an empirical study, conducted on 2000 reviews, we have identified three categories of (**MWAT**), mentioned below:

- **Category 1.** In the first category, the multi-word aspect term is composed of two (or more) single-word aspects as in the example **“La qualité d’écran est excellente.”** (*The screen quality is excellent.*). In fact, the two words composing the multi-word aspect term **“qualité d’écran”** are both single-word aspect terms, that can appear separately as aspects in other sentences.
- **Category 2.** In the second category, the multi-word aspect is composed of single-word aspect term(s) and non-aspect word(s). Considering the following MWAT **“triple caméra”** (*triple camera*). It is composed of the non-aspect term **“triple”** and the single-word aspect term **“caméra”**.
- **Category 3.** This category is totally composed of non-aspect terms. Taking this MWAT **“La reconnaissance faciale est** *efficace*.**”** (*Facial recognition is effective.*). It is composed of the words **“faciale”** and **“reconnaissance”** that are not aspect terms. These terms cannot be single-word aspect terms when they appear alone in other sentences. However, when they are combined, they can form **MWAT**.

3.2 Candidate aspects detection

To detect the candidate aspects, we used a hybrid method, combining the advantage of a linguistic knowledge-based method and a deep learning-based method. It consists mainly of two phases. In the first phase, numerous linguistic techniques (e.g. syntactic dependency relations, association rules, etc.) were employed to extract a list of candidate aspects with high precision. Although this list is characterized by high precision value in terms of the extracted candidate aspects, the total number of the extracted aspects remained low (low recall). So, in the second phase, we used a word embedding technique to find terms that are semantically similar to the highly-precise candidate aspects terms and add them to this list.

3.2.1 Extraction of candidate aspects using a linguistic knowledge-based method

This sub-section details the two steps followed to extract the candidate aspects. Firstly, a rule-based method is suggested to extract all the possible candidate aspects. For each review in the dataset, the different dependency relations existing between words are extracted using the Stanford dependency parser and each word is tagged with its POS tag. Then, this set of POS tags and dependency relations are used to construct a set of useful aspects extraction rules. As a result, we obtain a list containing highly recalled candidate aspects. In the second one, we proposed a method based on association rules and syntactic dependency relations to extract another list including only the highly-precise candidate aspects.

Step 1: Extraction of candidate aspects list by using rules. In this step, all the possible candidate aspects were extracted using a set of effective syntactic rules. These rules were designed according to two important assumptions. The first is related to the fact that aspect terms and opinion words are strongly correlated in sentences. Customers always express their opinions about the products’ aspects using opinion words [1,32]. For example, the aspect term **“design”** (*appearance*) is often associated with opinion words like **“joli”** (*nice*), **“magnifique”** (*beautiful*), etc. On the other hand, we assumed that aspect terms are often written near each other as customers always express their opinions on several different aspects in the same review [1,32]. For example, the aspect terms **“photos”** (*photos*) and **“vidéos”** (*videos*) appear together in the following review.

Belles **photos** et **vidéos**. (*Nice **photos** and **videos**.*)
amod (Belles-ADJ, photos-NOUN) **conj** (photos-NOUN, vidéos-NOUN)

To reveal the grammatical relationships between words and to create useful rules for candidate aspects’ extraction, we used syntactic dependency parser tool “Stanford” and the POS tagger. An empirical study on 2000 mobile phone reviews proved that only seven syntactic relations (i.e. nominal subject relation (nsubj), adjectival modifier-dependency relation (amod), oblique nominal relation (obl), object dependency relation (obj), nominal modifier dependency relation (nmod) conjunct dependency relation (conj) and appositional modifier dependency relation (appos)) were efficiently used in the aspect terms extraction task. After that, these relations were combined with specific POS tags (NOUN, ADJ, etc.) to construct a set of rules, as it is shown in Table 2. Taking the previously mentioned example, there is a **conj** (**photos**- NOUN, **videos**-NOUN) relation between the nouns **“photos”** and **“videos”.** Therefore, according to rule 2, these terms can be also treated as candidate aspects. In this work, the opinion words are detected using the opinion lexicon FEEL (presented in Section 4). The list of candidate aspects extracted in this step is called **CAL1** (**C**andidate **A**spects **L**ist).

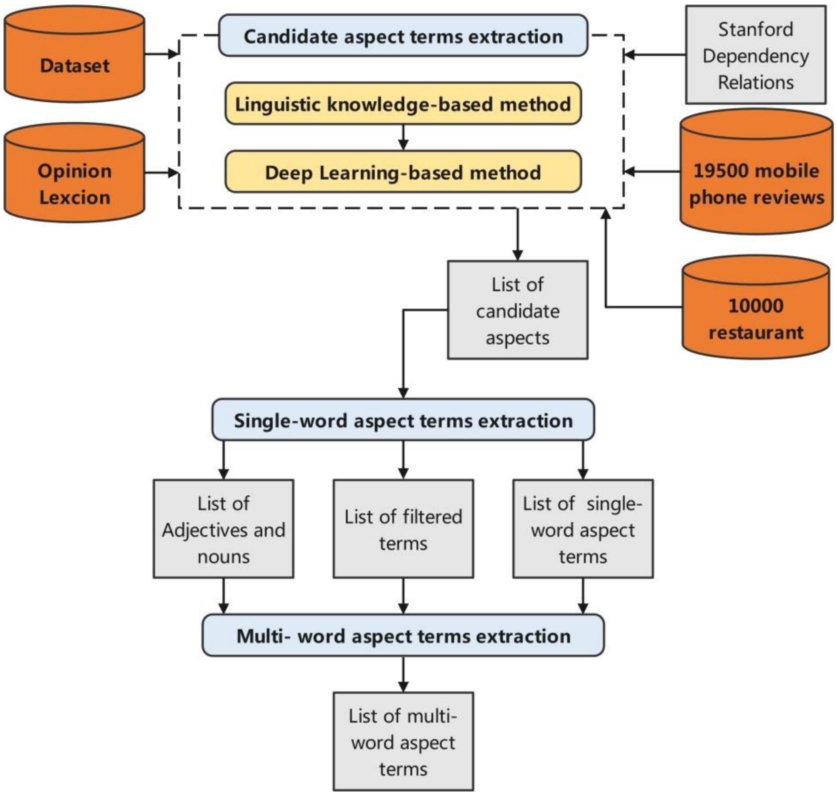

Fig. 1. The overall steps for aspect terms extraction method.

Although this method succeeded in extracting more than 96% of candidate aspects, it provided a very low precision rate (58.48%). In the next step, another list of candidate aspects with high precision was extracted from the **CAL1** list.

Table 2. Rules for candidate aspect extraction.

Number	Relations	Patterns	Rules
1	nsubj/obl/obj	(Noun, Opinion-Word)	If the relation is nsubj, obj or obl and the first word is Noun and the second word is opinion-word, then the first word will be a candidate aspect.
2	nmod/conj/appos	(Noun, Noun)	If the relation is nmod, conj or appos and the first word is Noun and the second word is Noun, then the first and the second words will be a candidate aspect.
3	amod	(Opinion-Word, Noun)	If the relation is amod and the first word is opinion word and the second word is Noun, then the second word will be a candidate aspect.

Step 2: Extraction of candidate aspects list with high precision using association rules and syntactic dependency relations. In this step, we employed the association rule mining method introduced by [33] to extract highly-precise candidate aspects. This method allows identifying the highly-correlated aspects that frequently appear together in the dataset. In fact, customers usually give their opinions about several aspects of the product in the review and not only one aspect. Subsequently, the probability of the appearance of aspect terms together in the same review was high. Therefore, to detect the correlated nouns in the dataset, we applied two steps using the association rules-based method. Firstly, the association-mining apriori algorithm was generated with a support value equal to 0.01 on the transaction file (transaction file contains all the nouns that are potential aspects appearing together in the dataset, where each line contains all the nouns existing in the same review). In the association rules, the support value reflects the frequency of appearance of all aspects together in the dataset. The empirical study conducted on 2000 mobile phone reviews showed that the best support value was equal to 0.01, which means that only the aspect terms appearing together, at least for 20 times, in the dataset were considered as highly-correlated candidate aspects (20/2000=0.01). In this sub-step, we created a list **CAL2** containing 20 highly-precise candidate aspects. After that, to increase the size of the **CAL2** list, we used the highly-precise dependency relation "nsubj" and the apriori algorithm to select the most accurate aspect terms. We examined the seven Stanford dependency relations employed in the previous step to extract the candidate aspects. It was obvious that the "nsubj" relation is the more convenient relation since it succeeded in extracting a high number of correct aspect terms. Therefore, it was prominently utilized in this step as a reliable source to extract the correct aspects. Then, the apriori algorithm was generated, for the second time, with a support value equal to 0.008 (according to an empirical study) aiming to produce a larger set of relations between nouns. Afterwards, each term in the "nsubj" relation was examined to determine its correlation with any high-precise term in **CAL2**. If a

correlation was identified, the term was added to a new list **(CAL3)**. The resulting list of candidate aspects is called **CAL4** which contains the candidate aspects from **CAL2** and from **CAL3 (CAL2+CAL3)**.

Fig.2 represents the algorithm designed for the extraction of a list of candidate aspects with high precision. This algorithm demonstrates that, for each generated association rule *r* (line 1), we checked whether the antecedent *ante(r)* (the left part of a rule.) and the consequent *cons(r)* (the right part of a rule.) were respectively included in the “nsubj” relation and in the **CAL2** (line 2) or not. If it was the case, then the term (*ante (r)*) would be added to the aspect candidates list **(CAL3)** (line 3) and deleted from the principal list **CAL1** (line 4). If *cons(r)* and *ante(r)* were included in the **“nsubj”** relation and in the **CAL2** (line 5) respectively, then the term (*cons (r)*) would be added to the list of candidate aspects number 3 **(CAL3)** (line 6) and deleted from the principal list **CAL1** (line 7). Therefore, the final list of candidate aspects **CAL4**, in this step, would include the list of **CAL2** and that of **CAL3** (line 8). This method succeeded to establish a list of candidate aspects with high precision (precision equal to 83.58% for mobile phone and 82.05% for restaurant), while the recall value (equal to 33.53% for mobile phone and 21.05% for restaurant) remained low. In the next step, the recall and precision values were enhanced by applying deep learning-based method named the word embedding.

Algorithm 1. Extraction of a list of candidate aspects with high precision.

```
1: For each association_rule r:
2:     if (ante(r) ⊆ nsubj and cons(r) ⊆ CAL2) then
3:         CAL3 ◄— add (ante(r))
4:         CAL1 ◄— delete (ante(r))
5:     else if (ante(r) ⊆ CAL2 and cons(r) ⊆ nsubj) then
6:         CAL3 ◄— add (cons(r))
7:         CAL1 ◄— delete (cons(r))
8: CAL4 ◄— CAL2 ∪ CAL3
```

Fig. 2. Algorithm for the extraction of a list of candidate aspects with high precision.

3.2.2 Extraction of candidate aspects using deep learning-based method

In the previous step, a list of candidate aspects with high precision was extracted. Since our objective is to detect a list of candidate aspects with both high precision and high recall, we applied a semantic similarity-based method to extract the remaining candidate aspects. As many aspect terms usually appear in similar contexts, many methods (e.g. PMI) and resources (e.g. WordNet, Probase), as highlighted by [34], were used to capture similarities between words. In this study, we used the word embedding technique based on neural networks architecture since it has proved to be efficient in extracting words appearing in similar contexts. Word embedding is one of the most important vector representations methods employed to measure the semantic and syntactic similarities between words by capturing both continuous distributed representations of the context. Like other deep learning-based techniques, word embedding should be trained on a large dataset of reviews to ensure that contextual information of words is well captured. Although there are many publicly-available trained word embedding vectors, we created new domain-related embedding vectors to get better results. However, previous researches (such as [10]) proved that using vectors trained on a specific-domain dataset always gives good results and improves the efficiency of the proposed aspects’ extraction methods. In order to achieve this step, we created a large domain-specific dataset and thus used it to train the embedding by applying the Word2vec model. To train the embeddings, we collected 10000 Yelp reviews for the restaurant domain and 19600 Amazon reviews for the mobile phone domain. After that, we used the Cosine measure to assess word similarity and verify whether each candidate aspect term exhibited similarity to any of the precise candidate aspects identified in the earlier step (**CAL4**).

Fig.3 represents the algorithm designed for extracting a list of candidate aspects using the word embedding method. This algorithm shows the steps of the selection of candidate aspects basing on the similarity between words. The similarity of each term *t1* in **CAL1** (line 1) was verified with, at least, one term *t2* in **CAL4** (line 2 and line 3). If it was the case, then the term *t1* would be considered as a candidate aspect and it would be added to the list of the candidate aspects **CAL5** (line 4). Therefore, the final list of candidate aspects **CAL6** in this step combine the two lists: **CAL4** and **CAL5** (line 6).

Algorithm 2. Extraction of candidate aspects using the word embedding method.

```
1: For each term t1 ∈ CAL1:
2:     For each t2 ∈ CAL4:
3:         If Similarity (t1, t2) == “True”
4:             CAL5 ◄— add (t1)
5:             break
6: CAL6 ◄— CAL5 ∪ CAL4
```

Fig. 3. Algorithm for the extraction of a list of candidate aspects using the word embedding method.

3.3 Extraction of single-word aspect terms

We described, in this section, the proposed method to extract the single-word aspect terms (**SWAT**). To achieve this method, we created a new filtering algorithm. In fact, we observed a significant presence of a certain category of terms in **CAL6** that cannot be considered as single-word aspects but rather as integral parts of multi-word aspects (**MWAT**). This is due to the high correlation existing between these terms and the single-word aspect terms in the dataset. Therefore, removing these terms from the list of candidate aspects can lead to the extraction of the final list of single-word aspects. To achieve this purpose, we propose a new filtering algorithm in this section. To implement this algorithm, we first need to construct a new list of adjectives and nouns called **LAN**. Indeed, after conducting an empirical study on the dataset (2000 mobile phone reviews), we noticed that the **MWAT** are often composed of candidate aspects in **CAL6**, adjectives, and nouns. Taking as an example the multi-word aspect term **"qualité sonore"** (*"sound quality"*) that is composed of the aspect term **"qualité"** (*"quality"*) and the noun "**sonore**" (*"sound")*. Since the non-aspect terms in **CAL6** form the **MWAT** category 2 and category 3, then their frequency of appearance in the dataset, with aspect terms (in **CAL6**), adjectives, and nouns is high. For that, we constructed a new list **LAN** containing respectively adjectives and nouns appearing with aspect terms (in **CAL6**), in the dataset. Subsequently, and to detect these incorrect aspect terms, we calculated for each term in the **CAL6**, the percentage measure (as shown in (1)). This measure identifies whether a term is a single-word aspect or not basing on its frequency of appearance alone in the dataset. If the candidate aspect term (in **CAL6**) mostly appears alone in the dataset (is not preceded or followed by any other aspects, adjectives, or nouns (in **LAN**)), then this term is probably a single-word aspect term. If the candidate aspect term (in **CAL6**) is often preceded or followed by any other aspects (in **CAL6**), adjectives, or nouns (in **LAN**), then this term is probably not an aspect term, but it is only used in the construction of **MWAT**. As shown in (1), to detect the percentage measure, we first calculated the difference between the two frequencies (Freq (t_A,d), Freq (P (t_A, t), d)) and then we divided the result by the frequency of the term's appearance in the dataset (Freq (t_A,d)). The obtained result shows the percentage of appearance of the candidate aspect term (in **CAL6**) alone in the dataset.

$$Percentage\ (t_A) = \frac{\mathrm{Freq}(t_A,d)*\mathrm{Freq}(P(t_A,t),d)}{\mathrm{Freq}(t_A,d)} * 100 \quad (1)$$

with t_A: term that belongs to **CAL6**.
with t: term that belongs to **CAL6** or **LAN**.
with P (t, t_A): pair of the two terms.
with Freq (t_A, d): The frequency of appearance of each term t (belongs to the **CAL6**) in dataset (d).
with Freq (P (t_A, t), d): The frequency of appearance of each term t with other terms in **CAL6** or in **LAN** list.

According to the obtained result, two different situations were presented:

- **Situation 1.** If the percentage value of the candidate aspect term "*t*" exceeded 50%, indicating that the term "*t*" frequently appeared alone then, the word could be classified as a single-word aspect term (that can be used in some cases in the construction of **MWAT**). In this case, we add the term to the **F**inal **L**ist of **A**spect **T**erms (**FLAT**). Taking as example the term **"écran"** (*screen*) that achieved a percentage value equal to 68%. It means that this term appeared alone in the dataset for most of the cases. It had appeared in the dataset for 544 times. Among these 544 times, it had only appeared for 175 times with adjectives and nouns (of **LAN**) in the dataset ((544-175)/544*100)). In this case, we consider this word as a single-word aspect and we add it to the **FLAT**.
- **Situation 2.** If the percentage value of the candidate aspect term t was less than or equal to 50%, then the term *t* would appear in many cases with aspect terms (in **CAL6**), adjectives and nouns in **LAN**. Consequently, such a term could be either (1) an incorrect single-word aspect term used only to construct the multi-word aspect terms or (2) a single-word aspect term. Taking the example of the word **"qualité"** (*quality*) that appeared in the dataset for 882 times. This word appeared alone in 335 cases in the dataset. While it appeared along with other aspects, adjectives, and nouns in 577 cases (of **LAN**) in the dataset. In this situation, the term **"qualité"** (*quality*) can be a single-word aspect term (since it appeared alone for many times) or a part of multi-word aspect terms (since it appeared for many times with aspects, adjectives, and nouns). To verify whether a word is a single-word aspect term or not, we proposed an extra treatment. In this treatment, we only focused on the cases where these terms appeared alone in the dataset (FreqA (t_A, d)) and were neither preceded nor succeeded by any of the aspect terms or the **LAN**'s terms (355 times for the term **"qualité"** (*quality*). So, for each candidate aspect term t with a percentage value less than or equal to 50%, we verify the cases where this term appears alone in the dataset. For each case, we verify whether the candidate aspect term fulfills at least one of the conditions presented by Table 3. In fact, to be a single-word aspect term, some conditions should be fulfilled. These conditions aim to verify whether a term has the same characteristics as the single-word aspect terms or not. Taking as example condition 1, if the candidate aspect term (in **"CAL6"**) appears alone in the dataset and it is described by an opinion word, then this term is probably a single-word aspect term. After that, we calculated, for each term, the number of cases that had verified at least one of the conditions in Table 3. If the number is less than half of the times where the candidate aspect term figures alone in the dataset, then the

word is considered to be as an incorrect aspect term and a part of multi-word aspect terms. In this case, we add it to a new list used to detect multi-word aspect terms' called filtered list ("**FL**"). Otherwise, we add the term to the **"FLAT"**. Taking as example the term "**qualité**" (*quality*) that has appeared alone in the dataset in 335 cases. This term verified the conditions presented by Table 3 for 224 times, then this term is a single-word aspect term (224> (335/2)).

Table 3. List of conditions.

Conditions	Rules	Examples
1	The term *t* has an nsubj, amod, obl or obj relation with an opinion word.	Les **photos** sont moyennes *(The **photos** are average.) nsubj (**photos**-moyenne)*
2	The term *t* is related to a single-word aspect term by one of the coordinating conjunctions (such as and, or, etc.) or with one of the symbols (",", "+", "/", etc.)	Photos, **qualité** suffit amplement. ***photos**, quality is more than enough.*
3	One of the negation words inverts the term *t*.	Mauvaise surprise! **pas** de **chargeur** dans la boîte. *(bad surprise **no charger** in the box)*

By the end of this algorithm, we obtained two lists. The first list is "**FLAT**", contains the final list of single-word aspect terms. The second list is "**FL**", contains the filtered terms that are useful for the extraction of **MWAT**. In addition, all the values used in these conditions were chosen after conducting an empirical study on the mobile phone dataset consisting of 2000 reviews. These values have been found to be effective in identifying multi-word aspects in the reviews.

3.4 Detection of multi-word aspect terms

The method proposed to extract multi-word aspect terms (**MWAT**) was described in this section. To implement this method, a set of 52 patterns was created. As previously mentioned, there are three categories of multi-word aspect terms. For that, we classified the patterns into three types in order to detect all the categories of **MWAT**. In the first type of patterns, we extracted the **MWAT** that are only composed of single-word aspect terms (category 1). While in the second and the third types of patterns, we focused respectively on categories 2 and 3 of the **MWAT** that are the combination of single-word aspect terms, filtered words and adjectives, and nouns.

Construction of patterns to detect category 1. In this category, we created a set of 24 patterns to detect the **MWAT** that are only composed of single-word aspect terms (category 1). These patterns are presented in Table 4. In this step, we used the single-word aspect terms present in **FLAT**. The following example is an application of pattern 24 where **A** refers to the aspect while **DET** refers to the determinant.

La **qualité photo** est excellente.
*(The **picture quality** is excellent.)*

Construction of patterns to detect category 2. In this part of the study, we constructed a set of 25 patterns to detect the MAWT category 2. These patterns are presented in Table 5. As we previously mentioned, category 2 of **MWAT** is composed of single-word aspect terms (in **FLAT**) and non-aspect terms that can be filtered words (in **FLAT**), adjectives, and nouns (in **LAN**). In the following example, we apply the pattern number 12 where A, N, AD FW, and DET respectively denote Aspect, Noun, Adjective, Filtered Word, and Determinant.

Ce téléphone est excellent au **niveau de caméra**.
*(This phone is excellent at the **level of camera**.)*

Construction of patterns to detect category 3. As we mentioned before, the **MWAT** can only be composed of filtered words (category 3). In fact, the filtered words are not fit to be single-word aspects, but they can form together multi-word as-pect terms. For that, we constructed, in this section, a set of 3 patterns (presented in Table 6) to detect the **MWAT** category 3. The following example is an application of pattern 1 where **FW** refers to the filtered word.

La **prise en main** est facile. *(The **taking at hand** is easy.)*

Table 4. Patterns to extract the category 1 of MWAT

Number	Patterns
1	AAAA
2	AAA
3	AA
4	AAA DET A DET A
5	AA DET A DET A
6	A DET A DET A
7	A DET A DET AA
8	A DET DET A DET A
9	A DET DET A DET AA

10	A DET DET AA DET A
11	AA DET A
12	A DET AA
13	AA DET DET A
14	A DET DET AA
15	AA DET DET A
16	A DET A DET DET A
17	A DET A DET DET AA
18	AAA DET DET A
19	AA DET DET A DET DET A
20	AA DET A DET AA
21	A DET A DET A DET A
22	AA DET A DET A
23	A DET DET A
24	**A DET A**

Table 5. Patterns to extract the category 2 of MWAT.

Number	Patterns
1	(N/AD/FW) A A A
2	(N/AD/FW) A A
3	(N/AD/FW) A
4	(N/AD/FW) A (N/AD/FW)
5	A (N/AD/FW)
6	A A(N/AD/FW)
7	A A(N/AD/FW) A
8	A (N/AD/FW) A
9	A (N/AD/FW) A (N/AD/FW)
10	(N/AD/FW) A (N/AD/FW) A
11	AA DET (N/AD/FW)
12	**(N/AD/FW) DET A**
13	(N/AD/FW) DET (N/AD/FW) DET A
14	(N/AD/FW) DET DET A
15	A DET (N/AD/FW)
16	A (N/AD/FW) DET A
17	(N/AD/FW) DET A A
18	(N/AD/FW) DET DET A DET A
19	A (N/AD/FW) DET DET A
20	(N/AD/FW) DET DET A A
21	A DET A DET (N/AD/FW)
22	A (N/AD/FW) DET A
23	(N/AD/FW) DET A (N/AD/FW)
24	A DET (N/AD/FW) DET (N/AD/FW)
25	A DET (N/AD/FW) A

Table 6. Patterns to extract the category 3 of MWAT.

Number	Patterns
1	FW FW
2	**FW DET FW**
3	FW DET DET FW

4. Experiments and Results

In this section, we present the different resources (datasets, lexicon) and the experimental results considered to evaluate the efficiency of the proposed aspects extraction method with those of some state-of-the-art benchmarks.

4.1 Dataset

Most of the previous aspect extraction-oriented research was conducted on English reviews due to the availability of English online-annotated datasets. However, we constructed French specific-mobile phone dataset on which the experiments were carried out on French reviews. 22000 French mobile phone reviews were collected from the Amazon website. Firstly, 2400 reviews were used to create and evaluate the proposed method. These reviews were manually annotated in our laboratory by two annotators: the first one is a member of our laboratory and the second one is a linguist from the faculty of Letters and Human Sciences of Sfax. 2000 of them were utilized in the empiric study to construct the developed method (extraction of rules, choice of support value, etc.), while 400 reviews were used to evaluate and experiment the single-word and multi-word aspect terms extraction methods. After that, the remaining 19600 Amazon reviews were employed to train the word embedding necessary to extract single-word aspect terms. In addition, we collected 10000 French restaurant reviews to train the word embedding-based model. Also, we used the SemEval-2016 restaurant dataset, containing 455 French reviews manually annotated by two annotators. From this dataset, we selected 335 comments (Restaurant 1) to assess the developed method, while the remaining 120 comments (Restaurant 2) were used to compare the performance of our method against other baselines.

4.2 Opinion Lexicon

Given the big dependency between opinion terms and aspects, the use of an opinion lexicon is necessary to extract aspect terms. In this work, we consider the French lexical dictionary FEEL (French Expanded Emotion Lexicon) containing 14,128 opinion terms divided into 5704 negative words and 8424 positive words.

4.3 Experimentation

To evaluate the suggested method, four experiments were conducted. The first and second experiments aimed to assess the performance of the proposed method for identifying candidate aspects and the proposed method for extracting single-word aspect terms (SWAE), respectively. However, in the third experiment, the performance of the introduced SWAE method was compared to some benchmark studies. In the last experiment, the accuracy of the suggested method in detecting the multi-word aspect terms (MWAE) was assessed.

4.3.1 Experiment 1: Evaluation of the proposed method for identifying candidate aspects

The obtained results (Table 7) show that the proposed method gave very encouraging results (89.15% and 77.69%, for both mobile phone and restaurant domains). As explained previously, the developed method is composed mainly of two steps. In the first one, a list of candidate aspects with highly-precision was extracted using a Linguistic-Knowledge-based Method (LKBM). Subsequently, the list of the extracted terms was enriched with another set of candidate aspect terms extracted using a Deep Learning-Based Method (DLBM).

In fact, the LKBM consists mainly of two steps. In the first one, a set of candidate aspects was extracted using a set of rules and a high recall value equal to 97.00% and 94.07% was obtained respectively for mobile phone and restaurant domains, as shown in Table 7. Findings demonstrate the efficiency of the applied rules to extract approximately all candidate aspects in the dataset. After that, only the high precise aspect terms were extracted using association rules and syntactic relations methods. The experiments conducted on mobile phone and restaurant datasets reveal that high precision (83.58% and 82.05%, respectively, for mobile phone and restaurant) was achieved, as demonstrated in Table 7. However, the recall value remained low for both domains.

The results summarized in Table 7 show that the developed method (DLBM) provide an acceptable precision rate equal to 70.94% and 70.22% and a recall rate equal to 62.87%, 60.52% for both studied domains.

The obtained results show that the LKBM method achieved a very high precision rate and a low recall rate (33.53% for mobile phone and 21.05% for restaurant). However, the DLBM method gave an acceptable percentage of F-measure equal to 66.66%, for mobile phone domain, and 65.01%, for restaurant. In order to ameliorate the experimental results, we combined the two methods. As illustrated in Table 7, the method, proposed to extract the candidate aspects, gave very encouraging results for mobile phone (84.51% F-measure) and restaurant datasets (77.02% F-measure). It also improved significantly the results obtained by LKBM and DLBM and achieved a high recall value and precision rate.

Table 7. Evaluation of the proposed method for identifying candidate aspects.

	Mobile Phone			Restaurant 1		
	Precision	Recall	F-measure	Precision	Recall	F-measure
Extraction of candidate aspect terms using a set of rules	58.48%	97.00%	72.96%	39.17%	94.07%	55.31%
Extraction of a list of candidate aspect terms with high precision using association rules	83.58%	33.53%	47.86%	82.05%	21.05%	33.50%
Extraction of a list of candidate aspect terms using deep learning method	70.94%	62.87%	66.66%	70.22%	60.52%	65.01%
Overall method	75.23%	96.40%	84.51%	72.94%	81.58%	77.02%

The obtained results prove the efficacy of the proposed method, mainly attributed to the effectiveness of the constructed rules and the significant number of comments used to train the Word2Vec model.

4.3.2 Experiment 2: Evaluation of the SWAE method

To identify single-word aspect terms, a new filtering algorithm was proposed basing on a set of measures and conditions. As presented by Table 8, this method achieved promising results, with an F-measure value equal to 87.27% for the mobile phone domain and 78.79% for the restaurant domain. These results demonstrate the efficient application of the proposed filtering algorithm in various dataset domains.

Indeed, the proposed algorithm has successfully extracted the final list of SWAT by removing a substantial number of non-aspect terms. Moreover, it has significantly improved the precision by approximately 9% for the mobile phones and 8% for the restaurants domain. These results are well encouraging and position our algorithm as one of the most proficient in this field.

Table 8. Evaluation of the SWAE method.

	Mobile Phone			Restaurant 1		
	Precision	Recall	F-measure	Precision	Recall	F-measure
SWAE method	84.35%	90.42%	87.27%	80.69%	76.97%	78.79%

4.3.3 Experiment 3: comparison of the SWAE method with the baselines

In this experiment, we compare the performance of the SWAE method with other baselines [18,35,36]. The experiments, in these studies [35,36], were conducted on the restaurant 2 dataset (Section 4.1), introduced by the SemEval-2016 task, which consists of 120 French comments. However, [18] did not specify which dataset they used to evaluate their method (restaurant 1 or restaurant 2). For instance, [18] used a Convolutional Neural Network (CNN) model to extract aspects. To implement this method, the authors first preprocessed the dataset. Subsequently, they converted each word in the sentence into a numerical vector representation known as a word embedding. These embeddings capture the semantic meaning and relationships between words. Finally, the CNN model took the sequence of word embeddings as input and applied filters to detect the aspects. Kooli and Pigneul [35] introduced a method for aspect extraction that combines a CNN for character representation, a Bidirectional Long Short-Term Memory (Bi-LSTM) for joint representation of characters and words, and a supervised Conditional Random Field (CRF) model for aspect identification. This method consists of several steps. Firstly, each character of the word was fed into a CNN model to extract morphological information about the word. Then, the Bi-LSTM model took the character embedding vectors, produced by the CNN as input, to generate new vectors containing contextual information. The resulting vectors, generated at the output of the Bi-LSTM, were then incorporated into the CRF model to predict the label of each word. Kane et al. [36] proposed a new model called CLC for the AE task in French. The CLC model combines three components: CNN, Bi-LSTM, and CRF. To implement the CLC model, the authors first used a CNN layer to extract local features from the input text. Subsequently, these features were incorporated into a Bi-LSTM layer, which captures long-term contextual dependencies between aspects and their related sentiments within a sentence. Finally, the CRF layer took the vectors generated by the Bi-LSTM layer as input to predict the aspects. This model takes into consideration the dependencies between adjacent labels to effectively detect the aspect terms. As shown in Table 9, the proposed method outperformed the existing models when applied on the restaurant 2 dataset. It can be considered as an improvement in the studies conducted by [18,35,36] by approximately 25%, 15%, and 9% respectively. This superiority can be explained by many factors. Firstly, our proposed method leverages the strength of both linguistic knowledge-based methods and deep learning-based methods, whereas the studies conducted by [18,35,36] used only machine learning and deep learning models. By combining these different methods, we can mitigate the limitations of each. For instance, machine learning models may struggle with detecting non-frequent aspects due to insufficient training data. However, by incorporating rules into the analysis, it becomes possible to identify specific aspects regardless of their frequency in the training data. On the other hand, deep learning algorithms can learn from the data and identify complex patterns and variations that may not have been explicitly captured by the rules. This combination yields a more comprehensive and robust method for addressing the limitations of the use of linguistic knowledge based method or machine learning-based method only. Secondly, deep learning models typically require extensive training on large datasets to yield optimal results. To this end, we trained our deep learning-based model using 10000 comments specifically related to the restaurant domain. However, the studies conducted by [35,36] trained their model on a considerably limited dataset (335 comments). Additionally, the use of a filtering algorithm considerably enhances the aspect extraction process by removing non-aspect terms.

Table 9. Comparison of the SWAE method with baselines.

	Precision	Recall	F-measure
[18]	-	-	61.20%
[35]	70.65%	71.30%	70.97%
[36]	-	-	77.02%
SWAE method	82.69%	90.32%	**86.34%**

4.3.4 Experiment 4: results of MWAE method

As shown by Table 10, the proposed MWAE method provided very good results in terms of precision (87.66%) and recall (77.55%) for the mobile phone dataset. However, it is not the case for the restaurant 1 dataset where acceptable percentages of precision (70.84%) and recall (75.60%) were obtained. This remarkable decrease in rates is explained by the following reasons. Firstly, the restaurant domain has some specific characteristics such as the high diversity in dish names appearing only once in the dataset. As shown in the following example, the multi-word aspect term **"Maison à colombage"** (*Half-timbered house*) appeared for only once in the restaurant dataset.

La **maison à colombage** qui abrite le restaurant a été rénovée.
(*The **half-timbered** house that houses the restaurant has been renovated*.)

In addition, we notice, in the restaurant dataset, the existence of some ambiguous cases where the multi-word aspect term is composed of single-word aspect term and opinion word. These cases are difficult to detect by the system. Taking the following example, the multi-word aspect term is composed of the aspect term **"produits"** (*product*) and the opinion word **"frais"** (*fresh*).

Un pain élaboré par un boulanger du coin, un steak haché frais, la qualité des **produits frais**.
(*A bread made by a local baker, a fresh minced steak, the quality of **fresh products**.*)

Some complicated aspect terms, such as "**mais grosse deception**" (*but big disappointment*) and "**loup de mer fraichement pêché avec sa ratatouille sur purée accompagné d'une huile d'olive aux agrumes et herbes**" (*freshly caught sea bass with its ratatouille on mashed potatoes accompanied by an olive oil with citrus fruits and herbs*), were also found in the dataset.

In this section, we did not compare our method with other benchmarks due to the lack of studies that treat the multi-word aspect terms task in the French language.

Table 10. Evaluation of MWAE method.

	Precision	Recall	F-measure
MWAE for mobile phone domain	87.86%	77.55%	82.38%
MWAE for restaurant domain	70.84%	75.60%	76.04%

5. Conclusion and Future Works

The aspect-based sentiment analysis task enables a better understanding of customer sentiments and facilitates for enterprises to make data-driven decisions. By understanding what customers think about different products, businesses can identify patterns and trends related to specific product features. This allows them to address issues, make improvements, and optimize their offerings accordingly. This task generally consists of two steps: Aspect Extraction (AE) and Sentiment Analysis (SA). In this paper, we focused on the AE task and proposed a new hybrid method to extract single-word aspect terms and multi-word aspect terms. To begin with, we employed a three-step process to extract the candidate aspects. In the first step, a set of highly-recalled candidate aspects was extracted employing the dependency relations existing between opinion words and candidate aspects as well as those existing between candidate aspects themselves. Subsequently, a two-step association rule method was applied to extract another list including the most precise candidate aspects. Finally, a fine-tuned word embedding technique, trained by neural networks, was used to extract the rest of the candidate aspects that are similar to the previously extracted accurate candidates. Once we have the list of candidate aspects we extracted during the first step, we employed a new filtering algorithm to extract the single-word aspect terms. This algorithm uses the list of candidate aspects as input and applies specific criteria to identify the single-word aspect terms from the candidates. To extract the multi-word aspect terms, a set of 52 patterns was created by conducting an empirical study on the dataset. At this level, the extracted single-word aspect terms were used.

In the future, we intend to improve the proposed method with a pruning algorithm that is based on an out-domain dataset and a set of rules. Also, we will increase the size of the dataset and we will test the deep learning algorithms (LSTM, CNN, etc.) on the aspects' extraction task. In addition, we will propose a new method for the implicit aspects' extraction task. Finally, we will introduce a new method for the sentiment analysis task.

References

[1] M. Hu and B. Liu, "Mining and summarizing customer reviews", *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, 2004, pp. 168-177, doi: 10.1145/1014052.1014073.

[2] G. Qiu, B. Liu, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation", *Computational linguistics*, vol. 37(1), pp. 9-27, 2011, doi: 10.1162/cola00034.

[3] S. Shariaty, and S. Moghaddam, "Fine-grained opinion mining using conditional random fields", *IEEE 11th International Conference on Data Mining Workshops*, 2011, pp. 270-277, doi: 10.1109/ICDMW.2011.85.

[4] A. Banjar, Z. Ahmed, A. Daud, R. Abbasi, and H. Dawood, "Aspect-based sentiment analysis for polarity estimation of customer reviews on Twitter", *Computers, Materials and Continua*, vol. 67, pp. 2023-2225, 2021, doi: 10.32604/cmc.2021.014226.

[5] M. Tubishat, N. Idris, and M.A. Abushariah, "Implicit aspect extraction in sentiment analysis: Review, taxonomy, opportunities, and open challenges", Information *Processing and Management*, vol. 54, pp. 545-563, 2018, doi: 10.1016/j.ipm.2018.03.008.

[6] A. Banjar, Z. Ahmed, A. Daud, R. Abbasi, and H. Dawood, "Aspect-Based Sentiment Analysis for Polarity Estimation of Customer Reviews on Twitter", Computers, *Materials and Continua*, 2021, doi: 10.32604/cmc.2021.014226.

[7] N. Ayub, M. Talib, R. Hanif, and M.K. Awais, "Aspect Extraction Approach for Sentiment Analysis Using Key- words", *Computers, Materials and Continu*a, vol. 74, pp. 6879-6892, 2023, doi:10.32604/cmc.2023.034214.

[8] P. Mishra and S.K. Panda, "Dependency structure-based rules using root node technique for explicit aspect extraction from online reviews", *IEEE Access*, 2023, pp. 30217-30229, doi:10.1109/ACCESS.2023.3287830.

[9] G. Hinton and T.J. Sejnowski, "Unsupervised learning: foundations of neural computation", *MIT press*, 1999, doi:10.7551/mitpress/7011.001.0001.

[10] S. Moghaddam and M. Ester, "Interdependent lda model for learning latent aspects and their ratings from online product reviews", *Proceedings of the 19th ACM international conference on Information and knowledge management*, 2010, pp. 665-674, doi:10.1145/2009916.2010006.

[11] S. Shariaty and S. Moghaddam, "Fine-grained opinion mining using conditional random fields", IEEE *11th International Conference on Data Mining Workshops*, vol. 10, pp. 270-277, 2011, doi:10.1109/ICDMW.2011.85.

[12] V.S. Anoop and S. Asharaf, "Aspect-oriented sentiment analysis: a topic modeling-powered approach", Journal *of Intelligent Systems*, vol. 29, pp. 1166-1178, 2018, doi:10.1515/jisys-2018-0299.

[13] B. Ozyurt and M.A. Akcayol, "A new topic modeling based approach for aspect extraction in aspect based sentiment analysis: SS-LDA", *Expert Systems with Applications*, vol. 168, pp. 1114-1231, 2021, doi: 10.1016/j.eswa.2020.114231.

[14] T. Heinrich and F. Marchi, "Teamufpr at absapt 2022: Aspect extraction with CRF and BERT", *Proceedings of the Iberian Languages Evaluation Forum (IberLEF 2022)*, 2022.

[15] S. Dargan, M. Kumar, M.R. Ayyagari, and G. Kumar, "A survey of deep learning and its applications: a new paradigm to machine learning", Archives of Computational Methods in Engineering, vol 27, pp. 1071-1092, 2020.

[16] I.H. Sarker, "Deep learning: A comprehensive overview of techniques, taxonomy, applications, and research directions", *SN Computer Science*, vol. 6, pp. 1-20, 2021, doi: 10.1007/s42979-021-00815-1.

[17] S. Hammi, S. M. Hammami, and L. H. Belguith, "Deep Learning Models for Aspect-Based Sentiment Analysis Task: A Survey Paper", *International Conference on Intelligent Systems and Pattern Recognition, Cham: Springer Nature Switzerland*, 2023, pp. 169-183, doi: 10.1109/MLISE54096.2021.00056.

[18] S. Ruder, P. Ghaffari, and J.G. Breslin, "Insight-1 at SemEval-2016 Task 5: Deep learning for multilingual aspect- based sentiment analysis", *arXiv preprint arXiv:1609.02748*, 2016, doi: 10.18653/v1/S16-1053.

[19] G. Zheng, J. Wang, L. Yu, and X. Zhang, "A hybrid approach for aspect sentiment triplet extraction via reinforcement learning and adversarial training", *Expert Systems with Applications*, vol. 184, pp. 115-546, 2023, doi: 10.1145/3614008.3614054.

[20] R. He, W.S. Lee, H. Neg, and D. Dahlmeier, "An interactive multi-task learning network for end-to-end aspect-based sentiment analysis", *arXiv preprint arXiv:1906.06906*, 2019, doi: 10.18653/v1/P19-1048.

[21] S. Chen, Y. Wang, J. Liu, and Y. Wang, "Bidirectional machine reading comprehension for aspect sentiment triplet extraction", *Proceedings of The AAAI Conference On Artificial Intelligence*, vol. 35, pp. 12666-12674, 2021, doi: 10.48550/arXiv.2103.07665.

[22] K. Sharbatian and M.H. Moattar, "Deep aspect extraction and classification for opinion mining in e-commerce applications using convolutional neural network feature extraction followed by long short term memory attention model", *Applied AI Letters*, vol. 4, pp-86-93, 2023, doi: 10.1002/ail2.86.

[23] N. Liu and B. Shen, "Aspect term extraction via information-augmented neural network", *Complex and Intelligent Systems*, vol. 9, pp.537-563, 2023, doi:10.1007/s40747-022-00818-2.

[24] S. Hammi, S.M. Hammami, and L.H. Belguith, "FreMPhone: A French Mobile Phone Corpus for Aspect-Based Sentiment Analysis", *International Conference on Computational Collective Intelligence, Cham: Springer Nature Switzerland*, 2023, pp. 237-249.

[25] S. Poria, E. Cambria, and A. Gelbukh, "Aspect extraction for opinion mining with a deep convolutional neural network", Knowledge-Based Systems, vol. 108, pp. 42-49, 2016, doi: 10.1016/j.knosys.2016.06.009.

[26] A. Laddha and A. Mukherjee, "Aspect Specific Opinion Expression Extraction using Attention based LSTM-CRF Network", *International Conference on Computational Linguistics and Intelligent Text Processing*, vol. 20, pp. 442- 454, 2019, doi: 10.48550/arXiv.1902.02709.

[27] G. Ansari, C. Saxena, T. Ahmad, and M.N. Doja, "Aspect term extraction using graph-based semi-supervised learning". *Procedia Computer Science*, vol. 167, pp. 2080-2090, 2020, doi: 10.1016/j.procs.2020.03.249.

[28] B. Ozyurt and M.A. Akcayol, "A new topic modeling based approach for aspect extraction in aspect based sentiment analysis: SS-LDA", *Expert Systems with Applications*, vol. 168, pp. 114-231, 2021, doi: 10.1016/j.eswa.2020.114231.

[29] P. Ray and A. Chakrabarti, "A mixed approach of deep learning method and rule-based method to improve aspect level sentiment analysis", *Applied Computing and Informatic*, vol.18, pp.163-178, 2022, doi: 10.1016/j.aci.2019.02.002.

[30] S. Hammi, S.M. Hammami, and L.H. Belguith, "An improved hybrid method for sentiment analysis", *International conference on innovations in intelligent systems and applications (INISTA), IEEE*, pp. 1-6. 2022, doi: 10.1109/IN-ISTA55318.2022.9894143.

[31] Y. Zhao, X. Mao, Z. Liu, and Y. Li, "Aspect sentiment classification with both word-level and aspect-level attention networks", *IEEE Access*, vol. 7, pp. 61832-61841, 2019, doi: 10.24963/ijcai.2018/617.

[32] L. Yao, C. Mao, R. Yan, Y. Li, and J. Huang, "Incorporating local dependency model into topic model for aspect term extraction in sentiment analysis", *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics*, vol. 1, pp. 10-20, 2019, doi: 10.1016/j.ins.2018.04.079.

[33] R. Agrawal and R. Srikant, "Fast algorithms for mining association rules", *Proc. 20th int. conf. very large data bases, VLDB*, vol. 1215, pp. 478-499, 1994.

[34] S. Hammi, S.M. Hammami, and L.H. Belguith, "Advancing aspect-based sentiment analysis with a novel architecture combining deep learning models CNN and bi-RNN with the machine learning model SVM", *Social Network Analysis and Mining, Springer*, 2022, pp. 97-117, doi: 10.1007/s13278-023-01126-4.

[35] N. Kooli and E. Pigneul, "Analyse de sentiments à base d'aspects par combinaison de réseaux profonds : application à des avis en Français", *Conférence sur le Traitement Automatique des Langues Naturelles (TALN)*, 2018.

[36] B. Kane, A. Jrad, A. Essebbar, O. Guinaudeau, V. Chiesa, I. Quénel et al., "CNN-LSTM-CRF for Aspect-Based Sentiment Analysis: A Joint Method Applied to French Reviews", *Proceedings of the 14th International Conference on Advanced Applied Computing (ICAART)*, vol. 1, pp. 498-505, 2021.

Authors' Profiles

Hammi Sarsabene is a lecturer at the Higher Institute of Computer Science and Multimedia (ISMIS) in Sfax, Tunisia. She obtained her BEng and MSc in Computer Science from the Faculty of Economics and Management of Sfax (FSEGS), Tunisia. She continued her academic pursuits and completed her Ph.D. in Computer Science from the same institution. Her research interests primarily lie in the fields of sentiment analysis, machine learning, and deep learning.

Hammami M. Souha is an assistant at the Institute of Advanced Commercial Studies of Sfax, Tunisia. She is a member of the Arabic Natural Language Processing Research Group (ANLP-RG) in the Multimedia, Information Systems, and Advanced Computing Laboratory (MIRACL). She received a Ph.D. degree in computer science in 2016 from the Faculty of Economic Sciences and Management of Sfax University, Tunisia. Her research is focused in various areas, including Natural Language Processing, machine learning and data science.

Belguith H. Lamia is a professor at the Faculty of Economics and Management of Sfax (FSEGS) at the University of Sfax, Tunisia. Alongside her teaching responsibilities, she holds multiple leadership roles within the university's research groups and laboratories. Specifically, she is the head of the Arabic Natural Language Processing Research Group (ANLP-RG) in the Multimedia, Information Systems, and Advanced Computing Laboratory (MIRACL). Additionally, she holds the position of co-Director at MIRACL Lab, showcasing her active engagement in pioneering research and advanced computing. Pr. Belguith obtained her B.S. degree in Computer Science and her M.S. degree in Management Information Systems from the FSEGS. She further pursued her academic journey and earned a Ph.D. degree in Computer Science from the same institution. She is interested in a wide array of research areas, including Natural Language Processing, opinion mining, machine learning and data science.

How to cite this paper: Hammi Sarsabene, Hammami M. Souha, Belguith H. Lamia, "A Hybrid Method based on Rules and Deep Learning for Enhancing Single-Word and Multi-Word Aspects Extraction from French Reviews", International Journal of Modern Education and Computer Science(IJMECS), Vol.16, No.4, pp. 1-16, 2024. DOI:10.5815/ijmecs.2024.04.01