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# Implicit Aspect Extraction Techniques in Sentiment Analysis: A Survey

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**Abstract**

*Sentiment analysis is a Natural Language Processing (NLP) research field that uses texture data and machine learning approaches in analyzing sentiments, behaviors, and emotions. People use social media to express feelings in various forms of sentiment. Feelings of fear, worry, sadness, anger, and gratitude were expressed in an online social network. It might sometimes be difficult to get the proper sentiment associated to the aspect. Several feedback texts in which the sentiment is expressed indirectly or implicitly. The task of detecting and extracting terms important for opinion mining and sentiment analysis, such as terms for product qualities or features, is known as aspect extraction. The primary purpose of this research was to discuss and classify techniques for implicit aspect extraction or feature extraction, as well as to address previous research works on sentiment analysis. A few limitations and challenges had been discovered from the previous studies and the future direction of sentiment analysis can be explored further in more depth.*

**Keywords:** *Sentiment analysis, online social network, implicit aspect extraction, feature extraction*

## 1. Introduction

People nowadays communicate primarily through social media platforms such as Facebook, Instagram, Twitter, WhatsApp, LinkedIn, and others. NLP is used in sentiment analysis (or opinion mining) to determine whether data is positive, negative, or neutral (Liu & Zhang, 2012). Sentiment analysis on textual information is frequently used to assist businesses in monitoring brand and product sentiment in customer feedback and understanding customer needs. Posting positive or negative opinions and reviews can affect or influence the feelings, judgment, or decision-making.

The use of Internet-based social media platforms to stay connected with friends, family, or peers is known as social networking. Social media can help people and businesses connect and raise brand awareness (BİLGİN, 2018). Social media has drawbacks, such as spreading misinformation and executing criminal acts (Gill et al., 2017).

Aspect term extraction is required for sentiment analysis at the aspect level. Sentiment analysis collects opinions expressed in social media and website comments before analyzing them to help users and stakeholders better understand public views on the issues raised. More detailed information is provided by aspect-level sentiment analysis, which is extremely useful in various domains (Pontiki et al., 2015).

In this survey paper, we expect to discuss how different techniques have been used in aspect extraction to perform sentiment analysis. The rest of the article is organized as follows: Section II will go over previous research about sentiment analysis and the techniques used for aspect extraction in greater detail. Section III goes over the methodology that has been used in this research work. Section IV will discuss results of review from previous research work. Future work on previous work was concluded with Section V.

## 2. Related Works

Sentiment analysis (SA), often known as mining opinion, is a type of natural language processing (NLP) study that uses text mining to extract sentiment orientation (positive, negative, and neutral) (Liu & Zhang, 2012). Sentiment analysis (SA) plays an important role in assessing and summarizing all the differing opinions. SA is the study of user reviews of a product on multiple e-commerce websites, social media platforms or company websites. As shown in Figure 1, SA can be performed at several levels of granularity: document level, sentence level, and aspect level (Hu & Liu, 2004).

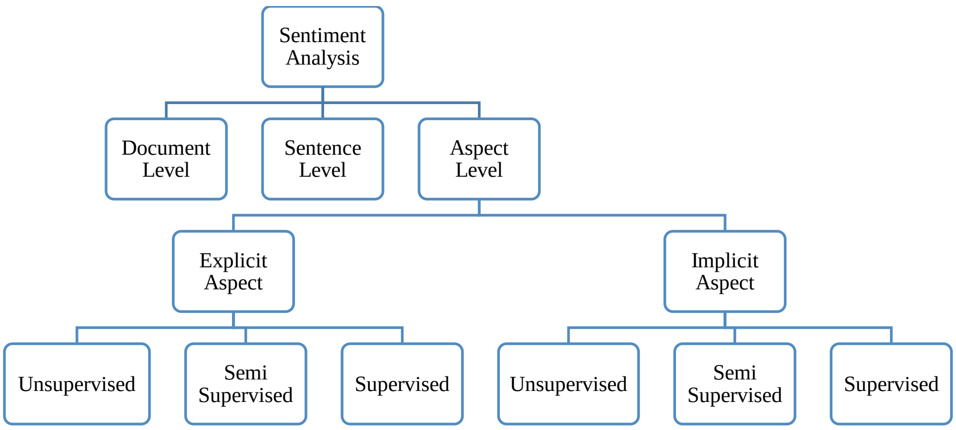


Figure 1: Taxonomy of Sentiment Analysis

The critical part of the document level and sentence level cannot determine whether people's thoughts like and dislike to imply the sentiments. The entity and aspect level, also known as the features level, is a fine-grained analysis that handles sentiments (both positive and negative) by focusing on the aspect (opinions). The extraction involved the discovery of sentiments by analyzing aspects and/or opinions and labeling them based on similar entities or classes. This aspect level can be divided into two parts: explicit and implicit. Explicit means that it is stated clearly in the sentences, whereas implicit means that statements with implicit aspects do not contain direct aspect terms.

Aspect-based sentiment analysis (ABSA) is a text analysis technique that categorizes data by aspect and identifies the sentiment associated with each one. Customer feedback can be analyzed using ABSA by associating specific sentiments with different product or service aspects. ABSA has divided the work into three categories: (i) Aspect Category Detection (ACD), (ii) Opinion Target Extraction (OTE), and (ii) Sentiment Polarity (SP), where ACD is used to detect entities and attributes, OTE is used to extract linguistic expressions from text, and SP is used to classify entities using polarity labels (Pontiki et al., 2016). Let's look at an example to understand ABSA better. Think about hotel review websites. “The room is huge, and the food is varied.” Room and food are entity aspects in this review. The entity's opinion target is spaciousness and variety, and both polarities are labeled as positive. The phrase "But it is quite expensive" denotes an implicit aspect, and the word expensive has a negative polarity. This means that ACD is concerned with explicit and implicit aspects, whereas OTE is only concerned with explicit aspects.

The subject of aspect extraction has been thoroughly researched and applied in various fields of sentiment analysis. On the other hand, current aspect extraction approaches are primarily concerned with extracting explicit appeared aspects. The problem of identifying implicit aspects remains a significant challenge in sentiment analysis. In this work, we provide a survey of several articles that related to implicit aspect extraction.

In comparison to other technologies, observations show that the completeness and accuracy of rules determine the accuracy of a linguistic rule-based aspect extraction technique. This paper discusses the developed a rule-based dependency methodology to address the problem of extracting aspects from product reviews (Poria et al., 2014). The authors of this study employed the Stanford parser to generate the dependency tree and then applied several dependency rules to unsupervised techniques to extract aspects from a sentence. (Poria et al., 2016) again researched use features extracted from a deep CNN for sarcasm detection. For extracting aspect opinion target expressions (OTEs), (Al-Smadi et al., 2019) and (Gandhi & Attar, 2020) developed a bi-LSTM with CRF model, as well as an aspect-based LSTM in which aspect OTEs are treated as attention expressions for aspect sentiment polarity classification.

In product review summarization, an ontology-based approach for aspect extraction was developed. The method successfully removed the previous issues with lexicon-based sentiment scoring (Rana & Cheah, 2015). However, it could not handle several key patterns or characteristics, such as nouns, verbs, and sentiment phrases, which are thought to have a significant emotional impact. This paper covers a review about topic modeling, especially the Latent Dirichlet Allocation (LDA) approach. The outcomes of various techniques have been summarized, evaluated, and presented in a sophisticated manner. The effectiveness of topic modeling for aspect extraction and categorization has been demonstrated (Rana et al., 2016). In customer evaluations, a semantic-based method was used to extract implicit aspects. The study used word meaning disambiguation and word semantic relations in the text to provide a larger semantic context from which the implicit component could be extracted (Schouten et al., 2015). It was revealed that the suggested method failed to reconcile semantic relations inside WordNet properly. The goal of this study was to propose a method for identifying numerous implicit features in a phrase. In the presence of many connected aspects, relationships between distinct entities with different aspects are represented as a hierarchy, which aids in increasing the accuracy of implicit aspect identification (Panchendrarajan et al., 2016).

## 3. Methodology

The purpose of this study is to offer information relevant to implicit aspect extraction techniques that are commonly employed in research. Peer review was performed on related publications published between 2016 and 2021. Scopus, ACM, Science Direct, and IEEE Xplore were used to search for the publications. The research keywords were selected when planning the study search. For the search, the following keywords were used: ("aspect-based sentiment analysis" AND "online social networks" AND ("machine learning" OR "deep learning")) and ("aspect extraction" AND "sentiment analysis" AND "social media" AND ("machine learning" OR "deep learning")) and ("Implicit aspect extraction" AND "sentiment analysis"). Since our focus is on implicit aspect extraction, we only chose and reviewed literature from categories of implicit aspect extraction. Finally, our survey, which includes 15 papers, exclusively includes articles about implicit aspect extraction.

## 4. Results and Discussion

The results and discussion are based on variety of criteria, including the implicit aspect extraction method used, datasets and languages employed, and the acquired performance of previous research works the limitations and challenges of various prior research works. Figure 2 illustrates the distribution of articles based on articles extracted from the subscribed database. Most of the articles related to implicit aspect extraction are available in the Scopus and IEEE Explore databases. The distribution of publications by year was obtained and is depicted in Figure 3. Most of the publications on implicit aspect extraction is available in 2019.

In accordance with the implicit aspect extraction taxonomy discussed in earlier sections, Table 1 depicts the researchers' preference for unsupervised, semi-supervised, or supervised learning approaches. According to Table 1, unsupervised approaches identified were used in 7 of the 15 articles, accounting for around 47% of the total articles analyzed for this study. Although five publications are examined for semi-supervised approaches and three articles, contain supervised techniques. It is shown that implicit aspect extraction with an unsupervised learning approach can be considered as most frequently chosen by researchers for their prior works. Although it can be concluded that data in supervised method research are often completely labeled and frequently employed in explicit aspect extraction. It might be claimed that semi-supervised and supervised methods have not yet been fully explored, leaving the potential for further research by other academics to develop new strategies.

It could be observed that the studies focused on implicit aspect extraction that using different techniques such as Dictionary Based, Dependency Parsing, Co-occurrence, Naive Bayes, Lexicon-Based, Topic Modelling, Decision Tree-Based, CNN, Particle Swarm Optimization, Bi-LSTM, BERT and Matrix Factorization. It can be inferred from this survey that implicit aspect extraction techniques were frequently used, including a hybrid strategy that combined WordNet (Dictionary Based) with other approaches such as Naive Bayes, SpaCy, and TF-IDF. Matric Factorization and Lexicon Based come in second and third place, respectively. This means that the unsupervised approach is the most commonly employed approach for implicit aspect extraction in recent studies. This is due to the fact that unsupervised techniques do not require both dataset annotation and training. Furthermore, when compared to earlier methodologies, the unsupervised methodology is substantially less expensive and faster.

Almost all the domains studied in this study are related to products reviews. Current areas, such as the ability to learn in a pandemic crisis, mental health workers working from home, community feelings when Covid-19 strikes, and vaccination acceptability among the community, are also great to explore through posting it on social media. However, topics that are difficult to extract in several related domains such as emotional detection, mental health, and behavioral interventions have yet to be addressed. The most current aspect extraction field, implicit aspect extraction, is ambiguous and more semantic than explicit aspect extraction. As a result, many studies point to implicit as a feasible future strategy. Most researchers are researching implicit characteristics and experimenting with different approaches to identify the best methods for achieving decent results.

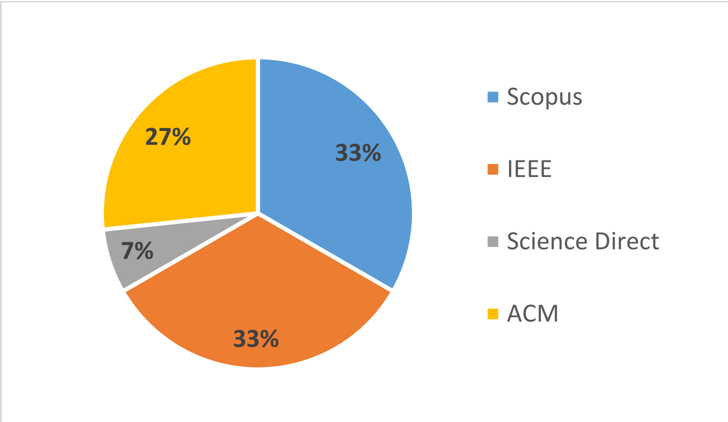


Figure 2: Distribution the extracted articles-based databases

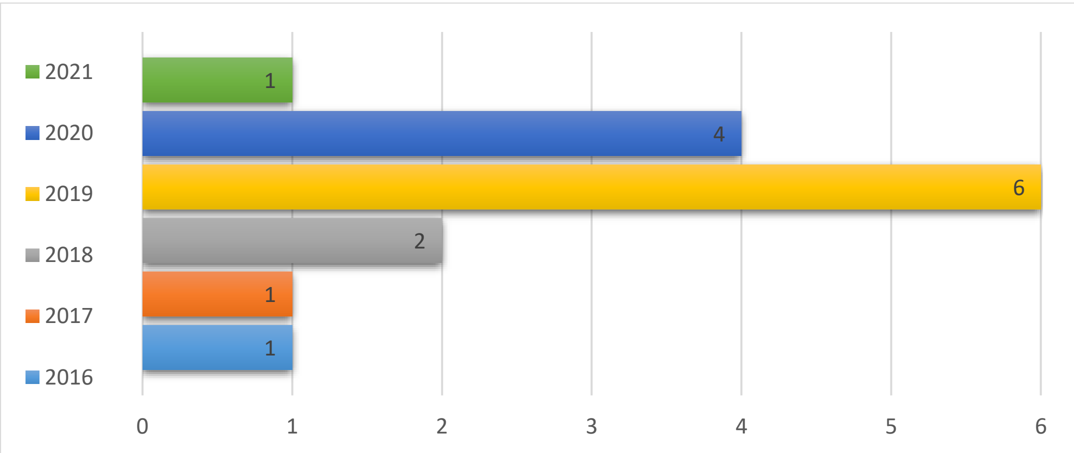


Figure 3: Distribution the extracted articles based on years

As seen in Table 2, there are several areas where additional study and solutions are needed. For example, there is no fixed method or technique for implying implicit aspect extraction. For testing and assessing implicit aspect extraction, there is no standard dataset available. Due to a shortage of publicly available standard datasets, the development of publicly accessible standard datasets is possible to develop publicly accessible standard datasets. Still, an additional study research in terms of aspects and categories on feature selection and extraction is needed. Another issue raised throughout the research is that labeling data, the implied element of resolving the single label or multiple label issue, necessitates a focus on this topic.

Table 2: Limitation and challenges associated with implicit aspect extraction techniques

| No. | Issues | Limitation & Challenges | References |
|---|---|---|---|
| 1 | Limit features extraction techniques | The Effect of the Number of Training Data.<br>The Number of Prediction Inconsistencies.<br>The Effect of Parsing Methods. | (Yu et al., 2019) |
| 2 | Aspects & categories | Aspect words or sentiment words clustering is not able. | (Feng et al., 2019) |
| | | A number of categories to large. | (Soni & Rambola, 2021) |
| 3 | Dataset | Not balance. | (Soni & Rambola, 2021) |
| | | Needed large dataset. | (Cambria et al., 2020) |
| 4 | Labelling data | Labelling data with a larger dataset and repetition of the sentence. | (Asif et al., 2020) |

## 5. Conclusion and Future Recommendation

This paper discusses extend and classify the most often used strategies for extracting implicit features. This study yielded some noteworthy results. Our analysis also reveals that most of the work in implicit aspect extraction is focused on unsupervised approaches. Due to a limitation of coverage in the field of implicit aspect extraction, additional attention from other researchers is required. Several research have found that implicit aspect extraction is more confusing and semantic than explicit aspect extraction. More research on implicit properties, as well as testing of various procedures, are required to determine the most effective methods for achieving acceptable outcomes. Still, there is an exciting outcome for strategies that employ supervised and semi-supervised methods.

Furthermore, current issues worth investigating include the ability to learn during a pandemic, mental health workers working from home, community attitudes when Covid-19 strikes, and community acceptance of vaccines. However, topics that are difficult to extract remain ignored in other connected disciplines, such as emotional detection, mental health, and behavioral therapy. As a result, focusing just on product reviews is insufficient; other sectors are equally significant and require more future research.

It is possible to conclude that several limitations and restrictions are frequently encountered when doing sentiment analysis research, particularly in terms of implicit aspect extraction. Researchers frequently confront relatively limited usage on features extraction, which affects the accuracy of the research. Data set difficulties include relatively limited, imbalanced data sets that need big data sets, and data that is not appropriately labelled in terms of categorization and aspect. The feature of the extraction strategies chosen in compliance with the dataset and learning technique must be correctly decided. The extraction features used have a significant impact on the polarity sentiment analysis's accuracy and efficiency.

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Table 1: The summary of implicit aspect extraction techniques based on learning approaches and dataset

| No. | *Author* | *Extraction Techniques* | *Learning Approaches* | | | *Dataset & Domain* |
|---|---|---|---|---|---|---|
| | | | ***S*** | ***SS*** | ***US*** | |
| *1* | (Hajar & Mohammed, 2016) | WordNet (Dictionary-Based) + Naïve Bayes | √ | | | Electronic products & Restaurants - corpora (Cruz-Garcia & Ganu) |
| *2* | (Soni & Rambola, 2021) | WordNet (Dictionary-Based) + SpaCy | | | √ | Samsung M21 mobile - Amazon |
| *3* | (Asif et al., 2020) | Lexicon-Based | | √ | | News – Facebook Pakistan |
| *4* | (Kama et al., 2017) | Lexicon-Based | | √ | | Product reviews - Donanim Haber (Turkey portal) |
| *5* | (Khalid et al., 2018) | Topic Modelling | | | √ | Opinion Reason - Twitter |
| *6* | (Yang et al., 2019) | Dependency Parsing | √ | | | Baby Care reviews- www.babytree.com |
| *7* | (Ray & Chakrabarti, 2019) | CNN + Rule Based | √ | | | Movie reviews - Stanford Sentiment Treebank) & Restaurant reviews – SemEval-20l4 |
| *8* | (Feng et al., 2019) | Co-occurrence | | √ | | Mobile Phone reviews - e-commerce website, Amazon, Jingdong and Lynx |
| *9* | (Yu et al., 2019) | CNN | | √ | | Laptop & Restaurant reviews – SemEval-2014 & SemEval-2015 |
| *10* | (Singh Chauhan et al., 2020) | Rule-Based + Bi-LSTM | | | √ | Laptop & Restaurant reviews – SemEval-2016 |
| *11* | (Maylawati et al., 2020) | TF-IDF + Particle Swarm Optimization | | √ | | Laptop reviews – SemEval-20l4 |
| *12* | (El Hannach & Benkhalifa, 2018) | WordNet (Dictionary-Based) + TF-ICF | | | √ | Crime Identification - Twitter |
| *13* | (Xu et al., 2020) | Matrix Factorization | | | √ | Product reviews - SemEval-2015 |
| *14* | (Ali et al., 2020) | Matrix Factorization | | | √ | Uber Service reviews - Facebook |
| *15* | (Cambria et al., 2020) | Bi-LSTM + BERT | | | √ | Symbolic and Subsymbolic segment - SenticNet 6 |

***S – Supervised***

***SS - Semi-Supervised***

***US - Unsupervised***

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