Aspect-Based Sentiment Analysis: An Extensive Study of Techniques, Challenges, and Applications

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***Abstract*—Aspect-based Sentiment Analysis(ABSA) has gained significant attention in recent years because of its ability to provide more fine-grained insights into customer preferences. ABSA, an NLP-based data mining technique, focuses on identifying user sentiments related to different aspects of a product or service. This paper presents a comprehensive overview of ABSA including aspect extraction, sentiment analysis, and aspect-based summarization techniques, and discusses its challenges, applications, and future scope. In addition, the paper presents a thorough comparative analysis of deep learning-based models for ABSA and also discusses the commonly used datasets. Deep learning-based techniques have produced better outcomes than the traditional ABSA methods.**

***Index Terms*—Aspect-based sentiment analysis, Aspect extraction, Artificial Intelligence, Machine learning, Deep learning, NLP**

I. Introduction

Natural language processing (NLP) technology combines the fields of computational linguistics, Machine Learning (ML), and Deep Learning (DL) models to process and analyze human language efficiently. It plays a major role in ML and DL-based real-world applications including Text Summarization, Sentiment analysis Speech Recognition and Social media analytics. ABSA is an NLP task that analyzes sentiment towards a specific aspect of the product based on textual product or service reviews. The main objective of ABSA is to identify and extract the text's aspects and sentiment polarity. Aspect term, Aspect category, Opinion term, and Polarity are the elements of ABSA.

Aspect term is the term explicitly in the text, which is the feature, or topic being talked about.

Aspect Category is the predefined set with the collections of aspects related to a specific domain.

Opinion Term is the term specified in the text which is used to describe or characterize the aspect.

Polarity gives the overall sentiment (positive, negative, or neutral) of the text.

Examples:

Text 1: The fried rice is amazing here.

Text 2: The cost is reasonable although the service is poor.

Elements of ABSA of Text 1 and 2:

Aspect term	fried rice
Aspect Category	**Food**
Opinion Term	amazing
Polarity	**Positive**

Aspect term	cost	service
Aspect Category	**Price**	**Service**
Opinion Term	reasonable	poor
Polarity	**Positive**	**Negative**

A textual review may have more than one aspect with varying sentiments as shown in Example 2. The main steps or tasks involved in ABSA are
1. Aspect Extraction,
2. Sentiment Analysis,
3. Aspect-Based Summarization.

The Steps involved in ABSA are depicted in Figure 1.

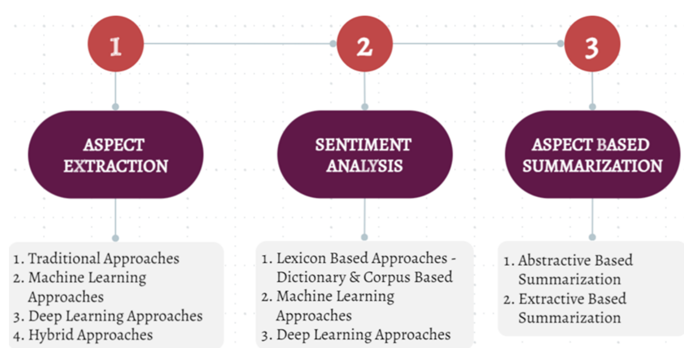

Fig. 1. Steps involved in ABSA.

ASPECT EXTRACTION – This mainly focuses on identifying and extracting the product's explicit and implicit aspects or features from the textual reviews. Table I shows various domains and their sample aspects. Explicit aspects appear explicitly in the text. Implicit aspects do not appear explicitly but are implied from the context. Identifying these aspects requires a deeper Context understanding and relations among the words. Table II Shows examples of Explicit and

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Implicit Aspects.

TABLE I
DOMAINS AND ITS ASPECTS

Domains	Aspects
Restaurant	Food, Quality, Parking, Location, Price, Service
Hotel	Room, Location, Food, Facilities, Service, Booking
Laptop	Processor, Quality, Price, Performance, Display size
Mobile Phone	Camera, Price, Sound, Quality, Screen, Charge
Camera	Lens, Battery, Quality, Shot, Flash, Resolution

TABLE II
EXPLICIT AND IMPLICIT ASPECTS

Text	Aspect Category	Type
The **battery** is very longer	Battery	Explicit
Incredible **graphics** and brilliant colors	Graphics	Explicit
This is an **expensive** bike	Price	Implicit
The **quality of the pictures** was great	Camera	Implicit

SENTIMENT ANALYSIS – This analysis is done to understand the user's sentiment (positive, negative, or neutral) towards a specific aspect or feature in the text. The three levels of sentiment analysis are:
Document level – It classifies the whole document with sentiments.
Sentence level - It identifies the sentiment expressed in a sentence/phrase.
Aspect level – It identifies sentiments expressed towards a specific product or service aspect. It is depicted in Figure 2.

Fig. 2. Levels of Sentiment Analysis.

ASPECT-BASED SUMMARIZATION: This focus on generating summaries with respect to the aspect of the product. This is of two types – Abstractive Summarization and Extractive Summarization. Various techniques used in ABSA are Machine learning (Supervised and Unsupervised), Deep learning, and Hybrid methods. Deep Learning based techniques play a major role in identifying the aspects and their sentiments in effective and efficient performance. The Traditional Sentiment analysis method only gives the text's overall polarity without considering the aspects. However, ABSA has several advantages over the traditional sentiment analysis methods. It assists in better comprehending consumer thoughts or opinions towards a specific aspect which will be highly beneficial for future product improvements.

The layout for the remaining sections is outlined as: Section II explains Aspect Extraction and its related work. Section III outlines Sentiment Analysis and algorithms. Section IV details Aspect-based Summarization and its types. Section V compares different papers on the ABSA algorithm. Section VI covers benchmark datasets used in ABSA. Section VII presents various evaluation methods for ABSA. Section VIII presents Inferences made from this survey and the future scope of ABSA. Sections IX and X discuss ABSA applications and challenges and finally, the conclusion with Section XI.

II. ASPECT EXTRACTION

Aspect extraction is an NLP task that mainly focuses on identifying and extracting specific aspects or features from text. The text may be customer feedback, social media posts, reviews of products, services, events, etc. Different challenges in aspect extraction are handling unlabelled data, contextual embeddings, and jointly extracting aspect and opinion terms.

A. *Traditional Approaches*

Traditional aspect extraction employs Rule-Based and Dictionary-Based methods.

*1) **Rule-Based**:* It uses predefined linguistic patterns or rules to identify implicit and explicit aspects. Ruskanda et al. [1] used the Sequential Covering algorithm with language features like PoS and dependency trees, constituent parse trees to generate rules based on various dependency relationships.

*2) **Dictionary-Based**:* It relies on lexicons containing aspect terms and their synonyms. Geli et al. [2] applied the collective classification algorithm to identify implied aspects through adjectives by utilizing lexical relationships.

B. *Machine Learning Approaches*

Supervised learning techniques, such as SVM, CRF, HMM are used for aspect extraction. Labeled data is required for training. Features like word embeddings, PoS tags, or syntactic patterns are used. R. Hegde et al. [3] proposed Incremental ML Algorithm for feature extraction and sentiment classification. Maximum entropy, NB, SVM, and RF are used for Opinion summarization.

C. *Deep Learning Approaches*

Techniques like Recurrent Neural Networks, Transformer-based models can be used for aspect extraction. RNN Models like LSTM and GRU, have been extensively used for aspect extraction. Sequential dependencies and contextual information are captured from the input text. Attention-based LSTM model by Wang [4] used for sentiment classification at aspect level. The CNN employs a convolutional layer featuring multiple filters to identify local patterns or n-grams within the input text. Hu Xu [5] used a double embeddings (general-purpose and domain-specific) based CNN model. Soujanya [6] integrated heuristic linguistic patterns with 7 layers CNN classifier for aspect extraction. Transformer-based Models such as BERT captures contextual information by focusing on different parts of the input sequence acting as an attention mechanism. Santos[7] proposed an MDAEBERT model addresses issues of inconsistency of aspects and context-based semantic distance between ambiguous aspects. Y. Gao[8] proposed a Collaborative Extraction Hierarchical Attention model with hierarchical units for extracting sentiment-guided and aspect-guided information.

D. *Hybrid Approaches*

Hybrid approaches combine multiple DL architectures to improve aspect extraction performance. Ray's[9] Hybrid Approach with Deep CNN and rule-based approaches for performance improvement of the aspect extraction method and sentiment scoring method. Hybrid unsupervised model [10] combines linguistic patterns with DL for ATE enhancement. Rules-based methods extract aspects, fine-tuned with word embedding for domain-specific relevance. These refined aspects serve as labeled data for training an attention-based model.

III. Sentiment Analysis

Traditional Approaches like the Lexicon-based method which includes Dictionary-based, and Corpus-Based methods for analyzing the sentiments.

A. *Traditional Approaches*

Lexicon-based Approaches: It determines the text's sentiment using predefined sentiment lexicons or dictionaries. The text is divided into tokens, each token assigned with a score. The aggregation of the scores gives the overall polarity of the text. Words in the lexicon have polarity values from (-1 to +1) for varying sentiments. There are two categories of Lexicon-based methods:

*1) **Dictionary-based Approach**:* It determines the sentiment of the text by using predefined sentiment dictionaries. Various approaches are using SentiWordNet, SentiFul, Senti-Words, SenticNet, and VADER.

*2) **Corpus-Based Approach**:* It trains models using labeled texts (corpus) for sentiment identification. It learns semantic and syntactic patterns to discover the text's polarity. The training text is annotated with polarity values(-1 to +1).

- **Statistical Approach:** It uses statistical models to analyze the sentiments expressed in the text. It utilizes labeled training data and learns the co-occurrence patterns.
- **Semantic Approach:** This approach focuses on capturing semantic relationships between words and contextual understanding of the text. Wordnet is most commonly used.

B. *Machine Learning Based Approaches:*

Different machine learning (ML) techniques were applied for sentiment analysis. Saad [11] compared classifiers like Multinomial LR, SVR, DT, and RF on the Twitter dataset, finding DT to be more effective than the other algorithms. Oyebode [12] used SVM, MNB, SGD, LR, and RF to analyze mental health app reviews. This is done by conducting thematic analysis on reviews for insights and building a recommendation system. He et al. [13] combined SVM and LDA for sentiment analysis of product reviews, introducing a sentiment contribution measurement for weighting. Bengesi[14] employed various ML algorithms (KNN, SVM, RF, Logistic Regression, MLP, NB, and XGBoost). Highest accuracy attained with TextBlob, Lemmatization, CountVectorizer, SVM model development approach.

C. *Deep Learning-Based Methods*

L. Yang [15] introduced the SLCABG sentiment analysis model, which incorporates sentiment lexicons, the BERT model, and attention mechanisms. This model effectively analyzes sentiment in product reviews by combining CNN with attention-based BiGRU. This extracts sentiment and contextual features using CNN and BiGRU, applies attention weights, and performs better than other methods. Khan [16] emphasized sentiment analysis by exploring text representations(n-grams, fastText). Also worked on various classifiers - ML (RF, NB, SVM, AdaBoost, MLP, LR) and DL (1DCNN and LSTM). LR with n-gram achieved the highest performance followed by SVM.

IV. Aspect-Based Summarization

Aspect-based summarization is a text summarization technique that provides an informative summary of a product based on the aspects. Deep Learning models, Transformer-based models, Sequence-to-Sequence (Seq2Seq) models with attention mechanisms are used for abstractive summarization. Graph-based models, Frequency-based models, TF IDF, Latent Semantic Analysis (LSA), and ML models such as SVM are used for extractive summarization.

A. *Abstractive Summarization:*

Y. Chen [17] developed an abstractive multi-text summarization method that generates review summaries using predefined topics and sentiments as templates. This method employs the TextRank algorithm to identify aspect-based polarities and select the most representative sentences for creating the summary.

B. *Extractive Summarization*

Zha's [18] framework for ranking product aspects includes identifying aspects, classifying sentiment, and ranking aspects. Furthermore, this approach is expanded to document-level sentiment classification and the generation of extractive summaries for reviews. ExopSum [19] is an extractive summarizer that employs aspect, sentence, and review ranking, followed by opinion extraction-based summarization. S. Avasthi [20] uses extraction-based summarization, focusing on aspects extracted from reviews. Insights from tourist attraction reviews are gathered using ABSA. Crowdsourcing, Fairsumm, and Centroid were the evaluation methods used. Crowdsourcing provides the best results for aspect-based summaries. Yauris

[21] proposed a game review summarization system that utilizes a modified Double Propagation method for aspect and sentiment extraction. The process involves aggregating aspects, categorizing them, and producing summaries.

V. Comparison Table - Deep Learning based ABSA Algorithms

Various Research works on DL based ABSA Algorithms with their datasets are compared and tabulated in Table 3.

VI. Dataset

The commonly used datasets for ABSA are:

1. SemEval 2014 Task4: This Dataset includes restaurant(3K) and laptop(3K) reviews.

2. SemEval 2015 Task 12: This Dataset includes restaurant and laptop reviews (nearly around 550 reviews) with annotated aspects with corresponding sentiments for the review.

3. SemEval 2016 Task 5: This is Multilingual dataset that includes various domains like hotel, electronic, and restaurant reviews with annotated aspects, and their corresponding sentiments for the review.

4. SemEval-2017 Task 5 Subtask 1: This dataset includes financial tweets about stock symbols nearly around 1800 tweets with sentiment scores between -1 to 1.

5. Amazon Reviews: This dataset contains Amazon product reviews (mobile phones, cameras, MP3 players, and laptops) which include 82.83 million distinct reviews from around 20 million users.

6. Yelp: This is a dataset with the collection of around 269,000 unique restaurant reviews from Yelp.

7. TripAdvisor: This is a dataset with the collection of around 3.1 million unique Hotel reviews from TripAdvisor.

8. Multi-Aspect Multi-Sentiment (MAMS): The MAMS dataset has two versions: ATSA with 13,854 instances and ACSA with 8,879 instances, having various sentiment polarities.

VII. Experiment Evaluation

The Effectiveness and performance of a Model are evaluated by computing the evaluation metrics. ABSA Model performance that is how correctly the model identifies and classifies aspects and sentiments is calculated by the following evaluation methods.

Confusion Matrix: The Confusion Matrix is constructed using TP, TN, FP, and FN for actual and predicted classes. It is depicted in Figure 3. An effective model will have high TP and TN, and low (close to zero) FP and FN values. TP and TN are accurate predictions, while FP and FN are incorrect predictions of aspects with sentiments.

PREDICTED CLASS

ACTUAL CLASS	Positive	Negative
Positive	**True Positive (TP)**	False Negative (FN) **Type II Error**
Negative	False Positive (FP) **Type I Error**	**True Negative (TN)**

Fig. 3. Confusion Matrix.

*1) **Accuracy**:* This metric quantifies the percentage of correctly categorized aspects and their corresponding sentiments. Its value ranges between 0 and 1. The good accuracy score is the value towards 1.

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

*2) **Precision, Recall, F1 Score**:* Precision is defined as the ratio of True positive (TP) aspects to the total number of aspects (TP+FP) predicted as positive. The model should aim to obtain High precision and High accuracy values. Recall metric is used to measure the proportion of actual positive that was identified incorrectly. The F1 score is computed with precision and recall value. An ideal F1 score value approaches 1.

$$Precision = \frac{(TP)}{(TP + FP)} \tag{2}$$

$$Recall = \frac{(TP)}{(TP + FN)} \tag{3}$$

$$F1Score = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \tag{4}$$

*3) **Mean Absolute Error**:* It measures the average magnitude of errors between the actual and predicted values. MAE Value should be low as minimum.

$$MAE = \frac{1}{n} \sum |x_i - x_i'| \tag{5}$$

*4) **Root Mean Squared Error**:* It quantifies the degree of variation in prediction errors. RMSE Value should be low as minimum.

$$RMSE = \sqrt{\frac{\sum (x_i - x_i')^2}{n}} \tag{6}$$

VIII. Inferences Made

Obtaining a highly accurate ABSA Model i.e., Obtaining correct sentiment towards specific aspects of the product is possible with the following inferences made from this survey:

1) Accurate aspect identification and extraction (Implicit and Explicit) with the level of granularity has an impact on the

TABLE III
COMPARISON TABLE OF VARIOUS METHODS OF ABSA

Year	References	Work	Methodology	Dataset
2023	[22]	Auto-Adaptive Model Transfer	BiLSTM	SemEval2014 SemEval2016
2023	[23]	Graph Neural Network	HGNN	Restaurant, MAMS
2022	[24]	BERT Model for Tweets on Covid Vaccination and Vaccine Types	BERT models	English tweets Turkish Tweets
2022	[25]	ABSA based on GCN Model Using CNN Over BERT-GCN	CNN over BERT-GCN model	Laptop Restaurant Twitter
2022	[26]	Affective Knowledge Augmented Interactive GCN	GCN and Multi-Head Self-Attention	4 Chinese datasets 6 English datasets
2021	[27]	XLNet Transfer Learning ADR Using Hybrid Ontology	XLNet model and Bi-LSTM networks	AskaPatient, WebMD DrugBank,Twitter N2c2, TAC
2021	[28]	Target-focused sentiment analysis with self attention	MSAT Networks	Semeval2014, Laptop from Dong et al.
2021	[29]	Attention BiLSTM	BiLSTM + Aspect Attention	SemEval 2014 Twitter data
2021	[30]	DNN model combining CNN and GRU	CNN, GRU	Chinese reviews of hotels,cars
2021	[31]	Multitask Multiview Neural Network (MTMVN)	CNN, LSTM, BiGRU	SemEval2014 English tweets
2020	[32]	Hybrid CNN-GA Approach	CNN with GA	Automobiles, Movies,Hotel reviews
2020	[33]	BERT Representation with Context-Aware Embedding	GBCN	SentiHood SemEval2014
2020	[34]	Transformer with Multi-Grained Attention (T-MGAN)	Transformer based MGAN	SemEval2014 Twitter
2020	[35]	NN framework in Combination of Recursive and RNN using Inter-Aspect Relations	GRU	SemEval2014
2019	[36]	Attention-Based LSTM with Position Context	LSTM	SemEval2014
2019	[37]	ABSA with Enhanced Attention(FEA-NN)	CNN, BiLSTM	SemEval2014, Twitter

accuracy of the model.
2) Fine-grained sentiment analysis discerns sentiment towards specific text aspects.
3) Understanding the context of the text in determining the aspect-based sentiments is one of the factors that define the quality of the model.
4) Advanced Deep learning algorithms are better than traditional methods.
5) High-Quality training data results in more accuracy.

The future Scope of ABSA includes Multimodal ABSA, Transferable ABSA Such as Cross-lingual and Cross-domain ABSA.

IX. Applications

The various applications of ABSA are Analyzing Customer Feedback on Product/Service Reviews and providing Customer Support, Sentiment Analysis, Market research and analysis, Recommendation systems, Social media analysis, Social media monitoring, and also on other various domains such as Healthcare, E-commerce, Finance, etc.

X. Challenges

ABSA faces several challenges that have an impact on its effectiveness. Some of them are Implicit Aspect Identification, Data Sparsity, contextual analysis of handling a word with different meanings and sentiments like Homonyms, subjectivity and tone, Emoji handling, Domain Dependencies, etc. There is a need for more fine-grained techniques for sentiment analysis for better accuracy and effectiveness. Numerous issues are still open and in need of further exploration and research.

XI. Conclusion

ABSA has become an increasingly popular research area in NLP. This survey paper discussed the Steps in ABSA which includes aspect extraction, sentiment analysis, and aspect-based summarization. Promising results have been achieved using advanced ML and DL algorithms. Various applications and challenges of ABSA are discussed. Furthermore, Future research could focus on addressing those challenges and developing more robust and effective models.

XII. Acknowledgment

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