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Aspect-Based Sentiment Analysis using Machine Learning and Deep Learning Approaches

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Abstract—Sentiment analysis (SA) is also known as opinion mining, it is the process of gathering and analyzing people's opinions about a particular service, good, or company on websites like Twitter, Facebook, Instagram, LinkedIn, and blogs, among other places. This article covers a thorough analysis of SA and its levels. This manuscript's main focus is on aspect-based SA, which helps manufacturing organizations make better decisions by examining consumers' viewpoints and opinions of their products. The many approaches and methods used in aspect-based sentiment analysis are covered in this review study (ABSA). The features associated with the aspects were manually drawn out in traditional methods, which made it a time-consuming and error-prone operation. Nevertheless, these restrictions may be overcome as artificial intelligence develops. Therefore, to increase the effectiveness of ABSA, researchers are increasingly using AI-based machine learning (ML) and deep learning (DL) techniques. Additionally, certain recently released ABSA approaches based on ML and DL are examined, contrasted, and based on this research, gaps in both methodologies are discovered. At the conclusion of this study, the difficulties that current ABSA models encounter are also emphasized, along with suggestions that can be made to improve the efficacy and precision of ABSA systems.

Keywords- Aspect-based sentiment analysis; Machine learning; Sentiment analysis, Deep learning, Deep learning algorithms in SA

I. Introduction

With the continuous advancements in web technologies a number of new ways have been paved for connecting the content generated by the user like, blogs, social networks, forums and website reviews. The individuals and organizations working in the field of data mining have been highly inclined towards this flow because of the significant influx of data and difficulties in handling the unorganized texts in natural languages [1]. One of the most basic human desires is to understand the behavior, thoughts and convictions of individuals. As stated earlier that, as a result of latest innovations in web applications social networks, blogs, e-commerce websites and other new forms of communication have emerged which produces huge volume of data. As a result, the demand for an automated service to organize and evaluate this volume of information is also growing [2]. In this regard, sentiment analysis is considered as one of the most crucial tasks in the field of NLP (Natural Language Processing) that has received a lot of attention from experts [3]. Sentiment analysis (SA) also called as the opinion mining can be defined as the field in which the emotion, thoughts, beliefs, attitudes regarding certain entities like service, events, situations, companies are analyzed and studied. This means that sentiment analysis can be used to monitor public sentiment about a certain subject and generate actionable insights. It's used in a variety of industries, including banking, commerce, educational, advertising, medicine, and journalism. This kind of information can also be utilized to comprehend, interpret, and forecast social phenomena [4]. SA is critical in the business sphere since it allows companies to develop strategies and acquire knowledge of client's opinion for their products. Acknowledging the client is becoming extremely important in today's modern consumer-based company culture for increasing their business [5].

Over the last few years, a number of methods have been proposed by various researchers that were based on NLP techniques and ML models were also utilized for extracting the sentiments from textual data. the basic and fundamental task of a SA technique is to identify and classify the polarities of

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statements or any file as positive, negative and neutral. Meanwhile, sophisticated sentiment categories including happy, sad, and angry can be extended from previous categories. This type of SA finds its application in analyzing the social networking text processing and hate speech identification on different platforms [6]. To understand this in a better way, let's consider an example, "I like this software, it really is better than windows movie maker,". In the given sentence, the phrase "software" evokes the positive feeling while as the phrase "windows movie maker" evoke negative emotions respectively. Also, the words like love and superior can be described as the opinion concepts in the given example. From the given example it is concluded that the expressive polarization of the aspect phrases can be derived from their associated opinion phrases [7]. Generally, in terms of theory SA can be divided into three levels (see Figure 1), one is called as the Document level, second one is called the sentence level and the third and final level is called as the aspect or feature level. In document level, the sentiments of the whole file or document are sensed and identified. While as, in case of the sentence level, the file or record is broken down into small sentences and then the polarity of each sentence is determined [8][9]. Similarly, in the third level of SA i.e., feature/ target level, the sentiments about a certain feature id analyzed to determine the people's feelings. Example of aspect levels is, "the processor has a high speed, yet the device is costly".

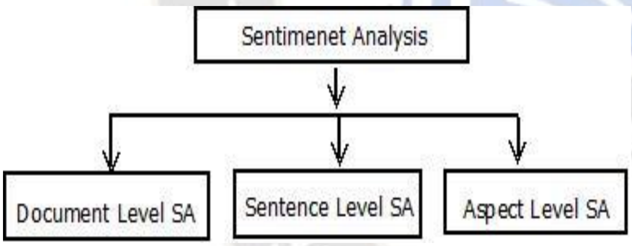

Figure 1. Level of sentiment analysis

Nonetheless, the sentiment analysis performed at the document level and sentence level identifies and detects the polarity of the overall sentence and doesn't consider the target entities and the features associated with them. On the other hand, when discussing the aspect-based sentiment analysis (ABSA), the sentiments are analyzed and detected for the target entity and then the polarity of every entity is determined [10]. The main aim of ABSA is to determine the polarities of a given viewpoint that is presented in the form of a reviewer's remark or rating. To determine the polarity in ABSA, several approaches were developed in the past few years. However, these approaches primarily focused on developing a final feature set called a bag of words and after that sentiment lexicon techniques were implemented for training the classifiers [11].

A. Review Motivation

The discipline of ABSA is not a straight path and has endured several modifications and entered different phases to consider. Scientists have already been trying hard to find solutions to multi-faceted problems which contain a variety of situations. To overcome these issues and to overcome them, they used several machine-learning approaches, particularly deep-learning approaches which demonstrated their essential ideas in the area. Utilizing various algorithms and neural-memory networks, researchers have given graphical representations and numerical modelling for addressing complicated concepts. As a result, the time has come for a thorough review to highlight the most recent progress of ABSA. In this perspective, a number of the newly enacted ABSA approaches for recognizing feelings/sentiments are reviewed in this study.

B. Organization of the survey

The poll begins with a short overview of ABSA and its critical importance. After this, different types of aspects and the process of detecting aspects (ATE, ATC and ATSC) are defined. Moreover, as the main focus of our review paper relies on ATE, therefore we studied the techniques used in determining ATE. Moreover, a brief introduction about the commonly used databases is provided, along with a comparison table. After that, the role of AI-based ML and DL methods is also highlighted in aspect-based sentiment analysis. Finally, a review is done for both ML and DL models along with the findings observed in them.

a) Aspect based sentiment analysis (ABSA)

ABSA can be defined as the type of SA in which attention is given to the specific aspect of a given task. Considering an example, "The course is obsolete but the teacher is excellent". In the given sentence polarity for the course and teacher is negative and positive respectively. The authors in [12] analyzed that to understand the polarity of the phrase it is important to understand its content as well as its aspect. Hence, it is crucial to comprehend the context by recognizing the aspect before assigning polarity to a given phrase. In order to determine the polarity of a sentence, ABSA techniques undergo through three stages i.e., Aspect Extraction (AE), Aspect Sentiment Analysis (ASA), and Sentiment Evolution (SE) to generate the final results. Figure 2 depicts the organization of the ABSA smaller tasks as a tree. In the Aspect Term Extraction phase, the polarity of the aspects is extracted which can either be implicit or explicit [13][14]. Moreover, aspect words [15], objects [16] and even the Opinion Target Expression (OTE) based aspects can also be extracted in ATE. While as, in the second phase of Aspect Term Categorization (ATC), emotion polarity is classified as a predefined attribute, object, or entity [17]. In addition to this, ATC is also responsible for extracting the connections, linkages and context-specific linkages across diverse data items such as

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target, object, aspect and sentiment words so that the accuracy of sentiment classification is enhanced [18]. In the last stage of ABSA i.e., Aspect Terms Sentiment Classification, the dynamic nature of individuals' attitudes regarding various events is determined. The principal reasons for SE are thought to be social factors and self-experience [19][20]. Here, our key emphasis will be on the Aspect Term Extraction phase, wherein focus will be given to different implicit and explicit aspects.

i) Aspect term extraction (ATE)

Aspect-based analysis which is sometimes also referred to as feature-based analysis is considered one of the finely grained methods for SA. It entails determining a user's feelings about a specific feature of an item or institution. Therefore, to effectively perform the sentiment classification task on aspects based, it is necessary to pull out the objects along with their related aspects. It entails determining a user's feelings about a specific feature of an item or institution. The consolidated opinion and its related visualization findings can be obtained as

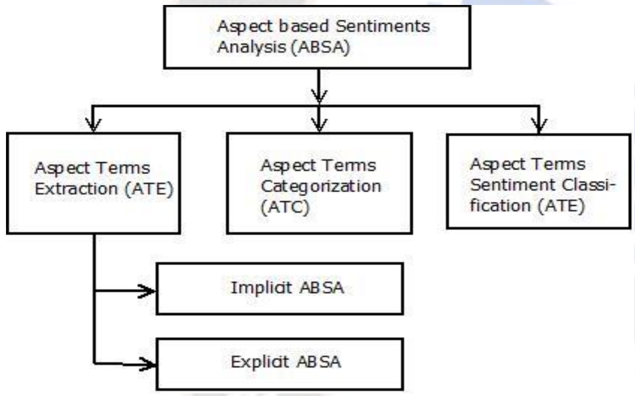

Figure 2. Sub tasks in aspect-based sentiment analysis

the final phase of ABSA. As mentioned earlier, usually two types of aspects are extracted from the sentences, one is implicit and the second one is explicit. The explicit aspects can be defined as the notions in the articulated statement which expressly define targets. For understanding the concept of explicit extraction, let's take an example of the statement, "I love my device's touchpad, but the battery capacity is too short". After analyzing the given sentences, it is observed that the terms like "touchpad" and "battery capacity" are included explicitly in the system which means that they are explicitly aspects. On the other hand, in the case of implicit SA, the aspects are mentioned indirectly [21]. Let's consider an example of another sentence demonstrating implicit SA. "This camera is elegant and quite economical," which implicitly expresses a positive judgement of the object camera's aspects "design" and "cost." Digging a bit too deep into the above-given examples to have a clear idea about the implicit and explicit aspects. The first example comprises two components, which are the touchpad and battery capacity. Because the two ideas given by the customer are completely opposite which means employing a sentence-level polarity identification algorithm, in this case, would produce incorrect polarization results that will be close to neutrality. As a result, aspects must first break down the phrase into product features before assigning a different polarity to all these characteristics. While talking about the second example for implicit SA, "The touchscreen of my cellphone is pretty great and its resolution is amazing," which has positive polarity, indicating that the reviewer enjoys the device. The positive feedback, though, is focused on the touchscreen and resolution. Be a result, these conceptions are referred to as opinion targets or components of this viewpoint. In order to extract the aspects from such opinionated texts, aspect extraction techniques have been used [22].

- *Aspect extraction techniques:* In this paper, the techniques that can be utilized for extracting the implicit and explicit SA are divided into three types, those are; Supervised, semi-supervised, and unsupervised techniques.

a. *Supervised aspect extraction techniques:* In this type of aspect extraction, supervised algorithms are used for determining the polarity from reviews. These types of techniques utilize the labelled data for extracting the implicit and explicit aspects from data. To put it another way, supervised approaches rely on methods which must be trained. Commonly utilized supervised techniques for extracting explicit, implicit and both implicit and explicit aspects are conditional Random Field (CRF) [23], hierarchy [24] and LSTM-based approaches [25], respectively.

b. *Semi-supervised aspect extraction techniques:* Methods that are able to identify aspects from reviews by using semi-supervised methodologies are referred to as Semi-supervised aspect extraction techniques. These techniques are helpful in determining and identifying the aspects of a given phrase in both labelled and unlabelled datasets. Semi-supervised strategies make use of strategies which need to be trained in a specific context. Some of the commonly employed semi-supervised techniques that are used for identifying aspects in implicit, explicit and both (implicit and explicit) are semantic-based, RNN [26][27] and lexicon-based [28][29], respectively.

c. *Unsupervised aspect extraction techniques:* Unsupervised procedures are methods which make use of the unsupervised methodology idea and are commonly used by scholars to retrieve distinctive aspects from review. Whenever a strategy extracts implicit or explicit aspects from unlabelled information, it is said to be unsupervised. To put it another way, it doesn't necessitate any training. Those approaches are applied to a variety of data fields,

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including language realms. Some of the commonly employed unsupervised techniques that are used for extracting explicit and implicit aspects are statistical [30] and topic modelling [31][32] respectively. Moreover, dependency parsing [33] is another unsupervised aspect extraction method that is widely used for detecting both implicit and explicit aspects.

All of these strategies, unfortunately, only produce the anticipated outcomes when adequate and appropriate databases are accessible. Hence, before we go into the specifics of the methodologies employed in aspect analysis, it is important to analyze some of the most widely utilized datasets, discussed in the coming up sections of this paper.

ii) Aspect term categorization (ATC)

The second phase in the process of ABSA is aspect term categorization (ATC) in which the phrases with synonymous aspects are grouped to form categories. Every category illustrates a particular aspect that is also referred to as the aspect category [34]. For understanding the concept of ATC, an example is considered, "I have to mention that they have one of the fastest delivery times in the city". in the given sentence, the term "Delivery time" represents the aspect term. Therefore, a number of similar group phrases with similar content can be put together into groups each having an aspect term. For example, concerning the delivery time, waiter and staff can also be included in the same aspect category of service. Although the two categories i.e., aspect category classification (ACC) and aspect term extraction (ATE) are closely related to each other, they are considered separately sometimes. Intrinsically, the learned knowledge from one learning assignment must influence another. In order to tackle both issues, the authors in [35], proposed a multi-task learning approach that was based on neural networks. As ACC was defined as the supervised classification job wherein the phrases are classified by using a portion of predetermined aspect tags, ATE was described as the sequence labelling job in which the phrase tokens, associated with the provided features were labelled by using a predetermined tagging strategy named as, Inside, Outside, Beginning or IOB. Moreover, they used the Bi-LSTM and CNN approaches together for ATE and ACC respectively to form a multi-task framework.

iii) Aspect term sentiment classification

In the last final step of ABSA comes the aspect term sentiment classification in which the polarity of the sentence or phrase is determined once aspect terms are extracted and classified from them. The authors in [36], proposed an LSTM-based two targeted approaches in which necessary information about the target is considered automatically. The authors validated the performance of their model on the Twitter dataset. Also, the simulated results attained by the authors demonstrated that the classification rate is significantly improved when target information is directly fed to the LSTM model. furthermore, it was observed that without employing any syntactic parser or external sentiment lexicons, the proposed model was able to achieve results similar to that of traditional approaches.

C. Datasets available

In order to detect the aspects from the reviews, sentences or phrases a number of datasets including the Twitter dataset, Sem Eval datasets, Amazon product dataset, and IMDB movie review datasets are available on the internet. other than this, there are some other databases as well, a brief description of the most popular databases is given below.

(i) Twitter dataset

This dataset is one of the most prominent and frequently used datasets that have been used by a number of researchers in their studies. This database can generate remarkable results because the training data was generated automatically rather than humans manually annotating tweets. They demonstrated the concept of positive tweets by using the ":)" symbol while the negative tweets were represented by the ": (" symbol. The Twitter database represents the sentiments for 140 datasets in which a total of 1,600,000 tweets are present that are extracted via the Twitter API. In order to detect the sentiments in the given dataset tweets are represented as 0 for negative, 2 for neutral and 4 for positive. The six fields of the Twitter dataset are target, ids, and date. Flag user and text [37].

(ii) Sem Eval 2014 dataset

In the year 2014, Pontiki and Pavlopoulos suggested a Sem Eval dataset for identifying and extracting aspects from the customer reviews. Sem Eval dataset can be defined as the collection of global NLP research events in which the primary objective is to enhance the traditional SA as well as assist in creating a unique dataset in rising to a variety of issues faced in language semantics. It is a domain-specific database in which information about laptops and restaurant reviews are mentioned. More than 6000 keywords for both domains are available with rich aspects present in the dataset [38]. The detailed information about the dataset is represented in table 1. This database has received a lot of attention from scholars while trying to extract the aspects from the sentences.

TABLE I. TOTAL REVIEWS IN THE DATASET

Domain	**Train**	**Test**	**Total**
Restaurants	3041	800	3841
Laptops	3045	800	3845
Total	6086	1600	7686

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(iii) Amazon product data

Another database that is used widely by researchers in their work for extracting the aspects from users is the Amazon product database. This dataset is a sub-category of the huge 142.8 million amazon review database which was made publicly accessible by T. Julian McAuley a professor at Stanford. In this database, the reviews of the customers received on different products from May 1996 to July 2014 are included. Ratings, content, useful comments, description of the product, category information, cost, manufacturer, and image attributes are all included in the database evaluations. In the year 2018, a new version of the database was also made publicly accessible for ABSA. The new version of the database contains information about the product reviews from May 1996 to October 2018 and comprises a total of 233.1 million reviews. The previous database can be accessed from the San Diego website whereas, the new version of the same dataset is available on GitHub. In both the datasets almost the same information which depicts the ratings, cost, item details, and useful comments are included, however some extra technical-based information, and product tables are included to make it more effective.

(iv) IMDB movie reviews dataset

IMDB is one of the huge movie datasets which includes around 50,000 reviews about the movies. This database contains only those reviews which are highly polarized. Moreover, the total number of positive and negative comments are equally added in the current dataset but still, the negative review received a rating of 4 out of 10 while the positive reviews received a ratio of 7 out of 10.

(v) Lexi coder sentiment dictionary

This sentiment analysis database is intended for use with the Lexi coder that analyzes the content for extracting aspects from it. In this database a total of 2858 negative aspects and 1709 positive aspects are included in the lexicon. Moreover, it also contains 2860 negative negations and 1721 positive phrases. The developers encourage anybody interested in testing this to deduct negative positive words from positive counts and vice versa.

(vi) Bag of word meets bag of popcorns

Another dataset that has been used for detection sentiments in reviews and has been used for a long time is Bag of Word meets Bag of Popcorns. The current database contains information about 50,000 IMDB movie reviews. In order to determine the sentiments of users, the current database uses the binary classification technique. It means if any movie has an overall rating less than 5, then its sentiment score is zero whereas, if the movie has an overall rating of more than or equal to 7 then its sentiment score is defined as 1 in the database. This database can be accessed easily from Kaggle.

In addition to the above-mentioned databases, there are several other datasets as well that can be used effectively for determining the aspects of the user reviews or sentences. Table 2 depicts some of the datasets that have been used by researchers quite often from 2011 to 2021. Though there are huge papers that used different datasets but some of the renowned works done recently are highlighted in the below table.

TABLE II. DIFFERENT DATASETS USED IN THE SENTIMENT ANALYSIS

Authors	Dataset used	Performance metrics	Observations
L. Wang et al. [39]	Used Sem Eval implicit database	Accuracy, and F1-score	Proposed BERT model with multiple classifiers. The SemEval implicit extraction data set has good accuracy.
S. Kalim et al. [40]	Used Sem Eval-2016 Task 5 database	Precision, recall, and F1-score	The proposed approach extracts POS tagging information, preprocesses and tokenizes reviews, maps tokens between languages, and creates vectors for preprocessed reviews for training and evaluation.
M S Neethu et.al. [41]	Twitter dataset	Precision, Recall, and Accuracy	Text sentiment analysis uses knowledge base and machine learning approaches. They used ML to analyze tweets. Sentiment analysis in a single domain shown how domain information affects sentiment classification.
R. Xia et al. [42]	Multi-domain dataset	Accuracy	DSA works by creating sentiment-opposite reversed reviews and using them in pairs to train a sentiment classifier and generate predictions.
R. S. Ramanujam et al. [43]	Twitter dataset	Hourly sentiment analysis	Text data from e-commerce websites will be used to forecast and estimate user sentiment. Machine learning will intelligently estimate users' emotions.
M. Bouazizi et al. [44]	Twitter dataset	Precision, Recall, and Accuracy	Proposed a Twitter sarcasm detector. The method uses tweet components.
G. Gautam et.al [45]	Twitter dataset that	Accuracy	Used ML and semantic analysis to classify

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	was based on customer review		sentence and product reviews from Twitter data. The unigram model improves the naïve byes approach, which outperforms maximal entropy and SVM.
S.A. Bahrainian et al. [46]	Twitter dataset that was based on Smartphones reviews	Accuracy	Introduced and compared PD and automated aspect detection techniques. Created sentiment summary system using multiple approaches and algorithms. Their target-oriented hybrid technique outperforms unigram baseline.
A. Agarwal et al. [47]	10,000 manually Annotated Tweets	Accuracy	Tree kernel and feature-based models exceed the unigram baseline. Feature analysis shows that words' prior polarity and parts-of-speech tags are the most relevant aspects for our feature-based strategy.
D. Gurkhe et al. [48]	Twitter Dataset	Accuracy	Naive Bayesian Classification is used to extract subjective information from textual data for social media sentiment analysis.

From the above table, it is concluded that the majority of the works have been done by utilizing the Twitter dataset and Sem Eval datasets because of their diverse nature.

II. Traditional Methods In ASBA

The technique for extracting aspects from the reviews or sentences is not new and has been widely used for a long time. However, the traditional method for resolving the ABSA issues was entirely based on extracting features manually from the data. The traditional way for ABSA primarily relied on developing a set of characteristics like Bag of Words and Sentiment lexicon to train the model for performing the classification task. A number of approaches were suggested by the scholars in this regard. The authors in [49], worked with the target-based Twitter sentiment analysis in which upon receiving a query, the tweets were categorized into three groups positive, negative and neutral based on the content depicted in that particular query. The authors considered a query as the target of their approach. The target-independent technique is often used in state-of-the-art methods to fix the issue that might ascribe inappropriate emotions to the supplied object. Furthermore, it was also observed the traditional methods analyzed tweets while trying to identify sentiments only and they entirely ignored the content of the tweets. Nevertheless, since tweets are typically short and vague, it is not always sufficient to classify emotion based on the most recent tweet. in this regard, they proposed an effective model for enhancing the performance of target-based twitter SA in which modifications were done at two stages. firstly, the target-based features were added to the system and secondly, in their approach they considered the related tweets also while determining the polarity of the tweets. The results attained by the suggested model depicted that the effectiveness and efficacy of the standard target-based SA were enhanced. In addition to this, some authors used statistical-based methods for extracting the aspects from sentences. The authors in [50], suggested a rule-based technique for recognizing aspects during the SA process. These methods were quite common in solving the aspect-based SA problems in previous times. In addition to this, a hybrid model that was based on MaxEnt-LDA was also proposed by authors in [51], for identifying and detecting the aspects of opinionated phrases. This model showcased its effectiveness by producing effective results even when the training data provided to it was quite small. All the traditional model was based on feature engineering which became a major disadvantage for these models with the continuous increase in data volume. Since feature engineering is time-consuming and requires a lot of labelled data the performance of the traditional model was degraded significantly. Nevertheless, with the advancement in the field of AI, several researchers have developed efficient automated methods. The main aim for opting for the automated ABSA methods is to produce usable low-dimensional abstractions from objects and their environments which in return aids in promising ABSA results.

III. Role of AI in Aspect based Sentiment Analysis

Sentiment analysis allows companies to get a better understand of their clients' feelings. It's being used by businesses to keep a record of social media posts, determine the severity of customer care requests, and interpret customer insights.

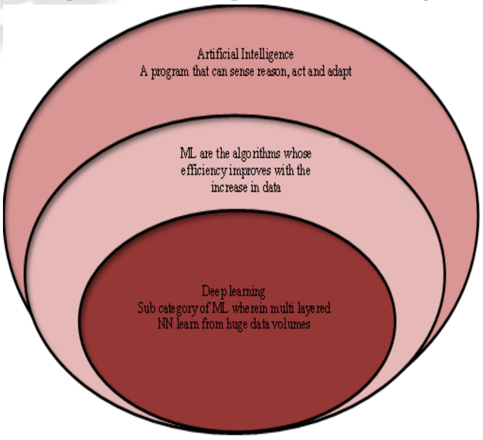

Figure 3. Evolution of AI

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With the introduction of Artificial Intelligence (AI) in the field of aspect analysis, machines can comprehend human feelings more effectively and efficiently from texts, which seemed an impossible task previously. Feelings or emotions of the users are considered as the major driven factors, which make consumers to decisions regarding the purchase and also serve as a good indicator for enhancing brand loyalty and client happiness. Moreover, the reviews of the customers also help organizations to make appropriate and suitable decisions for the betterment of their company. During the process of sentiment analysis, a typical AI model gathers information from the unstructured data that is related to the process of SA. Figure 3 shows the evolution of AI-based ML and DL methods. In the last few years, the surveys were done by dropping the comment or reviews at the bottom of the poll so that the individual can write their ideas or experience on using a specific product. On the other hand, the SA provides results accurately up to 90% when it comes to assessing text-based criticism like posts on social networking sites. In addition to this, there are some other sentiment technologies available that have been used in order to enhance consumer happiness by nearly 30% and also reduce call time management time by around 15% and also increased customer replies. Over the years, a large number of ML and DL-based techniques were utilized in the sentiment analysis process for detecting their polarity. Since the main focus of our review paper is on implicit and explicit aspect Extracting techniques, therefore, we will be reviewing the aspect extraction techniques in the light of ML and DL for both i.e., Implicit and explicit categories, but before that let's discuss the general process for identifying sentiments in text.

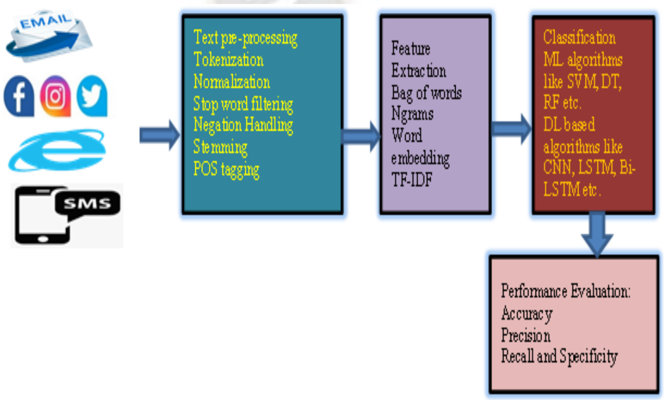

Figure 4. General process of detecting sentiments

(i) General process for detecting sentiments: The process of analyzing and detecting the sentiments or opinions from the text undergoes various stages like data collection, data pre-processing, feature extraction and selection and finally classification. Figure 5 Illustrates the diagram that depicts the general process for sentiment analysis. The above figure depicts the typical SA approach in which data is gathered by taking the datasets that are available on the internet like Twitter, IMDB, Amazon product dataset etc. This data is then processed by using different NLP techniques. After this, the critical features that help in determining the emotions or sentiments in texts are extracted. Both feature extraction and selection are the part of pre-processing step, where the main motive is to refine data for further processing. Once all this is done, different classification algorithms (including ML and DL) are implemented which determine the sentiments from texts. The output generated by each classifier may have different presentations. All of these phases and sentiment analysis can be handled with a variety of technologies.

(ii) ML based implicit and explicit aspect extraction techniques: During the process of aspect extraction, determining explicit aspects, objects, aspect grouping and OTE on the basis of which the sentiment is articulated is one of the major issues that need to be addressed. As discussed earlier the explicit aspect is the type of AE in which aspect is visible in the sentence. For example, in the sentence, "the camera of my smartphone is amazing", the words camera and smartphone depict the explicit aspect and entity respectively. The two entities of the given aspect are combined into a single class of aspects. Another example to understand the fact of aspect categories is illustrated as, "this mobile looks great but expensive" in which the two domains are specified one is the appearance of the mobile phone and the second is the price of the mobile phone. Moreover, the entity mobile can be depicted as the OTE in the given example [52]. On the other hand, in the case of implicit the aspects are not mentioned in the sentences or reviews. To understand this better, an example is considered which states that "I cannot use the camera as the battery is very low" where, the battery of a target i.e., the camera is represented. When comparing the implicit and explicit aspect levels in terms of their relevance, they should be treated with the same importance. Ironically, the majority of the scholars have paid more attention to the explicit based SA then the implicit based SA. During the last few decades, a huge number of methods and complex techniques have been suggested in order to control and train the automated devices for extracting the aspects from content. Each technique has some advantages and disadvantages, however, when they were utilized in tandem, they could provide extraordinary outcomes. The following are amongst the most commonly used machine learning techniques in sentiment analysis.

A hybrid rule-based technique is proposed in [53] in which they utilized the sequential patterns and normalized Google distances (NGD) for retrieving the explicit and implicit characteristics. In addition to this, they also utilized the google similarity distance along with the PSO algorithm so that the synonyms are clustered together. Similarly, the authors in [54], suggested an improved mechanism for extracting the explicit

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aspects from formal and informal texts by using supervised techniques. They integrated a total of 126 AE rules in their model to deal with the dynamic data wherein the user writes reviews about the product as a combination of formal and informal writings. The rules defined in the model comprised a few previously user dependency and pattern-based rules along with this, newly defined rules were also added to mitigate the issues of conventional rules. Furthermore, it was also discovered that most of the rules remained undiscovered in the prior research and many rules used were obsolete and hence must be eliminated from the rule set. As a result, a more thorough examination of the contained regulations is needed. To mitigate the problem of rule selection, the authors of this paper proposed an improved version of the standard Whale Optimization Algorithm (WOA) named, IWOA. The proposed model worked in two phases. In the first phase, the population diversity of the WOA is improved by using the Cauchy mutation method and in the second phase, they used the local search algorithm (LSA) for resolving the problem of local optima. They operated the proposed IWOA method on the entire rule set in order to choose the best rules and also eliminate obsolete rules. After this, they introduced the pruning algorithm (PA) to eliminate wrong aspects while retaining the correct ones. Furthermore, they tested the performance of the proposed approach on seven standard datasets to validate the supremacy of the proposed approach. In [55], the authors proposed an ABSA approach that was based on unsupervised algorithms. The main aim of the suggested model was to detect the aspects of the target object as well as sentiments. The authors used the lexicon technique in their work in which the number of linguistic resources was combined for improving the categorization considerably. Similarly, the authors in [56] analyzed that in today’s era majority of the people are shopping online where they buy a number of things online and leave comments or reviews once they try the product. In those cases, customer satisfaction is expressed through a series of tweets or comments on an e-commerce website. Therefore, reviews, comments or even ratings play a significant role in assisting the vendors to improve the product quality. However, manually reading the comments and assigning emotions to them is a challenging undertaking. This challenge can be addressed by developing an automated system that analyses consumer reviews and extracts their thoughts and opinions related to a specific feature. In this regard, the authors of this paper utilized the ML-based SVM for determining the aspects in sentences. The authors in [57], proposed a method which undergoes a number of phases including the data pre-processing, feature extraction and classification for determines the aspects related to the sentences. Part of Speech (POS) tagging, Named Entity Recognition (NER), and N-Grams are some of the features that were extracted from the given texts and finally they have been categorized with the help of four ML-based algorithms including CRF, DT, NB and KNN. The performance of the suggested approach was validated by comparing it with the traditional ABSA classifiers. The experimental results revealed that by using the four features the performance of all four classifiers was improved. The results also showcased that the proposed DT (j48) model generated the best results followed by the CRF and NB. In addition to this, the authors in [58], focused on recognizing the implicit-based aspects by analyzing the reviews received on Chinese products. Moreover, they suggested that using the explicit approach where information about each subject is already defined could outperform the standard feature selection techniques. Therefore, in order to develop an explicit model, they used the modified version standard LDA technique in which certain previous knowledge about must and cannot based links along with the relevance-based links was updated automatically. The experimental results revealed that the suggested explicit topic scheme overcomes conventional feature selection approaches by a significant margin and hence was able to identify aspects more accurately and quickly. The authors in [59], performed the task of aspect identification for crime tweets that involved implicit aspects conveyed by adjectives and verbs. The proposed model utilized the WordNet semantic relations and term Weighting techniques in their work in order to improve the efficacy of the training data for detecting and identifying the Crime's implicit aspects. The authors validated the efficacy of three classifiers including Multinomial NB, SVM and RF on three benchmark datasets to validate the efficacy of the suggested approach.

The researchers in [60], explained opinion mining as the practice of obtaining and evaluating people's perspectives about a particular object, whereas sentiment analysis reveals the underlying emotions in those views. However, the identification of feelings and aspects, as well as data classification depending on such characteristics is one of the biggest challenges in this procedure, which is often referred to as aspect-based feature extraction. In order to evaluate the opinions from the texts many ML-based algorithms which included maximum entropy, NB, SVM and RF can be utilized. In their approach, they used the reviews given by the customers as the input data source. Furthermore, the efficiency of the suggested iterative decision tree approach was compared with SVM, Baseline, and Naive Bayes in this research to demonstrate the superiority of the proposed model. Moreover, the authors in [61], proposed a model in which the aspects were analyzed in hotel reviews. In order to extract various ABSA jobs like identification of aspects, retrieval of expressions from targets and determining polarity, the authors used the human annotates-based Arabic database that was applied at the sentence and text levels. In the second phase of the model, the authors trained the SVM classifier on the given dataset and then experiments were conducted to validate the efficacy and supremacy of the current approach on the same

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dataset. In [62], suggests a novel method for identifying the explicit as well as the implicit aspects of the sentences. The authors used the WOA along with the web-based similarity technique in their work so that the optimal dependency factors from the available patterns can be selected for extracting the explicit aspects of the model. Furthermore, the implicit aspects were determined in the proposed approach by using a hybrid model that was based on corpus co-occurrence, dictionary and web-based similarity. The authors analyzed the performance of the suggested approach on standard datasets which was later on compared with the traditional model to prove its effectiveness. The authors in [63], offered a syntactic pattern model that was based on the feature observations to retrieve aspects from unorganized reviews along with this they thoroughly examined the various patterns associated with aspects. In addition to this, they also discussed certain technical challenges that arise by employing syntactic pattern extraction, while evaluating and analyzing the performance. The test findings revealed that the syntactic pattern method had various flaws that needed to be addressed.

In addition to this, some other ML-based techniques were proposed for determining the aspects from reviews, sentences or text. The authors in [64], proposed a multi-level-based implicit aspect detection model in which they used co-occurrence and similarity approaches. The authors used the implicit aspect hints so that the clues for the implicit target are extracted along with the true targets of the user's opinion were also identified. Their model worked in two phases; in the first phase, a set of guidelines were devised in order to find hints for implicit components in reviews. In the second phase of the model, a multi-level technique was proposed wherein the aspects were allocated based on the hints extracted in the previous phase. one of the main advantages of the suggested model was that not only the implicit aspects were extracted but the clues were also assigned to opinion terms where no correlation was found. By doing so, the model was able to identify implicit aspects effectively despite the fact that whether an opinionated text was present or not with explicit aspects. The experimental results obtained showed that the suggested approach was more effective and efficient in determining the implicit targets based on customers' opinions. Similarly, the authors in [65], proposed two strategies for extracting aspects in which they utilized Sem Eval restaurant database along with the Yelp and Kaggle databases. The authors proposed a multivariate filter technique in the first strategy for selecting only crucial features from the texts and also reducing their dimensionality. The method was proved to be effective in terms of F1-score when compared with the other similar approaches. In the second strategy, the authors used the selective dependency relations for extracting features by using the Standford NLP parser. Moreover, the results showcased that when features were extracted by using selective dependency rules were far better than the results in which features were extracted by using all dependency rules. The authors attained lemma and selective dependency relation-based features in the combined model which was able to attain an accuracy of 94.78% and an F1-score of 85.24%. In [66], the researchers proposed an enhanced multi-aspect opinion classification method in which they tried to mitigate the various challenges faced in extracting the implicit aspects and classifying multivariant aspects. To accomplish this task, they firstly utilized a probabilistic co-occurrence approach for identifying coreferential aspects in the text and combining them into a single group. Moreover, they also introduced an improved implicit aspect extraction method which links the sentiment terms along with their appropriate aspects for creating an aspect sentiment hierarchy. Finally, a multi-aspect-based opinion classification strategy was suggested in which they used the multilabel classification techniques for dividing opinions into specific polarities. The effectiveness and the efficacy of the suggested model were validated on standard datasets in which accuracy of 90% per label was achieved.

The researchers in [67], proposed a model that was based on the NLP metadata extraction approach for extracting the content from email conversations among financial experts and their customers. Ever since the beginning of e-commerce, a massive amount of transactional data is generated which makes it increasingly challenging to create and keep customized data. The authors developed an automatic <!metaMarker> model that was based on NLP and ML techniques for analyzing text-based data like emails, group discussions, posts etc. This <!metaMarker> model was able to collect explicit and implicit metadata items such as actual names, numerical notions, and theme info, among other things. Additionally, metadata elements that were influenced by Speech Act Theory, described the emotion, aim and intensity of the review. Moreover, customers regularly discuss things or products which they enjoyed or are interested in, during a typical conversation of them with financial experts. The efficacy of the suggested model was validated on the real-world dataset upon which accuracy of 90% was achieved for extracting the explicit and implicit aspects. Similarly, the researchers in [68], proposed a Syntactical-based Aspect Extraction (SAE) model in which DT and rule learning techniques were implemented for generating the sequence labelling-based patterns. To accomplish this task, they initially created a sequence labelling-based pattern set to detect aspect term candidates by using the DT and rule learning methods like ID3, J48, RT part and prism. Moreover, they selected aspect phrase possibilities using a collection of positive and negative opinion lexicon. Ultimately, to eliminate extraneous aspect terms the authors integrated the pattern-based technique along with the typed dependence for boosting the performance. In [69], the researchers utilized semantic relations for analyzing relations between the reviews and rare aspects for extracting implicit

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aspects and accurate sentiments respectively. They tested the compatibility of their model on a real-world-based database in which reviews about popular tourism websites like TripAdvisor and OpenTable were included. The results obtained showcased the effectiveness and efficacy of the suggested approach. Similarly, [70], proposed a data mining and ML-based sentiment prediction model in which they utilized the data generated by Twitter as an input source and produced output as sentiment prediction. The results demonstrated that the performance of the TF-IDF model along with the NB model is better with 81.24% accuracy results when compared with the traditional models. The researchers in [71], investigated the usefulness of multiple unsupervised approaches for discovering latent semantics as characteristics of ABSA. The authors used the shared task of Sem Eval 2014 database. Moreover, they utilized the labelled and unlabeled dataset for Czech and English languages for restaurant field. The suggested model was able to improve the results for Czech language over traditional results. In addition to this, another significant advantage of the current model was the creation of two new datasets, one labelled and unlabeled for supervised and unsupervised models for performing the ABSA operations. Table 3 compares various ML models of aspect-based sentiment analysis, which are used on different datasets and performed by different researchers.

TABLE III. COMPARISON FOR VARIOUS ML MODELS

Reference	Dataset used	Techniques used	Performance	Observations
[53]	NA	Sequential patterns, normalized google distances and PSO	Attains good results for determining implicit and explicit aspects	Instead of common-sense knowledge and dependency parser, this approach is similar to the rule-based architecture.
[54]	Seven datasets	Improved WOA, local search algorithm (LSA) and Pruning algorithm	Extracts explicit aspects from formal and informal texts	The proposed model aspect extraction can be used for official, informal, or both forms of reviews, which benefits sentiment analysis research. It applied to every linguistic rule, not only English.
[55]	NA	Unsupervised algorithms	Improved classification rate	Outlines an unsupervised aspect-based sentiment analysis method that identifies target entity attributes and their sentiments.
[56]	NA	SVM	Better performance	Created a SVM based sentiment analysis method.
[57]	NA	CRF, DT, NB and KNN	DT performs best	The model shows ABSA's efficacy in news content.
			followed by CRF and NB	
[58]	Chinese dataset	Improved LDA	Improves feature selection method by huge margin	Explicit topic model, which uses pre-existing knowledge, outperforms traditional feature selection approaches and other methods for identification.
[59]	Three Crime tweet dataset	Multinomial, NB. SVM and RF	Highly efficient	This research handles implicit aspect identification in crime tweets using adjectives and verbs. The hybrid model uses WordNet semantic relations and Term-Weighting strategy to improve training data for Crime Implicit Aspect sentences detection and identification.
[60]	Private dataset	Iterative DT	-	Maximum entropy, naive bayes, SVM model, and random forest can be used to summarize opinions.
[61]	Arabic hotel review dataset	SVM	Better performance than traditional model	The dataset had sentence and text-level annotations, a baseline approach where a Support Vector Machine (SVM) was trained as part of the ABSA tasks, baseline experiments and outcomes, and a common assessment technique to evaluate future research on the same dataset and ABSA tasks.
[62]	Standard dataset	WOA along with the corpus co-occurrence, dictionary and web-based similarity	Effectively identifies implicit aspects	Most explicit and implicit aspect extraction methods. Suggest a hybrid technique for explicit and implicit aspect extraction tasks.
[64]	Customer review dataset	co-occurrence and similarity approaches	Implicit aspects were classified efficiently	Used co-occurrence and similarity to identify implicit characteristics in a multi-level strategy. This research extracts implicit target clues and applies implicit aspect clues to identify true target opinions.
[65]	SemEval restaurant dataset along with yelp and Kaggle datasets	a multivariate filter technique and selective dependency relations	accuracy of 94.78% and F1-score of 85.24%.	Aspect-Based Sentiment Analysis analyses product reviews. This study offers two aspect extraction methods. and leverages Yelp, Kaggle, and SemEval restaurant review datasets. Multivariate filters select features.

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				Characteristics eliminate redundancy. F1-score beats Frequency-weighted relevant variables. Selective dependence extracts features.
[66]	Standard datasets	probabilistic co-occurrence along with the multi-aspect-based opinion classification strategy	accuracy of 90% per label	Proposed multi aspect-based review polarity classification. A unique aspect identification algorithm automatically recognizes explicit and implicit aspects and integrates coreferential aspects from visitor perspectives. This retrieves review text keywords and noun phrases. Using probabilistic co-occurrence, it blends coreferential qualities into groupings.
[67]	real-world dataset	<!metaMarker> model that was based on NLP and ML techniques	accuracy of 90% for Implicit and explicit aspects	NLP and ML automate and test user preference extraction on numerous email messages. The suggested system will automatically categorise data based on newly developed metadata items as Condition, Side Effects, Severity, Off-label Use, Cures to Mitigate Side Effects, Alternative Medicine, Source, Usage, and Attitude.
[68]	NA	Syntactical-based Aspect Extraction (SAE) model in which DT and rule learning techniques	Enhanced aspect determination process	Pattern-based and typed dependency improved speed.
[69]	real world database like TripAdvisor and OpenTable	semantic relations	effective and efficient	Semantic links between review terms extract implicit and unusual information for reliable sentiment predictions. TripAdvisor and OpenTable statistics were tested. The predictive framework extracts aspects and increases aspect prediction accuracy.
[70]	Twitter dataset	data mining and ML based sentiment prediction model	Accuracy 81.24%	Naïve Bayes classifier technique got the best results with 81.1% accuracy on the tweet dataset. Twitter streaming API received Twitter data. Twitter API information is vast.
[71]	SemEval2014 dataset	Multiple unsupervised techniques	Better performance	ABSA word-clustering. Languages improved. HPS handled considerable Czech morphology alone. GloVe, CBOW, and Czech stemming improved all four ABSA subtasks. Latest Czech findings.

- *Gaps finding discussion*

The common machine learning algorithm that are used in ASBA are Support Vector Machine (SVM), Naive Bayes, random forest and decision tree. However, machine learning algorithms cannot learn by themselves. They learn from the training data and make informed decisions on what it has learned. Nevertheless, with the continuous rise in data, it becomes difficult for ML techniques to process and detect aspects of sentiment analysis. The performance of the majority of the ML algorithms gets slow with the increase in data and it becomes difficult to select the appropriate hyperparameters. Moreover, some of the ML algorithms like DT are extremely sensitive to the data and with slight changes, the results change to a large extent. Furthermore, there were some other issues faced in the ML algorithms like Overfitting, difficult interpretation, difficulties in tuning the parameters, scaling etc. that motivates the researchers to move towards the deep learning-based techniques.

(iii) DL based explicit and implicit aspect extraction techniques:

DL can be described as the subtype of ML models which used deep neural networks for resolving learning issues. The total number of the input and output layers that are present in the network determines the depth of learning. At the initial levels of the DL model, abstract features are extracted, with the advancement in the learning process, more relevant and useful features are extracted from the remaining deep layers. These models treat simple input text as embedding words by using different word vectors like word2vec, GloVe, fastText etc. one of the major advantages of using the DL model is that they can extract features from the data on its own, which was not the case in ML algorithms. Another advantage of DL is that they make decisions intelligently by using their learning knowledge, in ML-based techniques make informed decisions by learning from the given data and then decisions are made on the basis of this information. Even though both ML and DL methods are a type of AI, the key reason for switching to DL approaches is their ability to efficiently manage huge datasets with high accuracy results. However, after thoroughly examining the literature, it is observed that the majority of the researchers have used CNN and RNN variants like LSTM and BI-LSTM in the Aspect based sentiment analysis approach (ABSA). Here, we

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have reviewed a total of twelve recently proposed ABSA papers that are based on CNN, LSTM and BI-LSTM techniques. These reviewed proposed papers are depicted in Table 4. In addition to this, some other DL techniques have also been proposed that are given in [84-90], along with their comparison in Table 5.

The researchers in [72], integrated the CNN, Bi-LSTM and CRF (Conditional random field) together and presented a new and improved DL-based CLC model for determining aspects in sentiment analysis. The effectiveness of the suggested model was validated on the Sem Eval 2016 French database. The results demonstrated that their approach outperformed traditional similar approaches and is also well-suited for other languages like English. The biggest attribute in their technique was its capacity to identify aspects and related emotions simultaneously which was not the case in other similar approaches that do so independently. Similarly, the authors in [73], analyzed those problems associated with the current RNN-based ABSA models and summarized that during the training period of these models they undergo issues like truncated backpropagation, gradient vanishing and exploration issues. In order to mitigate these issues, they proposed several attention-based models for determining the polarity of particular words in a particular review or sentence. The authors utilized the bi-directional encoder representation from Transformers (BERT) for building the vector of embedded words. After this, they implemented Intra and inter-level attention models in their work for generating hidden state representations in a given phrase. Moreover, they also used the multi-head self-attention and point-wise feed-forward network during the intra-level strategy. While as, a global attention-based technique was used in the inter-level attention methodology for acquiring the dynamic content across content and aspect keywords. In addition to this, the authors of this paper also implemented the feature-based attention technique in order to improve the rate of sentiment recognition. To prove the effectiveness of their models, they analyzed them on various standard ABSA databases. In [74], analyzed that standard ABSA model were blended with the NN so that they can learn high qualitative aspect features and also deliver cutting edge results. Unfortunately, the problem with these systems was that they overlooked the features associated with the sentiment terms and also their relationship with the aspect terms. In order to overcome this issue, the authors of this paper proposed a new and effective JAT-LSTM ABSA approach in which they integrated the Joint attention technique with the LSTM network for determining the polarity of sentences. Their proposed model combined the aspect and sentiment attentions together to present a joint attention-based LSTM model. The experimental results revealed that the suggested approach outperformed present conventional models on standard databases to prove its efficacy. Similarly, the experts in [75], summarized the importance of incorporating DL-based methods in ABSA and observed that a substantial number of DL-based ABSA methods were suggested already that were showing outstanding results. However, every DL technique is unique and had its benefits and limitations. For an instance, CNN is good in extracting features from the available data, while the RNN models were providing effective results in learning order dependency in sequential data. In this regard, the authors of this paper proposed a new deep ensemble learning-based model for determining the aspects in sentences. The authors integrated the benefits of four DL methods which included CNN, LSTM, Bi-LSTM and GRU models. The outcomes generated by these four models were then integrated with LR serving as the meta-learner by utilizing the stacking ensemble techniques. The efficacy of the suggested approach is validated by comparing it with the traditional DL based approaches on real databases. The results obtained demonstrated that the suggested model boosted the accuracy of ABSA systems by around 5 to 20%. The researchers in [76], suggested a system in which they classified the polarity of sentiments and also identified the aspects of products from the reviews given by customers. In their work, they analyzed the performance of standard ML techniques along with the DL methods including CNN, RNN and LSTM. Their model was effectively working while identifying the polarity and severity of comments and also analyzed the short-written terms that were frequently utilized by customers in comments. The suggested model was analyzed on the Amazon product dataset in which the LSTM model showed superior results with an accuracy of 93%.

In addition to the above-mentioned approaches, the researchers in [77], proposed a highly effective approach for ABSA in which they utilized the Skip-gram framework for extracting semantic and contextual features from words. Moreover, they utilized the LSTM network in order to understand the complicated patterns from textual inputs. To further increase the performance of the LSTM the authors used the adaptive Particle Swarm Optimization technique which optimizes the weights attributes of LSTM. Rigorous testing on four datasets showed that suggested APSO-LSTM significantly outperformed conventional LSTM, ANN, and SVM approaches in terms of accuracy. in addition to this, their suggested model was outperforming conventional models in terms of other dependency factors as well. The authors in [78], analyzed the performance of conventional ML techniques in order to determine sentiments from the Hindi language that was taken from a Twitter database. They proposed a Domain-specific sentiment dictionary and also discussed lexicon-based techniques which included Hindi Senti-WordNet, and NRC Emotion Lexicon that were used for SA in the Hindi language. Ultimately, a DL-based highly accurate algorithm was proposed that was based on CNN, RNN and LSTM techniques. The

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suggested model was able to determine sentiments from 23,767 tweets in the Hindi language which achieved an accuracy of 85%. In [79], a graph attention-based CNN was proposed in this paper for detecting the implicit SA. The graph CNN and attention mechanism models were used for propagating the semantic information and to calculate the emotional weightage in sentences. In addition to this, they also utilized the Orthogonal attention constraints in their approach due to which various attentions were able to save various emotional data so that the issue of multiple attentions storing the same information. Moreover, a score attention model in which emotional information is distributed unequally was also proposed to focus on limited but crucial words. The efficacy of the suggested model was validated on the implicit sentiments database which demonstrated an F-Score of 88.16%. The researchers in [80], proposed an approach in which they integrated the chi-square feature selection techniques along with the DL-based LSTM, Bi-LSTM and GRU networks. The effectiveness of each network was validated on two standard datasets namely, YELP and US airline databases in terms of various performance dependency factors like accuracy, precision, recall and F1-score. Through extensive experiments, it was observed that when the total number of features in the Yelp database was 500, the Bi-LSTM along with the Chi-square model achieved the best results with an accuracy of 100%. On the other hand, when only 20 features were selected in the US airline database, the GRU-LSTM model achieve higher accuracy of 97.9%. The authors in [81] utilized the DL-based technique in their model for detecting the sentiments from sentences. The proposed model was able to automatically extract features that offer greater performance, brighter appearance and more consistent outcomes over traditional feature selection techniques. Moreover, they also analyzed those conventional models that relied on time-consuming manual feature extractions which failed to produce consistent results. As a result, the goal of this research was to boost the effectiveness of the DL strategy wherein they merged automatic and manual feature extraction methods. In this regard, the experts of this paper proposed an enhanced-LSTM (ELSTM) model in which they tuned the parameters of the standard LSTM model. The results attained suggested a new and unique SA approach to set the bar in the field of textual categorization and an algorithm which described the procedure followed in the model. the efficacy of the suggested ELSTM model was analyzed in terms of the accuracy curve achieved during the training and testing that revealed that proposed ELSTM model achieves high performance. Similarly, the authors in [82], analyzed the performance of three DL models which included CNN, LSTM and Bi-LSTM. The authors used the database in which different comments that were posted on official pages of Tunisian supermarkets Facebook page. The selected database was able to categorize the text on the basis of the five annotations which included very positive, positive, neutral, negative and very negative along with remaining other twenty categories of aspects. The results achieved demonstrated the effectiveness of CNN and Bi-LSTM NN on selecting appropriate features. In addition to this, the authors in [83], analyzed that Weibo text SA method is becoming increasingly important in tracking public opinion with the enormous growth in its data. SA jobs are extremely difficult because of the sparsity and computational complexity of textual data, as well as the rich interpretations of natural language. In order to overcome these issues, the authors of this paper proposed an improved Weibo text SA model that was based on BERT and DL. To do so, they firstly utilized BERT approach for representing the input texts with dynamic word vectors and later on they implemented processed sentiment dictionary on these vectors so that their semantics increases. After that, they implemented the Bi-LSTM network for extracting the contextual attributes from the text and after this processed vector were weighted by using attention approach. Following weighing, the generated sentiment feature map was categorized by applying CNN that retrieved significant local sentiment characteristics in the content. A comparison experiment was performed on the Weibo text database acquired during the COVID-19 outbreak and the findings revealed that the suggested method outperformed previous similar ones substantially.

TABLE IV: COMPARISON FOR CNN, LSTM AND BI-LSTM BASED ABSA TECHNIQUES

Reference	**Dataset used**	**Techniques used**	**Performance**	**Observations**
[72]	SemEval2016 French dataset	CNN, Bi-LSTM and CRF	Determined aspects for many languages	Proposed a French-performing model. As seen for English, CLC is adaptable to different languages. The proposed model exploited the link between attributes and sentiment by simultaneously detecting them.
[73]	Various ABSA databases	Bi-directional encoder Representation from Transformers (BERT)	Effective performance on given datasets.	MAMN improved aspect-level sentiment analysis. Pre-trained BERT initializes word embeddings better than Word2vec and Glove. Attention created concealed sentence representations.
[74]	standard databases	Joint attention-based LSTM (JAT-LSTM)	Efficient	Aspect-level sentiment analysis using a joint attention LSTM network (JAT-LSTM) combines aspect and sentiment attention. The

				suggested technique outperforms the state-of-the-art on benchmark datasets.
[75]	Real datasets	CNN, LSTM, Bi-LSTM and GRU models	Improved accuracy of 5 to 20%. In ABSA models	Aspect-based sentiment analysis model proposed. Ensemble-learning deep neural network architecture was proposed. The suggested method generated and trained CNN, LSTM, BiLSTM, and GRU deep learning models. A logistic regression model combined base classifier outputs as a meta-learner. The proposed method outperforms the baseline method by 20% in precision.
[76]	Amazon product dataset	ML techniques along with the DL methods including CNN, RNN and LSTM	Best accuracy in LSTM with 93%	LSTM models outperformed machine learning. Polarity intensity, such whether a review is positive or very positive, is analyzed. The method identified positive and negative product attributes. It outperformed Machine Learning models. The model gave more accurate and extensive reviews to analyze product qualities and polarity.
[77]	Utilized four datasets	LSTM along with adaptive PSO	Outperforms traditional models	Word embedding extracts skip gramme features. Skip-gram Word-to-Vector encoding uses less memory and is more accurate. Without optimization, LSTM performs well. APSO optimized LSTM weight parameters for performance. APSO-selected LSTM neural network weight parameters improve accuracy and computational complexity. Amazon had 96.8% accuracy, travel advisor 97.8%, demonetization 93.2%, and book review 95.2%.
[78]	Twitter dataset	CNN, LSTM and RNN	accuracy of 85%.	It offered a Domain-specific Sentiment Dictionary and lexicon-based Hindi sentiment analysis (Hindi Senti-WordNet, NRC Emotion Lexicon). 23,767 Hindi tweets were categorised as good, negative, or neutral using a CNN, RNN, and LSM. The CNN technique was 85% accurate.
[79]	implicit sentiments database	graph attention-based CNN	F-Score of 88.16%.	It presented a graph attention neural network (GACNN) model for implicit sentiment analysis. Implicit sentiment analysis has no specific emotional language, making it harder to express mood and extract sentiment features. Orthogonal and score attention constraints were used to distinguish multiple attention and prioritise important words. This study did not examine how external knowledge affects implicit sentiment analysis.
[80]	YELP and US airline databases	integrated the chiSquare along with the LSTM, Bi-LSTM and GRU networks	On yelp dataset accuracy is 100% while as, US airline dataset achieved an accuracy of 97.9%	LSTM, Bi-LSTM, and GRU with chi-square extract quality features for all models. Unreduced features came via neural network preprocessing. Methods decreased dimensionality. Chi-square improves classifier performance for US Airline and Yelp datasets by removing irrelevant, noisy, and duplicated features. US Airline and Yelp datasets had 97.9% and 100% accuracy with this method.
[81]	Standard dataset	enhanced-LSTM (ELSTM) model	Effective performance during training and testing	DL extracted opinions in this study. This study proposes Enhanced LSTM (ELSTM) sentiment analysis.
[82]	Tunisian supermarkets Facebook dataset	CNN, LSTM and Bi-LSTM.	effectiveness of CNN and Bi-LSTM NN on selecting appropriate features	This study examined Tunisian dialect sentiment analysis at the sentence and aspect levels. This addresses Tunisian dialect sentiment analysis at the aspect level. Three DL algorithms—CNN, LSTM, and Bi-LSTM—were created. LSTM and Bi-LSTM performed best at sentence level

				with an F-Measure of 87%. Our aspect category model had an F-Measure score of 62%, and the sentiment model had 78%.
[83]	Weibo text database acquired during the COVID-19 outbreak	BERT, Bi-LSTM, CNN	Effective performance	Propose a BERT-deep learning sentiment analysis model. The model employed BERT to convert text words into word vectors, a sentiment dictionary to increase sentiment intensity, and a BiLSTM network to extract forward and reverse contextual information.

c) Other DL techniques:

In addition to the above-discussed DL-based ABSA method, there are some other approaches as well in which different classifiers were used. The authors in [84], proposed a two-fold Rule-Based Model (TF-RBM) approach in which they defined some specific rules that were based on sequential patterns generated from reviews given by the customers. The model extracted the aspects that were related to the domain independent opinions and domain-dependent opinions in the first and second folds respectively. In addition to this, they implemented frequency and similarity-based techniques in their work for enhancing the effectiveness of extraction. The results demonstrated that the proposed model outperformed the traditional models. Similarly, the authors in [85], proposed a DL-based adaptive architecture for the process of topic modelling from huge data. In their work, they implemented an online latent semantic indexing approximation restricted via a regularization-based method was also put forward. A deep network with feed-forward levels was used to build a classification model. The designed model was considered adaptive because it was able to collect data sequentially and returns dynamic topics. The framework provided temporal topic modelling as well as it also detected the implicit and explicit characteristics of phrases in order to obtain patterns and development of subjects. In [86], analyzed that ABSA concentrates on English for the most part, with only a small amount of employment accessible in Arabic. The majority of past work in Arabic has relied on standard machine learning approaches that rely on a small number of specialized techniques and support for processing and analyzing Arabic information, including such lexicons, however, the unavailability of such sources poses a new difficulty. In this regard, the authors of this paper proposed two DL-based models that were based on GRU. The first model was designed by combining the Bidirectional GRU along with the CNN and CRF models in which they extracted key opinionated texts by using the word and character representation. While as in the second model they designed an interactive attention network model along with the bidirectional GRU (IAN-BGRU) for recognizing the polarity of sentences. The authors analyzed the performance of their suggested model on the Arabic hotel review database.

The results achieved demonstrate that the suggested model improved the value of FScore by 39.7% and 7.58% for OTE and sentiment polarity classification. Similarly, the authors in [87], proposed a DL method for determining the aspects of tweets that were generated during demonetization. The suggested model undergoes pre-processing, aspect extraction, polarity feature extraction and classification stages. The authors selected some tweets that were posted during the demonetization from Kaggle.com. this data was then processed by using four stages of stop words elimination, elimination of punctuation, case sensitiveness and stemming to reduce its overall dimensionality. After this, the opinions were extracted from the processed data which were later on converted to specific features by using the Word2vec and polarity score computation. Once this was done, the authors implemented the Firefly and multi-verse optimizer so that the weight of the polarity scores is tuned. Finally, an RNN-based model was used in which they optimized the hidden neurons by the hybrid FF-MVO and FF-MVO RNN models that can easily identify the positive and negative sentiments. The results demonstrated the effectiveness and efficiency of the proposed DL model over traditional ML algorithms. Similarly, the authors in [88], presented a position-aware-based bidirectional attention network (PBAN) in which they utilized the concept of GRU. The suggested model not only focused on location information of aspect terms but was also responsible for representing the relationship between aspect terms and phrases by using the bidirectional attention mechanism. The efficiency of the suggested PBAN method was illustrated on SemEval 2014 Database where it proved its effectiveness. Moreover, the authors in [89], stated that the main goal of an ABSA method is to determine the sentiments or emotions that are attached to a text in a sentence. They analyzed some prior research that suggested the importance of relationships among aspects and contexts. In this context, they suggested a simpler hierarchical attention-based technique in which target and contextual information about the words were fused. Furthermore, upon decoding the phrase, many current models omit the aspect's location coordinates which are considered an important asset in determining aspects from sentences. To achieve this task, they proposed a hierarchical attention-based position-aware network (HAPN) in which they introduced the concept of position-aware among phrases. As per the result findings, the suggested methodology achieved higher performance results when compared with the traditional models. In addition to this, the researchers in [90], analyzed the

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performance of two Arabic databases named ASTD and ATDFS for two-class and multi-class categorization. They named the 2-layered CNN model MC1 in which global average pooling and dense layers were used. another model was named MC2 which was also 2 layers but with max pooling, Bidirectional GRU and then dense layers. The authors achieved an accuracy of 73.17% on complex ASTD 4-class tasks. While as, in the case of easier 2-class tasks, the suggested model achieved an accuracy of 90.06% for the MC1 model. moreover, they also analyzed the performance of the suggested model on multiple databases and also analyzed the importance of Arabic preprocessing. The authors focused on the two phases in which the emoticons were processed in the first stage and a custom stoplist was utilized in the second stage. The performance was again analyzed for the 4-class task and 2-class tasks in which an improvement of 4.27% and 5.48% was observed for processing of emoticons and 2.95% and 3.87% for custom stoplist. Linan Zhu et al. performed review on deep learning for aspect-based sentiment analysis, where they said that extracting accurately information is still a challenge because of massive amounts of data. Therefore, sentiment analysis solves this problem by identifying people's sentiments towards the opinion target [91].

TABLE V. COMPARISON TABLE FOR OTHER DL TECHNIQUES

References	Techniques used	Performance outcome
[84]	Two-fold Rule Based Model (TF-RBM)	Aspects were determined effectively
[85]	DL based online latent semantic indexing approximation constraint via regularization-based method	Effectively determined implicit and explicit aspects from text
[86]	Bidirectional GRU with CNN and interactive attention network with BGRU	improved the value of FScore by 39.7% and 7.58% for OTE and sentiment polarity classification
[87]	Applied DL techniques on Kaggle dataset	Outperformed traditional ML models
[88]	Position aware based bidirectional attention network (PBAN) and used SemEval 2014 dataset	Determined the location of aspects and their relationship with phrases
[89]	Hierarchical attention-based position-aware network (HAPN)	Better performance than traditional ABSA models
[90]	Used two dataset ASTD and ATDFS and proposed two CNN models	Efficient results in terms of accuracy

- *Gaps finding discussion*

The decision of using DL methods in determining the aspect sentiments has come a long way, with a massive number of scholars using this approach. However, the problem with the DL methods is It requires a very large amount of data to perform better than other techniques. It is extremely expensive to train due to complex data models. There is no standard theory to guide you in selecting the right deep learning tools as it requires knowledge of topology, training method and other parameters. Moreover, the majority of experts are using CNN, LSTM and BI-LSTM techniques which undergo the problem of overfitting and gradient vanishing. Furthermore, the cost of being utilized in training the DL architecture is also high.

IV. GENERAL PROBLEM IN ASBA

With the exponential use of web-based applications like Twitter, FB, Instagram, and blogs, the individual is generating a mammoth volume of data. As demonstrated in Fig.5, social media sites bring a variety of issues, including spelling errors, new terminology, and erroneous grammatical usage. All these challenges make the process of sentiment analysis a challenging task to be performed. One of the biggest challenges in SA is that users do not express their emotions clearly. For example, "y are u sooo rude". In the given sentence, "Why" is misspelt as "Y", "you" as "u" while "sooo" has been utilized to represent the sentence as more impactful. Moreover, the given sentences don't depict whether the person is angry or happy

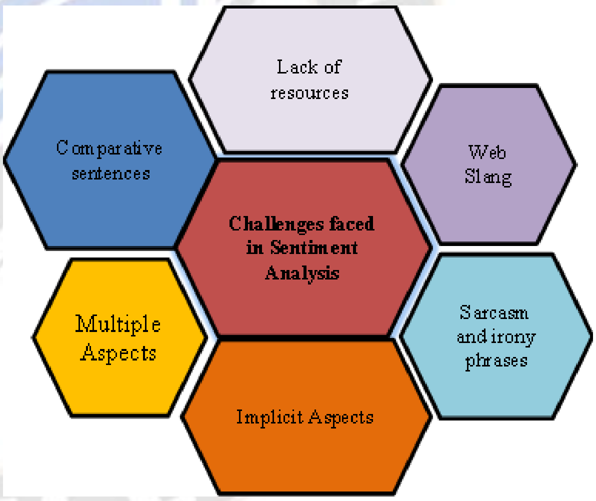

Figure 5. Challenges faced in ABSA

Another major challenge that is faced in current SA techniques is the non-availability of labelled resources. Moreover, the majority of the resources available are in the English language which makes it difficult for models to extract aspects from other languages. Another challenge in the SA is the use of web slang, which is mostly seen on social networking sites like Twitter, Instagram, Facebook etc. Most social media users are using slang like "LOL", and "FOMO" for expressing their laughter and anxiety respectively. Other web slang like, "OOTD", "EPIC", "ROFL" and so on are used also used by various individuals. This increasing dictionary of web slang hinders the performance of SA models. The articulation of

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numerous feelings in a single statement is another issue. The multi-opinionated statement makes it hard to discern numerous features and their associated feelings or emotions. For example, the phrase "the view from this point is so peaceful and beautiful, however, this area stinks" demonstrates two feelings, "disgust" and "comforting," in different ways. In addition to this, determining the polarity of sentences that are comparative in nature is also challenging. Figure 5 showing the various challenges faced in ABSA.

- *Review finding discussion*

After reviewing the literature, it can be concluded that the majority of the scholars are working with either ML techniques or DL techniques. To the best of our knowledge, not a single approach is available that can detect aspects of Web slang, sarcasm phrases, irony phases, comparative sentences etc. Furthermore, to enhance the accuracy and precision of aspect extraction models, hybridization of existing ML/DL, DL/DL or pre-trained models is recommended. By doing so, not only the above-mentioned challenges can be solved but the accuracy and time for determining the aspects of text can be improved.

V. CONCLUSION

The subject of sentiment analysis has gained a lot of attention from researchers over the last few decades due to the continuous rise of social media users over the internet. Millions and billions of individuals around the world are using social networking sites like Twitter, Facebook, Instagram etc. for expressing and sharing their thoughts, beliefs, emotions and opinions about different products, companies and items. This manuscript explores and categorizes frequently used classification algorithms for determining aspects in sentences or phrases. As the main focus of this paper is on ABSA, therefore, we reviewed some of the recently published articles related to it. After conducting the review, it is observed that traditionally features were extracted manually from texts for determining their polarity. However, with the exponential growth of data in the last few decades, manual feature extraction from texts turns out to be formidable. Therefore, researchers paved their way toward Artificial Intelligence (AI). To understand the concept of ABSA in the light of AI, we reviewed current ABSA approaches under two categories of ML-based ABSA and DL-based ABSA. From the review, it is concluded that ML-based binary classifier (SVM), tree algorithms like DT, RF, and NB were mostly used by researchers in their work for analyzing aspects in sentences, phrases or comments, as these techniques are simple and easy to implement. However, one of the prime drawbacks of SVM is that it doesn't perform well when multiple aspects are present in the text while as, the tree-based algorithms can cause instability because of minor changes in data. Additionally, ML algorithms were not able to handle the large and intricate datasets and they also tend to lose ample of information during pre-processing and feature extraction phases. To overcome these issues, researchers moved towards the DL based approaches. Substantial number of experts used CNN, RNN based LSTM, Bi-LSTM in their work because of their ability to detect features from text automatically. Despite the fact that DL methods can handle large datasets effectively but the need for huge training data and high error susceptibility affected the accuracy of detecting aspects from texts. At last, it can be concluded that the accuracy of detecting sentiments can be improved by using the hybrid DL approaches on standard datasets. The issues described subsequently show that sentiment analysis is still a growing subject of investigation.

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