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RESEARCH ARTICLE

A Hybrid Frequency Based, Syntax, and Conditional Random Field Method for Implicit and Explicit Aspect Extraction

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ABSTRACT Aspect extraction is the most important factor influencing the quality of Aspect-Based Sentiment Analysis (ABSA). Aspect extractions are divided into three approaches: supervised, unsupervised, and hybrid methods. Most previous aspect extraction algorithms focus on the explicit aspect, which lacks meaningful ABSA. Thus, considering the implicit aspect has become significant as most customer reviews consist of these by about 30%. Hybrid approaches have attempted to solve both aspects by integrating the frequency-based approaches (FB) with syntax, hybrid Conditional Random Field (CRF) with syntax, and hybrid FB with CRF, but the performance is still low. Extracting the implicit and compound noun aspects is challenging due to their hidden nature and special syntax needs. The implicit aspect needs FB, syntax dependency, and specialized tagging with feature embedding using natural language processing (NLP) solution, while the compound noun aspect needs FB, syntax dependency-based NLP solving. Therefore, this paper proposes a noble hybrid method combining frequency-based, syntax-based dependency, and CRF algorithms using tagging and labeling to extract both implicit and explicit aspects. It also provides a mechanism for extracting and calculating implicit and explicit aspects and a method for accurately identifying compound noun aspects. Experiments with the benchmark SemEval and Amazon review dataset validate the suggested hybrid model's effectiveness. The proposed method produced remarkable improvement in extracting explicit and implicit aspects and improved overall results with precision-recall and accuracy between 5-15 percent. Moreover, this study has shown the number and the list of explicit and implicit aspects. The proposed method has obtained (2269, 368), (523, 60), (322, 55) number of explicit versus implicit aspects for SemEval 16, Amazon (Canon), and Amazon (Nokia) datasets, respectively. Hybrid with frequency-based, CRF's superiority tagging and syntax help solve implicit and explicit aspects, including compound nouns.

INDEX TERMS Aspect extraction, aspects, implicit aspect, customer reviews, ABSA, sentiment analysis, CRF, NLP, hybrid method.

I. INTRODUCTION

Recently, the trend of sharing the customer experience of any business on social media platforms is increasing as the number of online reviews has increased substantially. In 2023, the online business grew by 20%; it is forecasted to be 26% in 2026 [1], anticipating the growth of customer reviews. In these customer reviews, customers share their sentiments about the services they have used, such as hotel reservations, purchasing products, or viewing films. These reviews are regarded as an important resource for customers and companies alike. The customer review contains comments on features or aspects of two types: explicit and implicit. Aspects are primarily nouns; explicit aspects are expressed clearly,

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and implicit aspects are hidden or implied. Besides, aspect words with more than one noun are called compound noun aspects. Explicit aspects sentiment analysis is good; however, they lack hidden aspects, which are important for business. For example, in the review sentence:" the phone is heavy, and its sound is not clear''. Here, the aspect ''heavy'' signifies the implicit aspect of 'weight' which is not expressed clearly but instead implied, and the second aspect 'sound' is the explicit aspect as it is expressed clearly by a noun word. Generally, users express explicit aspects by explicit words. Explicit aspect expressions are usually nouns and noun phrases, and implicit aspect expressions can be verbs, verb phrases, adjectives, and adverbs [2]. In another example review, ''The laptop screen is big''. Here, 'laptop screen' is a compound noun. Compound noun aspects are difficult to extract from reviews [3]. Thus, literature misses the extraction of these aspects and does not mention them in the result. Usually, customer reviews contain an important portion of about 70% explicit and 30% implicit aspects [4]. Many researchers have achieved substantial performance on explicit aspect extraction but less on the implicit aspect. Therefore, implicit aspect extraction is vital for both the customers who make their buying decisions on the aspects and the managers who can improve the product or services based on feedback from reviews. Identifying and extracting implicit aspects has become important research nowadays [5].

Detecting implicit aspects is challenging but critical, and limited studies focus on implicit extraction [4], [6]. Besides nouns, many implicit aspect expressions are Parts of Speech (POS) tags of adjectives and adverbs, e.g., expensive (price) and reliable (life). Implicit aspect expressions are not just adjectives and adverbs. They can be quite complex; for example, ''This phone will not easily fit in pockets''. Here, ''fit in pockets'' indicates the ''implicit'' aspect of "size" (and or shape). Implicit aspect expressions are not limited to one type of feature. Besides POS tags, they need syntax features and special labeling and tagging features of CRF through feature embedding [7] or tagging index terms [8], [9]. In addition, compound nouns need syntax features and special tagging to consider the semantic contextuality of text. Numerous researchers have delved into aspect extraction methods over the years, from early work by Hu and Liu [10] to recent contributions by Ho et al. [11] and Zhao et al. [12]. Aspect extraction approaches can be divided into supervised, unsupervised, and hybrid. Earlier literature used supervised or unsupervised approaches. The frequency based method [10], syntax-based method [13], [14] and topic-model based method [15] fall under unsupervised approach, while sequence labeling algorithms like Conditional Random Field (CRF) [7], [16] use a supervised approach.

Despite the strengths and weaknesses of each approach, hybrid approaches show the best solution to extract either or both implicit and explicit aspects extraction by hybridizing more than one method. Researchers have proposed various hybrid methods employing frequency-based [10], syntax based approaches using dependency parsers [13], Latent Dirichlet Allocation (LDA) [15], and conditional random field (CRF) algorithms [16], [17]. Many researchers have achieved substantial performance on explicit aspect extraction but still less on the implicit aspect. However, the specific challenge of implicit aspect extraction remains unaddressed by existing hybrid methods [17], [18]. Moreover, analysis results of the previous research show that hybrid methods potential could be improved using natural language processing (NLP) such as part of speech (POS) tag [10], syntax features [13], and dependency parser [19], [20]; CRF's exceptional ability of labeling and tagging [7], [16] has offered a substantial solution to extract implicit aspect. Therefore, this paper proposes a novel hybrid method of frequency-based, syntax-based dependency, and CRF algorithms to improve both the explicit and implicit aspect extraction for ABSA. We contend that the proposed hybrid method can be effective for implicit aspect extraction improvement, solve aspect extraction issues and contribute to better ABSA.

The remainder of this article is structured as follows: Section II presents related work for aspect extraction approaches and methods. Section III shows the proposed hybrid aspect-extraction framework, while section IV shows the experiment and results of the proposed solution. Finally, in section V, the conclusion will include some recommendations for further research.

II. RELATED WORK

Aspect extraction is the core task for aspect-based sentiment analysis. Aspect extraction methodologies can be broadly categorized into three main approaches: supervised, unsupervised, and hybrid [21], [22]. Unsupervised approaches primarily rely on unlabeled data, while supervised approaches utilize labeled data. The salient advantage of unsupervised methodologies lies in their capability to extract numerous aspects, whereas supervised methods excel in extracting relevant aspects. Conversely, the drawback of unsupervised approaches is their inability to discern unrelated aspects, whereas supervised methods may struggle to identify undefined aspects. On the other hand, natural language processing has its strengths to draw grammatical syntax and semantics of contextual words through features such as POS tag and dependency parser. Against this backdrop, the hybrid approach emerges by effectively combining the strengths of the methods of both unsupervised and supervised approaches. Thus, hybrids prove instrumental in extracting both explicit and implicit aspects. Therefore, the hybrid is an optimal solution, presenting a comprehensive and nuanced understanding of the subject matter in ABSA. The approaches and methods of aspect extraction are described below.

The unsupervised approach represents an early paradigm employed for aspect extraction, manifesting through three prevalent methods: frequency-based, syntactic relation-based, and topic model-based methods. Hu and Liu [10] is credited as a pioneer in proposing a frequency-based method that identifies the most frequently occurring nouns.

Subsequent enhancements to this method were introduced by Long et al. [23] and Wang et al. [24]. The latter authors addressed the limitation of characterizing high-frequency nouns or noun phrases as aspects by comparing the frequency of a potential aspect and baseline statistics derived from a corpus comprising 100 million words of spoken and written conversational English. Notably, Caputo et al. [25] introduced the Sentiment Aspect-Based Retrieval Engine (SABRE), which is predicated on extracting candidates from words associated with the subject of the aspect and emotional expressions linked to textual aspects. This approach relies on term-frequency probabilities and a model utilizing the non-symmetric Kullback-Leibler divergence method to compute the difference distribution for a word across a specific domain and a comprehensive corpus. Ultimately, the TF-IDF weighting method is applied to retrieve the top-N documents with the most significant opinion scores for document retrieval. In further refinements, literature [26] used a frequency-based method for reducing non-frequent aspects; it used two steps of pruning: (a) determining each word's frequency and selecting its most frequent aspects, and (b) analyzing the semantic similarity of less common words and removing aspects that are not semantically related to the product. Frequency-based methods have been proposed as efficient methods to extract aspects, especially the explicit aspects. However, the main limitation is that it extracts too many unrelated aspects and drops the non-frequent aspects. Another study by Pradhan and Sharma [27] used a frequency-based method but had the issue of extracting compound nouns owing to not capturing the bigram aspect. Therefore, syntactical relations need to be described to get good coverage for implicit aspects and compound nouns.

The syntax-based method considers the contextual grammatical syntax while extracting the aspect in a sentence. This method has the advantage of finding the aspects with syntactical relations. The authors in [28] and [29] have used extraction rules combining dependencies. The literature [29] used 30 syntactic rules according to the characteristics of the Arabic subjective text to extract only explicit aspects. In addition, [19] researched the performance of several types of dependency relations with various POS tag patterns to pre-extract candidate aspects from customer reviews. It identified the dependency relationship with 13 rules and its POS tag pattern for aspect extraction. Later, [30] used a sequential rule-based approach for aspect extraction. To improve further, Zhao et al. [12] are one of the latest researchers that used the syntax method with dual encoder for aspect extraction and achieved good results. However, it didn't show the implicit or explicit aspect; instead, it showed the overall result. In addition, another literature by Kabeer et al. [3] used syntax rules in finding aspect and sentiment pairs and described compound nouns as an issue of parent-child relations. The literature has limitations in finding these aspects. This syntax-based method mainly relies on grammatical rules and linguistic restrictions. Defining many syntactic rules is a long and delicate process and can negatively affect detection [20]. Moreover, people do not consider these guidelines while expressing their opinions. This renders these methods susceptible. Thus, some researchers tried to find a solution using another unsupervised approach with a topic model.

On the other hand, a topic-based model is also an unsupervised approach. It uses Latent Dirichlet Allocation (LDA) algorithm to extract aspects based on the topic to solve the too many unrelated aspects [31]. This approach defines a document containing many topics as subjects. The advantages of topic models are their ability to group related aspect expressions and their unsupervised nature. However, LDA faces many unlabeled topics, so it fails to find the relationship between subjects and particular aspects. Furthermore, the drawback of this method is that the aspects extracted are not fine-grained [31], as it contains global topics rather than domain-related topics. Reference [15] used LDA to find topics in hotel reviews on Indonesian hotels. In addition, [31] used unsupervised (LDA) with only the n-gram feature as an aspect; thus, it missed other implicit and compound noun aspects. LDA mostly takes global features, so domain-based features are ignored. This makes this method vulnerable and unsuitable.

Besides the strength of the above methods, both the frequency-based and syntax-based methods have limitations in tracing the meaning of words, ignoring the semantics. On the other hand, the LDA topic model-based method missed domain affinity. To offset these limitations, the supervised approach is discussed below.

The supervised approach necessitates labeled data for aspect extraction, wherein these labels correspond to identified features. The labeled data actively considers the contextual cues of words to discern underlying semantics. Literature [32] focused on extracting named entities with associated sentiment from the Tweets dataset, utilizing a combination of entity names and sentiment levels to create sequences of labels. It used a mix of entity names and sentiment levels to create sequences of labels, utilising styles of nodes at each word or position. Later, comprehensively extracted named entities along with their related sentiment. The strength of supervised approaches depends on the features; they sometimes consist of feature creation to produce more salient features that generalize better than basic bag-of-words or part-of-speech features. Some researchers use feature embedding, while others use seed aspects or aspect indexes for better learning and tagging [8]. Literature at [33] has proposed a method to generate a seed set for reviews' top five frequently mentioned aspects by examining word co-occurrences. This aids in finding the implicit aspects of a review. Reference [9] proposed a seed-based strategy for establishing semantic relationships among review terms, while [34] introduced a three-step seed-based technique for feature extraction. The first is selecting the top four topics in restaurant reviews—food, service, price, and ambiance. The second step entails appropriately tagging and indexing terms, and the final step involves classifying indexed words based on their proximity. This seed aspect index relies on the grammatical connections between seed sets and terms in reviews to identify key aspects.

In addition, another supervised method with CRF algorithm considers the word's context with word or feature embedding to find the semantics through probabilistic properties of labeling and tagging. Reference [7] used this algorithm for finding implicit aspects. It used clustering to enhance the CRF position features and train the model with these additional position features for aspect term extraction. It used the SemEval dataset and achieved good performance but didn't mention implicit aspects. Furthermore, [35] used CRF with the combination of clustering for aspect extraction and achieved good performance.

Hybrid approach comes in various combinations of supervised and unsupervised methods. As previously indicated, several researchers have studied the benefits and drawbacks of supervised and unsupervised aspect extraction approaches. Therefore, they were allured to propose a hybrid method for aspect extraction by combining two or more methods or algorithms with cutting-edge solutions to overcome the limitations of each method. The hybrid methods have improved the aspect extraction performance of ABSA, either explicit or implicit aspect or both aspects extraction as well [7], [12], [18], and [36]. The important hybrid literature are highlighted here.

Popescu and Etzioni [37] is one of the pioneered hybrid approaches employing Pointwise Mutual Information to identify potential aspects, which classifies possible aspects, which are then fed into the Naive Bayes (NB) classifier to produce a collection of explicit aspects. It achieved the result with a precision of 72% and recall of 80% using hotels and the Amazon dataset. Meanwhile, [38] utilized AspectFrameNet to detect aspect patterns as a sequence-labeling job, using aspects as a sequence-labeling task by CRF. Reference [7] suggested Multi-Feature Embedding (MFE) to enhance text representation and capture more semantic information. The authors then utilise the kmeans++ method to get MFE and word clustering to enhance the CRF position features. Finally, the MFE clustering classes and word embedding train the CRF model for aspect term extraction as additional position features. The results with SemEval-14, SemEval-15, and SemEval-16 datasets were better. However, this has the problem of recognizing conjunctions. Reference [36], used a hybrid of frequency-based and unsupervised (LDA). It used sentence segment LDA (SS-LDA), a frequency-based technique (n-gram feature) for aspect extraction. It used the SemEval-2016 dataset (Turkish restaurant reviews) and achieved moderate results. This literature has the drawback that, as LDA takes mostly global features, the domain-based feature is ignored. On the other hand, Asghar et al. [39] used heuristic patterns in which nouns (single word), noun phrases, and verbs were assumed to be the candidate words for the aspects. Reference [40] used hybrid with Conditional Random Field and word embedding, but this embedding method suffers where semantics ambiguity or the dataset is limited. Mashrekul et al. [18] used hybrid with syntax and dependency and lexicon for aspect extraction. The hybrid technique extracts common aspects by determining the Part of Speech (POS) tag for each word in each review line. Then, it used syntax dependency for aspect extraction. However, it could not extract all implicit aspects and worked with the hotel dataset of Europe. Agerri's hybrid with CRF and a combination of clustering features trained with CRF and the SemEval16 dataset (English) achieved P-74.11%, R-70.90%, and F1-73.51%. It could not extract all implicit aspects [35]. Chen et al. [17] proposed a hybrid of n-grams (Span-based) and achieved P-79.90, R-79.41, F1- 80.38% with the restaurant dataset. The author conjectures that the reason is that the restaurant has more samples, and the deep-level interaction information may not be enough to promote aspect extraction efficiently.

Asghar et al. [39] used hybrid with heuristics, where nouns, phrases, and verbs were used as POS features for the aspect extraction, improving precision. However, it could not extract implicit and multiple aspects in a sentence.

Recently, some literature use deep learning as a supervised approach, and combining methods to form hybrid [17], [41]. Deep learning has the inherent disadvantage of using the black box method. Besides the difficulty in interpreting methodology, it has limitations in grasping syntax and semantic information [42]. Thus, it has limitations in identifying and extracting important aspects, especially implicit ones, from the context. Wu et al. [41] hybrid with dependency and POS tagging employing deep learning. It aimed to find the dependency relationship between aspect and sentence with the model to extract (target, aspect, and sentiment) triples from a sentence. The model fails to extract (NULL, SERVICE #GENERAL, negative) triple due to target conflict when the target contains implicit. Li et al. 2023 [43] also used hybrid with supervised deep learning using the SemEval 14 dataset, achieved F1 77.3-81.28, and with laptop achieved F1-73.86-78.47%; it didn't mention extracted aspect types. The recent literature by Zhao et al. [12] used syntax and semantic information with deep learning and achieved the precision of P-70.09-77.97%, recall of R- 62.11-71.77%, and F1-65.86-74.74%, with the SemEval15 and SemEval16 datasets.

To provide a structured overview of the field's advancements, Table 1 presents a comparative analysis of the performance of eleven hybrid methods literature for aspect extraction with benchmark datasets and aspect types from 2005 to 2024. This table highlights the importance and impacts of various hybrid combinations. It shows the column titled author and year, hybrid methods, dataset, aspect types, and results.

Table 1 shows that most researchers used the SemEval dataset from 2014 to 2016 to show their proposed performance evaluation. Six researchers used SemEval 2016 [7], [12], [17], [35], [36], and [41] while three researchers used restaurant review datasets of SemEval-14 [35], [40], [43], and three used SemEval-15 dataset [12], [35], [41]. On the other hand, [39] used the Amazon product review dataset, [38] used

TABLE 1. Comparison between hybrid methods and results for aspect extraction.

Author and Year	Hybrid Methods	Dataset	Aspect Type	Result (in percentage) **
Zhao et al. (2024) [12]	Syntax and semantics with deep learning	SemEval15 and SemEval 16 Restaurant	Not mentioned	70.09 and 77.97 62.11 and 71.77
Li et al. (2023) [43]	Supervised deep learning	SemEval 14 and Laptop 14	Not mentioned	F1-77.31-81.28 and 73.86-78.47.
Chen et al. (2022) [17]	Frequency with deep learning	SemEval16 (Restaurant) SemEval2014 (Laptop)	Explicit	P-70.28, R-79.41, F1- 80.38 P-79.90, R-70.5, F1- 70.39
Wu et al. 2021[41]	Syntax dependency with frequency-based (deep learning)	SemEval 2015 and SemEval 16	Explicit	P-83.62
Majumder et al. 2020[40]	Conditional Random Field (CRF) and word embedding	Sem Eval-14 (Restaurant) & Laptop	Not mentioned	F1- 70.85 64.37 & F1- 68.68 67.27
Ozyurt et al. (2020) [36]	Frequency-based with LDA	SemEval-16 (Turkish restaurant reviews dataset)	Not mentioned	P- 65.58, Recall 59.23, F1- 62.25.
Agerri et al. (2019) [35]	Hybrid Frequency-based with CRF	SemEval 2014, 2015 and SemEval 16 (English)	Both	F1-74.11, 70.90, 73.51
Asghar et al. (2017) [39]	Heuristics with frequency-based	Amazon customer reviews	Not mentioned	P- 83.46, R-71, F1-77
Xiang et al. (2018) [7]	Hybrid Frequency-based (embedding) with CRF	SemEval-16 (restaurant) and SemEval-14 (laptop)	Not mentioned	P- 86.41. R-82.35 and F1-84.33 and P-87.81, R- 67.82, F1-76. 53
Chatterji et al. (2017) [38]	AspectFrameNet with CRF	Customer reviews (mobile)	Both	P-79.22, R-70.93, Accuracy- 82.76
Popescu et al. (2005) [37]	Pointwise Mutual Information with NB Classifier	Hotel (Trip Advisor) and Reviews (Amazon)	Explicit	P-72, R-80

** P=Precision, R=Recall, and F1=f measure / F score.

customer reviews, and [37] used the hotel and Amazon review dataset.

Only two researchers mentioned that their methods can extract explicit and implicit aspects [35], [38]. Some of them did not mention the aspect types [12], [36], [39], [40], and [43], while others improved the explicit aspect only [17], [37], and [41].

Upon analyzing the methods mentioned above, [12] and [41] stood out with the most favorable results. Reference [41], merging frequency-based with syntax-based approaches demonstrated superior performance (83%) using SemEval 16 dataset. This confirms that frequency-based with syntax-based has better performance acceptability as one of the hybrid methods to extract explicit aspects. Conversely, three literature [7], [38], and [40] have proposed hybrid CRF, but [38] and [40] have shown less performance, while [7] has achieved the highest precision result (84.13%) using the same dataset.

CRF used by [38] and [40] suffered from semantics ambiguity and consequently could not extract implicit aspects, while [7] faced conjunction problems, and thus, the implicit aspects were still not solved fully. Therefore, hybridizing Frequency and syntax dependency with CRF is believed to improve the explicit and implicit aspect extraction method. The CRF has the potential uses to extract implicit aspects by hybridizing [43] with [7] and has the potential to address both explicit and implicit aspects by overcoming conjunction problems of [7] through the incorporation of POS tag features.

III. PROPOSED HYBRID MODEL

The proposed hybrid frequency based, syntax, and CRF algorithm (HFSC) model for aspect extraction is shown in Fig. 1 below. It includes five major modules: 1) Inputs, 2) Preprocessing, 3) Proposed Hybrid Model, 4) Output, and 5) Evaluation of Results. The proposed hybrid model consists of two modules. The first module is frequency-based method with syntax dependency, and the second is the CRF module. The experiment used the SemEval16 review and Amazon dataset as input, which is further explained in section IV. The output is implicit and explicit aspects after the CRF module. The performance evaluation is carried out when all the aspects have been extracted.

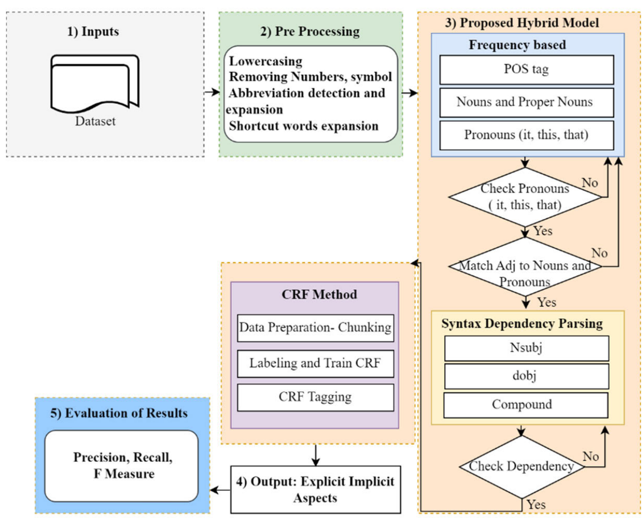

FIGURE 1. The proposed hybrid frequency, syntax, and CRF method (HFSC) model for aspect extraction.

A. PRE-PROCESSING

Data preprocessing follows the standard NLP cleaning process, which includes tokenizing the string, lowercasing, and removing stop words. Tokenization is used to split the strings into individual, meaningful tokens. The tokenization used the NLTK module, which later converted each word in the string to lowercase and removed stop words that do not add significant meaning to the text, such as 'I', 'we', 'own', and 'only', using the NLTK list. In the stemming process, most previous research performed stemming by converting a word to its most general form with NLTK's Porter stemmer. However, we did not use stemming because stemming process will reduce words to their root forms, transforming words like "challenging" to "challeng," "recognize" to "recogn," and "expression" to "express. It obscures the original meaning of words. Subsequently, this problem in understanding the meaning of the words affects aspect identification in the context of the chunk sentences, making it difficult to identify and locate significant aspects. The other important pre-processing tasks are discussed below.

1) ABBREVIATION HANDLING /SHORTCUT

Effective abbreviation handling is indispensable in NLP tasks like aspect extraction, enhancing the accuracy of systems by ensuring a comprehensive understanding of the context and allowing for precise identification of aspects. Table 2 shows shortcut words and abbreviation handling. The word what is written as what's is converted to "what is".

TABLE 2. Abbreviation/shortcut handling.

Input	After Abbreviation Handling
"what's"	"what is",
"what're"	"what are",
"who's"	"who is"

2) SENTENCE SPLITTING

The paper used the NLTK's sentence tokenizer for sentence splitting. It is breaking a paragraph or a block of text into individual sentences. In natural language processing, this step is crucial for analyzing and understanding the meaning of each unit of information. The review: "Nice hotel with very friendly and helpful staff. The great choice of breakfast. The staff are helpful ". The output will be three sentences, as shown in Fig. 2 below.

```
'nice hotel with very friendly and helpful staff. nice hotel \n , with very friendly staff and helpful
- great choice for breakfast , something for everyone.'
```

FIGURE 2. Example output of sentence splitting.

3) PREPROCESSING OUTPUT

The review after preprocessing is the aspect token sentence. The second column in Fig. 3 shows the clean Review.

	Hotel Name	Review	Reviewer Name	Date	Reviewer	Rating
0	Hilton Garden Inn New York Times Square North	comfortable, friendly, good.\n\n \n it was in ...	Laura	December 2021	Chile	8.0
1	Hilton Garden Inn New York Times Square North	\n No clean towels in 6 days or room cleaned,...	Danielle	December 2021	United Kingdom	7.0
2	Hilton Garden Inn New York Times Square North	Enjoyed our stay.\nMake sure you get your park...	Berkley	January 2022\n	United States	9.0
3	Hilton Garden Inn New York Times Square North	modern hotel in a great location but with limi...	Karin	January 2022\n	United Kingdom	7.0
4	Hilton Garden Inn New York Times Square North	excellent staff , near to Times Square.\n\nRoo...	\nParas	2022-02-01 00:00:00	India	7.0

FIGURE 3. The output after preprocessing the dataset.

B. HYBRID MODEL OF FREQUENCY BASED, SYNTAX DEPENDENCY, AND CRF METHOD (HFSC)

The three modules of the hybrid model for aspect extraction are: Frequency based method, Syntax dependency, and CRF module. These are discussed below.

1) FREQUENCY BASED METHOD

Frequency based method considers nouns as aspects. Prioritising POS tagging involves searching for nouns and noun phrases. POS tagger extracts frequent aspect words, often nouns and proper nouns. Proper nouns (it, this, and that) are not often employed in literature, but in this work, they are utilised since they are connected to the nouns that identify the aspects. This proper noun is significant since it refers to the aspects of the text and the phrases. It will be the preceding aspect if there is not a noun. The frequency-based module of this hybrid method first finds frequent aspects. A POS tagger extracts the frequently occurring aspect terms with proper and nominal nouns. The top 20 often occurring aspects listed for the restaurant domain using the SemEval 16 dataset are shown in Fig. 4 and Fig. 5 below.

```
+-----+-------------+--------+
| Row |   Aspects   | Counts |
+-----+-------------+--------+
|  1  |    food     |  240   |
|  2  |   service   |  148   |
|  3  |    place    |  122   |
|  4  | restaurants |   50   |
|  5  |    time     |   36   |
|  6  |    staff    |   35   |
|  7  |    pizza    |   28   |
|  8  |    decor    |   26   |
|  9  |   dishes    |   26   |
|  10 | atmosphere  |   25   |
|     |             |        |
| 715 |  furniture  |   1    |
| 716 |    money    |   1    |
| 717 | toiletries  |   1    |
| 718 |   garage    |   1    |
| 719 |    wifi     |   1    |
+-----+-------------+--------+
```

FIGURE 4. Frequent aspect distribution.

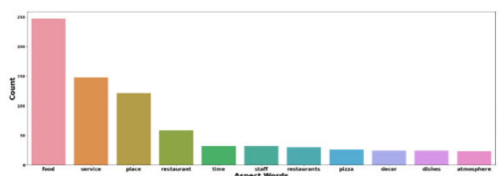

FIGURE 5. Visualization of frequent aspects.

2) SYNTAX DEPENDENCY PARSING

The collection of aspect sentences is processed to derive syntactical relations. In the experiment, a dependency parser was used to capture grammatical relationships and identify the implicit aspects in the text. Therefore, the list of sentiment words from the pre-processing stages is put through a dependency parser to identify specific relations, which helps determine implicit aspects. In addition, the syntax dependency feature used in our experiment is (1) 'nsubj': nominal subject, which is the syntactic subject. (2) 'dobj': direct object, a noun phrase used as a direct object of the sentence. (3) 'compound': noun compound modifier used to identify multi-word or compound nouns. Syntax dependency parsing output of the two reviews is shown below in Fig. 6 and Fig. 7.

FIGURE 6. Syntax dependency parsing output.

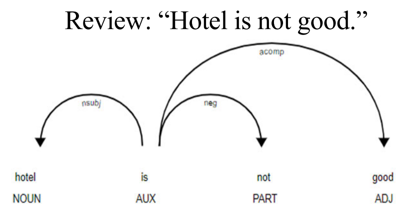

FIGURE 7. Syntax dependency parsing output with negation.

3) CRF METHOD

Conditional Random Fields (CRF) stand as a prominent probabilistic algorithm extensively applied in sequence labeling tasks, such as Named Entity Recognition (NER) and, in the context of this study, aspect extraction. Aspect extraction entails identifying and labeling specific aspects or features within a given text.

It performs the tasks described below: data preparation chunking using CRF, labeling and training CRF features, and tagging for aspect extraction.

a: DATA PREPARATION -CRF CHUNKING

The input data is represented as sequences of tokens, where each token represents a word or a sub-word unit. Additionally, each token may have associated features, such as part-of-speech tags, word embeddings, or syntactic information. The chunking process uses the Python CRFsuite.

Subsequently, this prepared data is meticulously divided into the training and test data to facilitate the extraction of attributes that convey the characteristics of each word in the dataset. This dataset is partitioned into training (80%) and testing (20%) subsets.

b: LABELLING AND TRAINING CRF FEATURES

Relevant features are labeled from the preprocessed training data. The data typically comprises a sequence of words constituting a sentence or document. Each word in the sequence is associated with a set of features, including word features, part-of-speech (POS) tags, n-grams, contextual features, or other linguistically pertinent features. CRF is employed for the critical tasks of labeling. To elucidate this process, an illustrative example is presented with the review "food is great and inexpensive," showcasing the tagging of POS tags for each word. Fig.8 shows how review-generated word features are labeled.

Review: "food is great and inexpensive"

```
[['bias',
  'word.lower=food',
  'word[-3:]=ood',
  'word[-2:]=od',
  'word.isupper=False',
  'word.istitle=False',
  'word.isdigit=False',
  'postag=NN',
  'BOS',
  '+1:word.lower=is',
  '+1:word.istitle=False',
  '+1:word.isupper=False',
  '+1:word.isdigit=False',
  '+1:postag=VBZ'],
 ['bias',
  'word.lower=is',
  'word[-3:]=is',
  'word[-2:]=is',
  'word.isupper=False',
  'word.istitle=False',
  'word.isdigit=False',
  'postag=VBZ',
  '-1:word.lower=food',
  '-1:word.istitle=False',
  '-1:word.isupper=False',
  '-1:word.isdigit=False',
  '-1:postag=NN',
  '+1:word.lower=great',
  '+1:word.istitle=False',
  '+1:word.isupper=False',
  '+1:word.isdigit=False',
  '+1:postag=JJ'],
```

FIGURE 8. Example sequence labeling of CRF feature: "food is great and inexpensive."

It checks the digits of words for labeling POS tags. Internally, CRF generates features from attributes, and the subsequent training involves an implicit seed index of the context. After that, CRF is trained with a seed implicit index [Step 15], where features are labeled. The contextual feature, acting as an implicit aspect seed index (restaurant), is detailed in Table 3.

TABLE 3. Implicit aspect seed index.

Aspects	Implicit form Index
location	access, transport, tickets, night, taxis, terminal, sunsets, morning, nights, reach, vicinity, proximity, shopping market, airport, bus stop, metro station.
food	bacon, ration, eats, meal.
service	feature, privilege, grace, courtesy, mercy, indulgence, blessing, benefit
comfort and facilities	light, airy, windows, noise sleeping, floor, boat, smell.
experience	bars, atmosphere, quality, maturity, policy.
cost	expensive, bucks, toll, levy, charge, payment, total.

The training dataset is then labeled using the pre-defined four tags as the labels for general features: aspect explicit (A_Exp), aspect implicit (A_Imp), opinion (O), and irrelevant (I), tags, and the tagging is carried out.

c: TAGGING- ASPECT EXTRACTION

This proposed model employs the conditional random field (CRF) algorithm for better aspect extraction. It uses tagging from the label. CRF used four tags as the labels for general features: aspect explicit (A_Exp), aspect implicit (A_Imp), opinion (O), and irrelevant (I), as shown below. The aspects are extracted as output as per the tags. Fig. 9 shows an example of the output.

```
[('judging', 'I'),
 ('from', 'I'),
 ('previous', 'O'),
 ('posts', 'A_Exp'),
 ('this', 'I'),
 ('used', 'O'),
 ('to', 'I'),
 ('be', 'I'),
 ('a', 'I'),
 ('good', 'O'),
 ('place', 'A_Exp'),
 ('but', 'I'),
 ('not', 'I'),
 ('any', 'I'),
 ('longer', 'I')]
```

FIGURE 9. Aspect extraction by CRF. The word, POS tag, and its label.

C. ALGORITHM

Fig. 1 above in section II describes the proposed hybrid frequency, syntax, and CRF algorithm (HFSC) model for aspect extraction. The proposed method algorithm in pseudocode is in Fig. 10 below. The detailed description of the steps is also provided.

The pseudocode steps are described below:

1) The Review dataset of CSV file is taken as input. The reviews are marked as R1, R2, R3…, and Rn.

2) Lower casing texts preprocess data, removing punctuations/symbols, numbers, and characters. (pre-step to step 1). Then, data is split into sentences, addressing conjunction and punctuation by an algorithm [step 5]. This aspect opinion sentence output after preprocessing is the primary step towards the task of aspect extraction. This sentence has aspects, opinions, or sentiments. In addition, the rating of the review dataset is given on a scale of 10, so we calculate the given rating on a scale of 1. The sentence is split further to tokens [step 5] for finding tokens.

3) The Modules in Fig. 1 show the steps of the aspect extraction experiment from input to the result as output. This module consists of three sub-modules: frequency-based, syntax dependency-based method, and CRF. The steps and tasks are discussed with pseudocode, as below.

- POS tagging is done first to seek nouns and noun phrases. Frequent aspect terms, which are usually nouns and proper nouns, are extracted with POS tagger [steps 7-8]. In most literature, pronouns (it, this, and that) are not used, but this paper uses them because these pronouns relate to the nouns that indicate the hidden implicit aspects. This pronoun is important as the subsequent sentences in writing refer to the aspects of this pronoun. If there is no noun, then it will be the previous aspect. In addition, proper nouns are used to extract both explicit and implicit aspects. The frequencybased module of this hybrid method first finds frequent aspects and includes them as aspect tokens [step 11].
- To capture grammatical connections in the text and to discover the implicit aspects, used a dependency parser in the experiment. Therefore, the list of sentiment words from the pre-processing stages is put through a dependency parser to identify specific relations, which helps determine implicit aspects. In addition, the dependency syntax used in our experiment are: (1) ‘nsubj’: nominal subject, which is the syntactic subject. (2) ’dobj’: direct object, which is a noun phrase used as a direct object of the sentence [steps 7 to 10]. And for compound noun issues, we add the ‘compound’ feature syntax as: (3) ’compound’: noun

```
Input:
Reviews = [R1, R2, R3, …, Rn]
Pre-Process:
Punctuation = [‘,’, ’.’]
Conjunction = [‘but’, ‘and’, ‘or’, ‘that’, ‘if’, ‘because’]
Output: aspects_list [A1, A2, A3,….,An]
here, ‘propn’ = proper noun, ‘nsubj’ = nominal subject
1. Initialize aspect_list = []
2. for all reviews, do
3.  Transform review into sentences.
4.  for all sentences do
5.   Split sentence based on punctuation and conjunction
6.   for all sentences do
7.    POS tagging sentence to tokeni
8.    if token.pos= (‘noun’ or ‘propn’) then then check
token dependency
9.     if (token_dependency = ‘nsubj’) do
10.     for all tokens where token_dependency =
‘compound’ do
11.      aspect = tokeni : tokeni+1
12.      for all sentences/ words/tokens do
13.       preprocessing chunking [ CRF]
14.       for all words, do
15.        train the crf //explicit/implicit seeds and labeling
16.        if tagging words/tokens, where, A_exp=explicit
            aspect, A_imp =Implicit aspect
17.         aspect = words/tokeni
18.        end if
19.       end for
20.      end for
21.      Append aspect to aspect_ list
22.     end for
23.    end if
24.   end if
25.  end for
26. end for
27.end for
```

FIGURE 10. Pseudo code for the hybrid aspect extraction model.

compound modifier used to identify multi-word nouns or compound nouns [step 10].

- CRF is applied to our processed dataset and index terms for implicit aspects and more explicit extraction through its probabilistic properties of labeling and tagging. This paper uses Python CRFsuite, in which chunking is first carried out [Step 13]. After that, CRF is trained with seed implicit index [Step 15], where features are labeled. Then, tagging is carried out [step 16]. Tagging words are used, where, A_exp = explicit aspect, A_imp = Implicit aspect. This is efficiently reiterated till aspects are identified as words/tokens for output [step 17]. These aspects are appended to the aspect list [step 21], and the process ends at step 27.

IV. EXPERIMENT RESULTS AND DISCUSSION

This section includes the experimental setup with dataset details, evaluation metrics, and the experiment results.

A. EXPERIMENTAL SETUP

The dataset used for the experiment is the SemEval-16 and Amazon review dataset. ABSA tasks were introduced in 2014 as a SemEval task, providing benchmark (BM) datasets of English reviews and a common evaluation framework [44]. Thus, SemEval 16 is the benchmark dataset. Besides, to assess the effectiveness of the proposed model, the paper uses two more datasets of Amazon product reviews (Canon and Nikon products). The details of the three datasets are shown in the table below. Table 4 shows details of the dataset. It includes the name and properties of the dataset, and the properties are described in three columns, one each for the three datasets.

TABLE 4. Details of dataset.

Name and Properties of Dataset	Dataset 1 SemEval 16 (Restaurant)	Dataset 2 Amazon (Canon)	Dataset 3 Amazon (Nokia)
Sentences	335 review texts (2039 sentences)	642	587
Data properties	The CSV file contains five fields	CSV file contains only text	CSV file contains only text in notepad
Size	363.45 kb	323.19 kb	353 kb
Data fields	i) Rid: Reviews id ii) sentences__ sentence __id iii) sentences_ sentence __text iv) Opinions_ Opinion __category v) Opinions_ Opinion __polarity	i)No of aspects and ii) aspects	i) No of aspects and ii) aspects

Further detailed information on the SemEval16 dataset is given in Table 5 below.

Table 5 shows data divided into three subsets: train development and test subset, each listed under five properties as abbreviated. The abbreviations 'NEU', 'POS', and 'NEG' stand for the counts of neutral, positive, and negative triplets, respectively. Similarly, '#S' and '#T' denote the number of sentences and triplets, respectively.

TABLE 5. Statistics of SemEval16 dataset.

Data Subset	Properties				
	NEU	POS	NEG	#S	#T
Train	50	Train	50	Train	50
Dev	11	Dev	11	Dev	11
Test	29	Test	29	Test	29

Later, Fig. 11 shows the data snippet of a SemEval 16 restaurant review sentence.

```
▼<sentence id="1730014:1">
  <text>Service here was great, food was fantastic.</text>
  ▼<Opinions>
    <Opinion target="Service" category="SERVICE#GENERAL" polarity="positive" from="0" to="7"/>
    <Opinion target="food" category="FOOD#QUALITY" polarity="positive" from="24" to="28"/>
  </Opinions>
</sentence>
```

FIGURE 11. Data snippet of semeval 16 dataset (Restaurant).

Later, Fig. 12 below shows the data snippet of a sentence from the Amazon dataset (Canon) review.

105	canera[+2]##this camera has canon 's great colorimetry , plus what you see in the lcd is what you get .
106	print[+2]##the prints are beautiful !
107	##and you get about 120 images on a 256mb card at highest quality .
108	##i tried out some other brands in the stores , and was disappointed by the battery life of the other company ; plus what you see in the lcd (no optical finder) is n't what you get - not even for color ; the output was less than i expected .
109	battery[+1]##although canon 's batteries are proprietary , they last a really long time , recharge fairly quickly in the camera , plus if you want ' more power ' , you can even find a knockoff charger and spare batteries right here on amazon .

FIGURE 12. Data snippet of amazon dataset (Canon).

B. EVALUATION METRICS

Precision and recall, including the F-measure, are three evaluation metrics based on the gold standard used to assess the performance of the experimental models. This study utilizes four effective measures derived from the confusion matrix output: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN).

The typical formulae to compute these measures are as follows:

$$\text{Precision, P} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall, R} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1 Score, F1} = 2 * \left[\frac{(PR)}{(\text{P} + \text{R})}\right] \tag{3}$$

The evaluation of Precision, Recall, and F measures is expressed shortly as P, R, and F1, respectively.

C. EXPERIMENT RESULTS

We conducted the experiment with the Semeval16 dataset and two Amazon datasets of Cannon and Nokia. The result is studied from two perspectives. Firstly, the result of the proposed hybrid model. Secondly, the comparison of results with the benchmark literature.

1) THE PROPOSED HYBRID MODEL RESULT

The experiment results of aspect extraction, including explicit and implicit aspects, are obtained and displayed in Table 6. From the experiment, we obtained 2,269 explicit and 368 implicit aspects from the SemEval16 dataset. From the Amazon dataset (Canon) has obtained 523 explicit and 60 implicit aspects, while the Amazon (Nokia) has 332 explicit and 55 implicit aspects. The results of SemEval16 with evaluation metrics of precision, recall, and F-measure are 91%, 89.53%, and 91.20%, respectively. The Amazon dataset (Canon) result was obtained with precision (92.35%), recall (90%), and F-measure (91.10%), while the Amazon dataset (Nokia) result was obtained with precision (93.40%), recall (87.95%) and F-measure (90.05%). The result is shown in Table 6 below with datasets, number (no.) of aspects explicit, no. of aspects implicit, and the result expressed with three metrics: precision, recall, and F1.

TABLE 6. Result of aspect extraction, including explicit and implicit aspects.

Dataset	No. of aspects (explicit)	No. of aspects (implicit)	Result in P, R, and F1 (in %) **
SemEval 16	2269	368	P- 91, R -89.5 and F1-91.20
Amazon dataset (Canon)	523	60	P-92.35, R-90.20, F1-91.10
Amazon dataset (Nokia)	332	55	P-93.40, R-87.95, F1-90.05

** P=Precision, R=Recall, and F1=F measure / F score.

Furthermore, Table 7 shows explicit and implicit aspects with aspects tags, percentage of aspects, aspect category, and the number of aspects. Aspects tag contains noun, propn (proper noun), and compound, either as explicit and implicit aspect category. The table shows the number of explicit nouns, 1892, while the implicit noun is 340. The explicit propn aspects are 69, propn implicit aspects are 8, while the explicit compound aspects are 308, and compound implicit aspects are 20.

TABLE 7. Explicit and implicit aspect (Noun, Propn, and Compound) of SemEval16.

Aspect Tag	Percentage	Category_ imp_exp	Number of Aspects
Noun	85	explicit	1892
		implicit	340
Propn	2	explicit	69
		implicit	8
Compound	13	explicit	308
		implicit	20

Table 8 lists sample explicit and implicit aspects for the three datasets. It has three columns indicating the dataset, explicit aspects, and implicit aspects.

TABLE 8. Sample explicit and implicit aspects.

Dataset	Explicit Aspects	Implicit Aspect
SemEval16 (Food)	Menu, cuisine, dishes, meals, courses, appetizers, starters, entrees, mains, desserts, specials, delicacies, bites, servings, recipes, platters, selections, offerings, creations, plates, preparations, gastronomy, fare, eats, provisions, refreshments, sustenance, nourishment, foodstuffs, and edibles.	Accessibility, convenience, location, proximity, Accessible, convenient, nearby, hard to find, remote, zone, vicinity, surroundings, reachable, centrality, neighborhood, landmark. well-located and strategic.
Amazon dataset (Canon)	zoom, focus, sharpness, prime, wide, telephoto, image stabilization, aperture, fisheye, life, charger, shots-per-charge, indicator, grip, performance, longevity, eco-mode, dual-slot, touchscreen, articulated, resolution, brightness, size, interface, viewfinder, OLED, LCD, and protective.	trends, innovation, satisfaction, needs, future-proof, noise, dynamic range, bokeh, resolution. repair rates, buffer, engagement, loyalty, and exceed,
Amazon dataset (Nokia)	lens, battery, shutter, flash, sensor, LCD screen, Wi-Fi, Bluetooth, buttons, interface, menu.	experience, ease, satisfaction, enjoy, feel, recommend, last, withstand, survive.

2) COMPARISON OF RESULT WITH BENCHMARK LITERATURE

The result of our proposed hybrid model experiment is compared with the benchmark literature. Table 9 shows the literature, the method, the dataset, and the results. The evaluation matrices used in the results are precision, recall, and F measure. We used nine state of the art literature from 2017 to 2024. The table clearly shows that our proposed method has obtained outstanding results (marked in bold) compared to other state of art benchmark literature. The proposed method has obtained precision (91%), recall (89.53%), and F-measure (91.20%) for dataset SemEval16. We use the SemEval 2016 Restaurant Review dataset because it is a public standard dataset that the state-of-the-art literature have widely used. Thus, this benchmark dataset is followed by academicians for the ABSA tasks.

The experiment results are encouraging and demonstrate the superiority of the proposed hybrid above baseline experimentor even comparable work on the same dataset (SemEval 16, Amazon (Canon) and Amazon (Nokia)). The evaluation outcomes, as shown in Table 9, can be summed up as follows:

- The benchmark results for SemEval 16 are obtained by [7] and [41], which obtained precision of 86.41% and 83.62%, respectively.
- Most literature [7], [35], [36], [40], and [41] combined a frequency-based method for hybrid with Wu literature as

TABLE 9. Result comparison between the proposed hybrid model and other approaches.

Ref. Literature	Method	Dataset	Results of AE (in percentage) **		
			Precision	Recall	F-measure
Zhao et al. 2024[12]	Syntax and Semantics with deep learning	SemEval 16 and SemEval15 Restaurant (Res)	77.97 70.09	71.77 62.11	74.74 65.86
Li et al. 2023 [43]	Supervised deep learning	SemEval 14 (Res) and Laptop 14	-	-	81.28-77.31 78.47-73.86
Chen et al. 2022[17]	Frequency with deep learning	SemEval2016 SemEval2014 (Laptop)	70.28 79.90	79.41 70.5	80.38 70.39
Wu et al. 2021[41]	Hybrid Frequency and syntax dependency with deep learning	SemEval2016	83.62	-	-
Pradhan et al. 2021[27]	Frequency based	Digital Camera and Cell Phone	63 61	78 81	69 67
Ozyurt et al. 2020[36]	Hybrid Frequency based with LDA	SemEval2016 (Turkish Res reviews dataset)	65.58	59.23	62.25
Agerri et al. 2019 [35]	Hybrid Frequency based (clustering) with CRF	SemEval2016 dataset (English)	74.11	70.90	73.51
Xiang et al. 2018 [7]	Hybrid Frequency based (embedding) with CRF	SemEval-16 (Restaurant) SemEval-14 (Laptop)	86.41 87.81	82.35 67.82	84.33 76. 53
Asghar et al. 2017 [39]	Heuristics with frequency based	Amazon customer reviews (Laptop)	83.46	71	77.6
Our hybrid model (HFSC)	Frequency based syntax dependency with CRF	SemEval2016, Amazon (Canon) Amazon (Nokia)	**91** **92.35** **93.40**	**89.53** **90** **87.95**	**91.20** **91.10** **90.05**

** P=Precision, R=Recall, and F1=F measure / F score.

a baseline result with the SemEval16 dataset, achieving a precision of 83.62%.

- Wu literature combined syntax dependency hybrid as a baseline with the SemEval16 dataset and achieved the highest precision of 83.62%.
- Three literature combined CRF for hybrid with Xiang as a benchmark with SemEval16 dataset achieved precision, P-86.41%, recall- 82.35%, F1- 84.33%.
- The recent literature of 2024 by Zhao used deep learning and the SemEval15 and SemEval16 datasets but could not achieve benchmark results. It achieved precision, P-70.09-77.97%, R- 62.11-71.77%, and F1-65.86-74.74%.
- We can sum up from the results that the benchmark literature of hybrid combination exhibits superiority over the other frequency methods by [41], and the syntax dependency benchmark by Wu et al. [41] has the highest precision, proclaiming that syntax dependency is a better method to form hybrids.
- CRF's performance among three hybrid literature proves CRF's usability in hybrid with the highest precision of Xiang et al. [7].
- From the analysis of the result it is evident that, frequency based, syntax dependency, and CRF are the high achieving methods. Therefore, the proposed hybrid with these methods will be unique towards achieving the best fit hybrid.
- Further comparison of the results with the SemEval 16 dataset is shown in Fig. 13 below.

In Fig. 13, the comparison of results is plotted in three evaluation metrics of precision, recall, and F1 score, value along the Y axis marked from 0 to 100. The three metrics of each literature are plotted sidewise on the X axis. Precision is plotted in green colour, followed by recall in ash colour, and lastly, F1 in blue colour. The seven literature are plotted in the X axis from left to right from Zhao 2024 to our proposed hybrid. Zhao and Wu's literature results in only one metric (in precision). It can be concluded from the graph that the precision of Ozyurt is the lowest; Wu has the highest at 86.41%, and Xiang has the second highest at 83.46%. Our proposed model has achieved the highest 91%. Similarly, Ozyurt is the lowest in recall, Xiang has the second-high score, and our proposed hybrid has the highest. Lastly, in F1, Ozyurt is the lowest, Xiang has a second high of 84.33%, and our model is the highest with 91.20%. It is evident from the

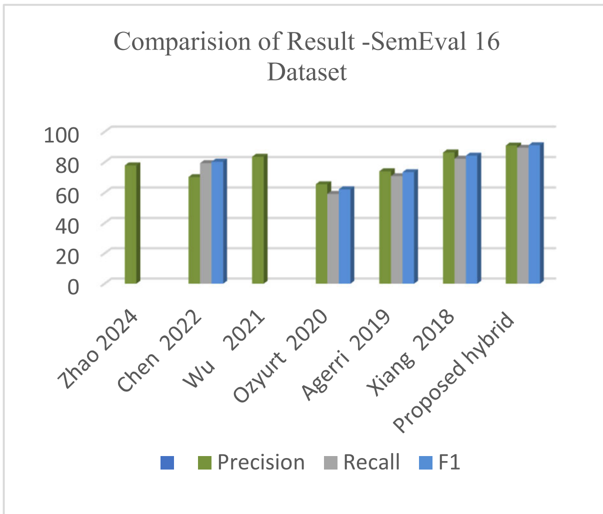

FIGURE 13. Comparison of result with BM Literature (SemEval 16).

comparison chart and graph that the proposed hybrid method fetched the best result in all three evaluation metrics for the aspect extraction.

V. CONCLUSION

In conclusion, this research underscores the pivotal role of aspect extraction in Aspect-Based Sentiment Analysis (ABSA), particularly concerning implicit aspect extraction in customer reviews. The paper introduces an innovative hybrid method that integrates frequency-based, syntactic dependency, and Conditional Random Field (CRF) algorithms to overcome the challenges of identifying and extracting implicit aspects. In addition, compound nouns are extracted using the proposed model. The proposed hybrid model was evaluated using the benchmark SemEval16 dataset and Amazon product reviews, demonstrating its effectiveness in improving aspect extraction. The contributions of the proposed aspect-extraction framework are three-fold: (a) the proposed hybrid method has improved accuracy by 5-15 percent compared to the state-the-art method. (b) An effective mechanism has been developed to calculate implicit and explicit aspects. (c) This paper also shows the total number of compound nouns for each explicit and implicit aspects.

The proposed hybrid method achieved impressive precision rates of 91%, recall rates of 89.53%, and an overall accuracy rate of 91.20% with the SemEval16 dataset. In addition, we obtained 320 explicit compound and 20 implicit compound aspects. The evaluations of two Amazon review datasets similarly attest to the model's efficacy for aspect extraction. Furthermore, the proposed model adeptly extracts explicit and compound noun aspects, detailing each variant. These robust findings underscore the proposed model's potential as a valuable tool for tracking customer experiences, empowering managerial decision-making, and helping elevate product or service quality for a competitive advantage. The quantifiable nature of the extracted aspects further enhances their utility in discerning nuanced insights into customer preferences and facilitating trend analysis. To propel this research forward, future endeavors should concentrate on refining the proposed method's performance across more challenging datasets. The experiment is conducted in English language text and on text reviews only. Therefore, it could be tested with a multilingual dataset and applied to other reviews with images and photos. Additionally, the promising potential exists in extending the hybrid model to tasks beyond aspect extraction, such as sentiment extraction to form aspect sentiment pairs and comprehensive sentiment analysis for ABSA.

DATA AVAILABILITY

Data will be made available on request.

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