Received 29 April 2024, accepted 29 June 2024, date of publication 18 July 2024, date of current version 29 July 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3430092*

RESEARCH ARTICLE

# Target-Aspect-Sentiment Joint Detection: Uncovering Explicit and Implicit Targets Through Aspect-Target-Context-Aware Detection

**MOHAMMAD RADI**[1,2], **NAZLIA OMAR**[1], **AND WANDEEP KAUR**[1]

[1]Center for Artificial Intelligence Technology (CAIT), Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi, Selangor 43600, Malaysia

[2]Abu Dhabi Polytechnic, Abu Dhabi, United Arab Emirates

Corresponding author: Mohammad Radi (p105315@siswa.ukm.edu.my)

This work was supported by the Universiti Kebangsaan Malaysia under Grant TAP-K007009.

**ABSTRACT** Target Aspect Sentiment Detection (TASD) is challenging because it involves various Natural Language Processing (NLP) subtasks including opinion target detection and sentiment polarity classification. Despite significant advancements in this area, most studies have neglected the interrelation between opinion elements and contexts, primarily when a target opinion is expressed implicitly. This study proposes Aspect-Target-Context-Aware Detection for Target Aspect Sentiment Detection, which is a joint learning neural-based framework. The Aspect-Target-Context-Aware Detection model incorporates opinion context syntactic information by utilizing dependency relations associated with opinion terms, and considers head nodes as a primary element for identifying relevant opinion contexts. The Target Aspect Sentiment Detection task was divided into aspect sentiment classification and opinion target extraction tasks. For aspect sentiment, multiclass classification was employed for aspect-sentiment pairs. A BIO tag inference scheme is adopted to detect the opinion target and determine its type (implicit or explicit) for opinion target extraction. The approach was evaluated using two restaurant datasets: Task-5 of SemEval-2016 and Task-12 of SemEval-2015. The proposed approach demonstrated cutting-edge performance when extracting multi-opinion elements from the TASD task, with notable improvements in Macro-F1 values: 3.28% for SemEval 2015 and 5.97% for SemEval 2016. The model also identifies various opinion types and offers valuable insights for future developments, particularly for implicit opinion detection.

**INDEX TERMS** Aspect-based sentiment analysis (ABSA), dependency relations, explicit opinion, implicit opinion, target-aspect-sentiment (TASD).

## I. INTRODUCTION

Sentiment analysis is considered a cornerstone for assisting in the recognition of emotional tones conveyed within a text in Natural Language Processing (NLP) [1], [2], [3]. However, owing to the diversity and complexity of sentiments, traditional document-level sentiment analysis may fail to provide detailed insights into sentiments expressed towards distinctive attributes related to products and services. This has led to the development of Aspect-based Sentiment Analysis (ABSA), which has recently gained considerable interest recently [4], [5], [6].

Aspect-based Sentiment Analysis (ABSA) allows for more in-depth Sentiment Analysis (SA) at the aspect level, enabling businesses to better understand customer preferences better [7].

ABSA can be applied in various fields, including marketing and social media monitoring, to enhance products and services and improve customer satisfaction [8]. ABSA involves three (3) primary tasks: opinion-target extraction, aspect detection, and sentiment polarity detection. An opinion target refers to the entity under discussion. Simultaneously,

The associate editor coordinating the review of this manuscript and approving it for publication was Frederico Guimarães.

aspect detection represents a predefined category related to that entity and sentiment indicates the polarity orientation towards that aspect, which can be negative, positive, or neutral. An opinion is a subjective statement about an aspect typically expressed as a word or phrase [9], [10]. For instance, the sentence 'The waitress was not attentive at all.' In this case, the sentiment for 'SERVICE#GENERAL' and target 'waitress' is negative. This shows that both aspects and targets depend on the opinion term or phrase, which implies a sentiment polarity. However, most studies have overlooked the correlation between opinion elements, particularly when a target entity is implicitly expressed. According to Wan et al. [11], one-fourth of the opinions in the golden dataset for the restaurant domain in SemEval-2015 (Res15) and SemEval-2016 (Res16) had implicit targets. However, most studies on opinion target extraction omit implicit opinions and focus solely on explicit ones [12], [13], [14], [15], [16].

Owing to the complexities of implicit opinions, constructing aspects and relevant opinion terms associated with implicit opinions is remarkably intricate [17]. Hence, sentence-level classification rarely performs satisfactorily for implicit opinion identification. As illustrated in Figure 1, the aspect and sentiment are identical for targets "pad penang" and "NULL' The first target, "pad penang," represents an explicit opinion target, while "NULL" represents an implicit opinion target.

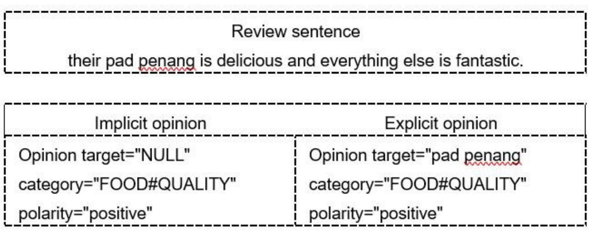


**FIGURE 1. Multi-opinion elements share the same sentiment and aspects, and one of the opinion targets is expressed implicitly.**

For this type of sentence, identifying the target of an opinion within the sentence can be challenging, especially when the target is not explicitly stated. Hence, opinion-related words or target-dependent information should be incorporated to provide clues regarding the existence of an opinion target, particularly implicit ones Brun and Nikoulina [18] developed a method that combined target and aspect-sentiment detection tasks. However, this method has several limitations. For example, it combines the errors of two (2) subtasks, indicating a reduction in the performance of the model. Moreover, this approach neglects the relationship between target and aspect, thereby affecting the accuracy of the results.

Wan et al. [11] designed a "neural-based method for target-aspect-sentiment joint detection." The authors utilized binary text classification to establish whether implicit targets existed, followed by a sequence labelling method to extract explicit targets. According to Wu et al. [19], Multiple-Element Joint Detection (MEJD) is designed to identify relationships within a context. The MEJD employs a graph convolutional network, enhancing its ability to recognize the interplay between targets, aspects, and sentences. However, the model struggled to accurately determine sentiments when the aspects indicated two (2) different opinion targets, primarily when the target was expressed implicitly.

Zhang et al. [20] introduced an end-to-end paraphrase modelling approach for predicting sentiment quads, including aspects, targets, opinions, and sentiments. This approach merges sentiment annotations with a pre-existing template to generate a cohesive sentence in natural language as the desired output sequence. The authors employed a Seq2Seq modelling paradigm to convert aspect sentiment quad prediction into a content generation challenge for predicting all quads in an opinionated sentence. However, it should be emphasized that a single word does not always represent both the opinion term and target. Consequently, the model may require assistance in identifying the exact span of the desired target, which could affect the accuracy of the results.

In addition, the syntactic structure of implicit opinions can be ambiguous, and does not follow a structure similar to that of explicit opinions. It has been observed that words with implied meanings can be considered opinion terms and opinion targets. For instance, phrases like "creamy," "fresh" and "artificial" have been labelled as both opinion targets and opinion terms in specific sentences in the golden dataset. Therefore, implicit opinion terms can provide clues regarding the existence of implicit opinion targets even in cases where these targets are not explicitly mentioned [21].

Hence, developing a model that considers the mutual relationship among opinion elements is imperative, especially when two (2) different opinion targets are present or when the target is implicit. This is essential for effectively performing the Target Aspect Sentiment Detection (TASD) task. This paper proposes an efficient approach that can simultaneously detect opinion elements (target, aspect, and sentiment) in a sentence, focusing on cases in which the opinion target is implicitly expressed and aligned with a typical TASD task. To effectively address the TASD challenge, the number of aspects is limited (typically approximately 10–20) and is easily obtainable in most application fields. This information was used as auxiliary input for the model in this study. This approach entails employing a dual-problem collaborative approach, grounded in contexts related to specific aspects. One (1) sub-problem revolves around ascertaining the sentiment polarity of aspects, reducing it to a multi-class classification problem. The other subproblem aims to incorporate sequential context information and syntactic structures related to the opinion term by converting them into a sequence labelling problem to establish the relation among opinion term-related contexts. A neural model built using the pre-trained BERT model addresses both subproblems [22]. The results demonstrated superior performance compared with existing Target Aspect Sentiment Detection (TASD) task methods.

This study makes three (3) main contributions. First, a novel contextual syntactic method that efficiently identifies opinion-term-related contexts is proposed by utilizing the dependency tree of a sentence, effectively capturing the syntactic relationships between the opinion term and its surrounding context using head-node dependency relations. Second, a novel tag schema for opinion-type inference was introduced, which empowers the classifier to distinguish between implicit and explicit opinions. Finally, an Aspect-Target-Context-Aware Detection (ATCAD) module was developed, which simultaneously captured the interrelationships among the target, aspect, and context. This has led to improved target-aspect-sentiment detection and a more comprehensive understanding of opinion expression. These contributions represent significant advances in sentiment analysis and opinion mining, particularly in handling implicit and complex linguistic structures.

The article's structure is as follows: the first section introduces the paper, the second section discusses the research objectives, the third section examines the relevant literature, the fourth section introduces the proposed methodology, the fifth section explains the specifics of the experiments, the sixth section thoroughly analyses the outcomes, and the seventh section summarises the conclusions drawn from the study.

## II. RESEARCH OBJECTIVES

The primary objective of this study is to propose a novel joint learning model for extracting various opinion elements within a sentence, including targets, aspects, and sentiments. This approach focuses on situations in which the opinion target is implicitly conveyed and aligned with a typical TASD task. The study set out to:

- To propose a novel contextual syntactic algorithm designed to capture the opinion context, head node dependency relations are effectively utilized to leverage the interdependent relationships between opinion terms and related words.
- To propose a BIO tag-inference scheme for efficient opinion type classification.
- To propose a novel joint learning framework called Aspect-Target-Context-Aware Detection (ATCAD) for identifying opinion triples (comprising target, aspect, and sentiment) using pre-trained BERT, incorporating sequence labelling for opinion targets and multiclass classification for aspect-sentiment pair classification.
- To conduct an extensive experiment to evaluate the ATCAD model using the Macro-F1 score and compare its performance with state-of-the-art methods for Target Aspect Sentiment Detection (TASD) using two restaurant benchmark datasets, SemEval-2016 and SemEval-2015.

## III. LITERATURE REVIEW

Increased Internet surfing and extensive use of social media have spurred an increasing demand for sentiment analysis [23]. ABSA addresses emotions and sentiments related to specific aspects, product features, or services, and can provide fine-grained sentiment analysis that provides a thorough assessment summary at the aspect level [24]. The initial phases focused on identifying single-aspect-level sentiment elements [20]. However, owing to its complexity, a deeper understanding of aspect-level opinions is required, beyond the extraction of a single element. This necessitates a more thorough investigation of the relationships between these elements. Recent trends in ABSA have focused on extracting opinions and their multiple elements [25]. Several studies have addressed target aspect-sentiment (TASD) tasks. Brun and Nikoulina [18] suggested an approach that relies on the existing parser- and domain-specific lexicons. However, the performance of the proposed method decreased Wan et al. [11] suggested a novel approach to ascertain the target aspect sentiment, known as the TAS-BERT model, which streamlines the joint detection problem into binary sentence classification and sequence labelling tasks.

Similarly, Wu et al. [19] suggested using MEJD to extract a sentence's opinion triples, including aspects, targets, and sentiments. The method leverages a pre-trained BERT model to acquire the initial embedding vector for the joint input of the aspect and sentiment. Subsequently, it employs Graph Convolutional Network (GACN) and bidirectional long short-term memory (Bi-LSTM) methods to capture the dynamic interactions between a sentence and its aspects. Moreover, this approach incorporates POS-tagged words to enhance target extraction performance. A virtual POS-TAG is also added to the dimensional vector to encode the information of implicit opinion with "N/A" in the sentence sequence classification task. However, this model was also ineffective in extracting the complete opinion triple when the sentence contained multiple opinions with identical aspect-sentiment pairs, primarily when an implicit opinion target existed.

Zhang et al. [26] introduced a unified generative framework for triple-opinion detection. The task was transformed into a text generation problem. The authors annotated the original dataset sentences with the desired sentiment elements, and addressed the problem using sequence-to-sequence learning by treating them as the output sequence for a general model to acquire mapping connections. This model struggled to determine the target within a sentence. However, it provides results that closely match the word meanings in the text.

Zhang et al. [20] suggested an all-encompassing strategy for sentiment and quad predictions by fusing annotated sentiment components with a pre-existing template, ultimately yielding a natural-language sentence as the target sequence. The authors transformed the task into a text-generated challenge to predict a complete sentiment comprising the aspect, target, opinion term, and sentiment related to the sentence using a Seq2Seq modelling paradigm. However, the opinion terms and targets are not always singular. The model often fails to detect the exact span of a desired target.

Gao et al. [27] suggested a comprehensive generative model known as LEGO-ABSA, which utilizes a prompt-based approach to conduct aspect-based sentiment across multiple tasks by leveraging prompts. The model guides the generation process and handles aspect-based sentiment analysis across multiple tasks. Nonetheless, further enhancement of the model's performance in the TASD task is possible. This is primarily because the unsupervised training method is not well suited, particularly considering that the aspect categories and sentiment polarity are not initially included in the text.

Mao et al. [28] proposed Seq2Path, which addresses the TASD task and employs a Seq2Seq model to produce sentiment paths represented as sequences in a tree structure. The model iteratively predicts the aspect of each path by converting the task into a path generation problem for the target, opinion, and sentiment terms. However, the performance of the model faces the challenge of dealing with multiple aspect categories associated with a target opinion.

Gou et al. [29] suggested a multiview prompting (MVP) model that focuses on enhancing aspect-sentiment tuple prediction in TASD tasks by incorporating prompts and utilizing multiple views or perspectives of input data. By leveraging prompts from different perspectives, this method improves the accuracy and reliability of predicting aspect-sentiment tuples, particularly within the TASD context.

Lee and Kim [30] proposed a Sentiment Element Named Entity Recognition (SENER) model that focuses on identifying sentiment-related named entities. It specifically targets the task of recognizing named entities associated with sentiment. SENER enhances the analysis of sentiment-bearing entities by incorporating sentiment element recognition within the ABSA framework, thereby enabling more profound comprehension of sentiment aspects. However, the model performance revealed shortcomings in the subtasks related to the classification within the TASD task.

Ke et al. [31] introduced an SimCPD model for joint target aspect sentiment detection, which leverages contrastive prompts in its approach. The framework encompasses several steps, including extracting target aspects from the text, creating contrastive prompts that encompass both positive and negative examples for each aspect, training a sentiment classification model with these prompts, and subsequently employing this model for sentiment analysis of new textual data by incorporating contrastive prompts. The objective was to identify a tuple (target, aspect, and sentiment) within the text, particularly when the target was not mentioned. This is a common task in target-aspect sentiment detection. The model employs every aspect-sentiment pair as supplementary input data to identify all target-aspect-sentiment tuples. In addition, Aspect-Target-Context-Aware Detection (ATCAD) is a component crafted to enhance the precision of extracting triples comprising target-aspect-sentiment and the associated context by capturing their relationship.

## IV. PROPOSED METHODOLOGY

This section introduces a novel joint-learning framework, ATCAD, to detect target aspect sentiments. The proposed contextual syntactic algorithm addresses the complex relationships between multiple opinions expressed in a sentence, particularly when dealing with implicitly expressed opinion targets. It captures the underlying meaning of contextual opinions to enhance the model's understanding of syntactic and semantic features. Section IV-B represents the problem reformulation. Finally, Section IV-C offers an extensive explanation of the proposed ATCAD components.

### A. CONTEXTUAL SYNTACTICS

Syntactic dependency parsing has been extensively studied and utilized in natural language processing. It provides helpful predictions of the semantic relations between dependent words and headwords and can assist in a range of subsequent natural language processing applications, including ABSA, speech-tagging, and machine translation [32]. Several studies have shown that syntactic structures can facilitate the identification of sentiments that correspond to an opinion target [33], [34]. However, while dependency parsing can help analyze the grammatical structure of sentences, it has limitations when modelling the complex relationships between multiple opinions expressed in a sentence. The static syntactic tree produced through dependency parsing has a single root and cannot adaptively capture the nuanced and diverse ways languages can express opinions.

Wang et al. [35] proposed a novel approach for sentiment classification involving the transformation of a conventional dependency parse tree into a target-centered dependency tree structure. This transformation was accomplished using a relational graph attention network (R-GAT). However, considering the opinion target as a root node does not provide syntactic relations when implicitly expressed. Therefore, this study focused on developing a contextual syntactic method for opinion terms. The proposed algorithm primarily focuses on opinion-related terms, reconstructing dependency trees to unveil associated contexts. Uncovering related contexts linked to a given opinion term. The first step involves locating the head nodes connected to the term and incorporating them into a token list (TL). This approach aligns with the findings of Sharma and Kaur [36], who emphasize that the most significant information is often tied to the head node of a word. Consequently, this approach utilizes these head nodes as a foundation for identifying the relevant opinion contexts.

To capture the depth of the connection, a variable indicating the level of dependency connection is introduced for each connection to the head node. Subsequently, the researchers captured the head node associated with each word added to the token list and these new words were appended to the token list. This process was repeated iteratively until all relevant head nodes were identified. Finally, the stop words were removed from the token list. Part-of-speech labels were attached to each word in a given sentence, and aligned to each token in the list. Any words that did not exist in the token list received a tag of 'O,' and this information was integrated into the Contextual Syntactic list. Algorithm 1 outlines the procedure for determining the syntactic context of opinion terms.

**Algorithm 1** (Opinion Term Contextual Syntactic)

```
Input: Sentence S= (w1, w2, wn),
Aspect Term T= (w1, w2, wn), Dependency tree D, Stop-word
list SL, Part-of-speech (POS) P= (P1, P2, Pn), Dependency
Level L
Output: Contextual Syntactic list: CSL []
    Initialise CSL []
    Initialise a variable R-level to 0
    Initialise token list TL []
    Add opinion term from T to TL []
    R-level +1
    Add Head token of opinion term from D to TL []
    If L = R-level then
      For each word in S do:
        If word in TL [] then
          Add POS tag related to word from P and not in
          SL to CSL []
        else
          Add "O" to CSL []
        Return CSL []
    While L is greater than R-level:
      Add related tokens to the head token in D to TL [] if
      not already exist
      R-level +1
      Repeat this step.
    For each word in S do:
      If word in TL [] then
        Add POS tag related to word from P and
        not in SL to CSL []
      else
        Add "O" to CSL []
    Return CSL []
```

### *B. PROBLEM REFORMULATION*

The TASD task involves identifying and extracting the components (t, a, s) from a sentence. In this context, 'T' represents the target, 'A' signifies the aspect category label selected from a predefined set 'A' and 'S' denotes the sentiment polarity. In cases where the sentence does not explicitly mention the target and no specific object is specified, it is labelled NULL. For instance, consider the sentence, "Their pad penang is delicious and everything else is fantastic." This example identifies two opinion elements, pad penang (FOOD#QUALITY, positive) and NULL (FOOD#QUALITY, positive). These elements capture the target (pad penang) and its corresponding aspect category label (FOOD#QUALITY) with sentiment polarity (positive) expressed in the sentence. The second element represents the implicit target (NULL), indicating positive sentiment in the food quality aspect.

In the past, the identification of specific targets has typically been addressed as a sequence labelling task. A prevalent method uses a conventional B, I, and O tagging system to conduct five-class classification of individual tokens [37], [38]. However, most studies use binary classification [11], [19], [31]. It is worth noting that binary classification may not be well-suited for sequence detection tasks, particularly in the case of implicit opinions, as opinions are context-dependent. Context plays a crucial role in understanding implicit targets, because the binary classification approach may not effectively capture the nuanced relationships between opinion expressions and their corresponding targets. Therefore, more sophisticated methods are required to address the challenges associated with implicit opinion detection in a sequence-detection framework.

This study proposed a tag inference approach based on the BIO schema to effectively label opinion targets related to explicit opinions, while also inferring the corresponding opinion types. Furthermore, this approach was extended to label opinion terms related to implicit opinions and consider them as inferences of the existence of implicit opinions. This perspective is corroborated by the findings of Yu et al. (2018), highlighting that words containing implicit connotations can be perceived not just as expressions of opinion, but also as subjects of opinion. In the example sentence, "Their pad penang is delicious and everything else is fantastic.", two (2) opinion elements can be identified. The first opinion element is an implicit opinion, representing the opinion target by "NULL." In this case, the opinion target is inferred from the opinion term "fantastic" as well as other words that are connected and related to it. The sentiment associated with this implicit opinion was positive.

The second opinion element is an explicit opinion, and the opinion target is identified as the word "pad penang." The sentiment associated with this explicit opinion is also positive. A tag inference mechanism is introduced at the top of the BIO tagging schema to enhance the classification process and provide additional information regarding the target type. This tag inference mechanism helps the classifier incorporate information regarding opinions. Figure 2 illustrates the constructed BIO-tag inference schema.

| BIO Tag-inference | Their | pad | penang | is | delicious | and | everything | else | is | fantastic |
|---|---|---|---|---|---|---|---|---|---|---|
| Explicit Opinion Tag | O | B-EO | I-EO | O | O | O | O | O | O | O |
| Implicit Opinion Tag | O | O | O | O | O | O | O | O | O | B-Null |

**FIGURE 2.** **BIO tag-inference schema.**

The label set LA = (B-EO, I-EO, O) was defined to label the explicit opinions in the sentence. B-EO denotes the commencement of an explicit target and I-EO indicates the continuation of an explicit target. O denotes words not associated with an explicit target. Similarly, to label the implicit opinion in a sentence, the label set LO = (B-NULL, I-NULL, O) is defined. B-NULL designates the initiation of an opinion term; I-NULL represents the ongoing presence of an opinion term; and O is used to identify words that fall outside the scope of the opinion term. The aim of the TASD task is to identify opinion elements in a sentence, including targets, aspects, and sentiments. To optimize the TASD, the proposed approach combines various aspect-sentiment combinations into the model. Based on this rationale, the task was split into sentiment classification and sequence labelling subtasks. The sequence classification subtask involves multiclass classification, which aims to categorize aspect-sentiment pairs related to the target. In this subtask, the model performs a multiclass classification task by assigning a specific aspect-sentiment pair label to each target identified in the sentence. The aspect-sentiment pair label represents the combination of an aspect and sentiment associated with the target. The sequence labelling subtask involves assigning labels to individual words within a sentence to denote the presence of opinion targets. This subtask uses a BIO tag inference schema to denote the target, nontarget, and opinion types in the sequence of words.

### C. THE ATCAD MODEL

Figure 3 depicts the architecture of the ATCAD model comprehensively, providing a detailed view of its constituent elements. It encompasses the input layer, BERT encoder, Contextual Syntactic embedding layer, Bi-LSTM layer, and Conditional Random Field (CRF) layer before concluding with the output layer. This section presents a comprehensive breakdown of all the modules from the input to the output.

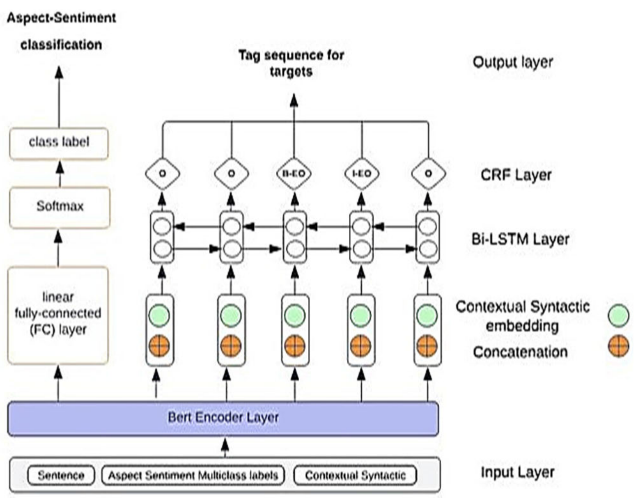


**FIGURE 3. The overall structure of ATCAD.**

#### 1) INPUT LAYER

The TASD task involves the analysis of target-aspect-sentiment pairs, where each sentence may contain multiple opinions. It is essential to pre-process the training dataset to effectively instruct the suggested model for the TASD task. The aim of this step is to convert the unprocessed data into a format appropriate for training and assessing the model. Within the training dataset, a tuple (S, a, c, T) is created for each sentence pair and aspect sentiment. where S represents the sentence, a denotes the aspect-sentiment category, c denotes the contextual syntactic information of the opinion term, and T denotes the BIO-tag inference label sequence.

#### 2) CONTEXTUAL SYNTACTIC AND BERT EMBEDDINGS

The input sequence for the model combines a class label that represents the aspects associated with sentiment in textual sentences. The sequence format was "[CLS] + class label + [SEP] + text sentence + [SEP]."…The input sequence is converted to a lower-dimensional embedding representation using the BERT encoder, $B \in R^{(n+4)\times d_w}$, where $d_w$ represents the embedding dimension produced by the BERT. As a supplementary input, aspect-sentiment pairs are incorporated into the sentence.

In addition, the contextual syntactic method extracts Parts-of-speech (POS-tagging) information from the input sequence. This information corresponds to word embeddings and is concatenated to form embedding matrix $E_w \in R^{(n+2)\times d_p}$, where $d_p$ represents the target context embedding dimension. The word and POS-tagging representations were concatenated to create a comprehensive embedding representation. This results from the embedding matrix $E \in R^{(n+2)\times d}$, where d $= d_w + d_p$.

#### 3) BI-LSTM LAYER

The proposed approach uses a Bi-LSTM model to associate opinion-related context in a sentence. By employing this method, a complete embedding E is created by combining sentence and opinion contexts. This embedding was then fed into a Bi-LSTM layer consisting of forward and backward LTSM. Hidden states h and →h are generated from these LSTMs and concatenated to form a feature representation H. The resulting representation captures the connection linking the sentence's opinion target and opinion context.

#### 4) CRF LAYER

The Conditional Random Field (CRF) incorporates Markovian properties. It is commonly used in sequence-labelling tasks. By taking into account The interrelations among consecutive labels in a sequence were considered. Examining the interplay between neighboring labels enables the derivation of a label sequence that fits the context. Therefore, CRF was used for sequence labelling. In a formal context with regard to the sentence, $x = (x_1, x_2, \ldots, x_n)$ with a predicted label sequence $y = (y_1, y_2, \ldots, y_n)$, $o_{i,y_i}$ representing the certainty rating of the $y_{i_{th}}$ label for character $c_i$. The anticipated outcomes were as follows:

$$s(x, y) = \sum_{i=1}^{n} \left( o_{i,y_i} + T_{y_{i-1,y_i}} \right) \tag{1}$$

$$P(x|\, y) = \frac{exp^{s(y,x)}}{\sum_{\tilde{x}\in x_y} exp^{s(y,\tilde{x})}} \tag{2}$$

where T represents the scores of any two labels next to each other and $\tilde{x}$ encompasses all conceivable label sequences. In the decoding process, the Viterbi algorithm is used to identify the tag sequence with the highest score.

$$y^* = argmaxs(x, y)$$
$$y \in y_x \tag{3}$$

The definition of loss of function is as follows:

$$Loss_t = -\sum_{i=1}^{n} \log p\left(y_i \mid x_i\right) \tag{4}$$

#### 5) FULLY CONNECTED LAYER AND SOFTMAX FOR ASPECT-SENTIMENT CLASSIFICATION

The output vector $T_{[CLS]}$ from the final layer of BERT is used to represent the entire input sequence in the aspect sentiment classification subtask. This vector is processed through a linear fully connected (FC) layer, where a linear transformation is applied, introducing nonlinearity with an activation function. Then, another linear layer, which is succeeded by a SoftMax function, produces a likelihood distribution over the aspect-sentiment class labels. During priming, the model learns to minimize cross-entropy loss by comparing the envisaged probabilities with the ground truth labels. To be more exact, the label for the "Aspect-Sentiment" label shows the probability distribution vector g ∈ R2 is illustrated as follows:

$$P_{[CLS]} = \tanh\left(w_1 T_{[CLS]} + b1\right) \tag{5}$$

$$g = softmax\left(P_{[CLS]}\right) \tag{6}$$

where $w_1 \in R^{d\times 2}$ and $b_1 \in R^2$ are trainable parameters. The loss function is defined as follows:

$$Loss_s = -\sum_{i=1}^{c_i} \alpha_i \left(1-\tilde{y}_i\right)^{\gamma} \log \tilde{y}_i \tag{7}$$

where $\alpha$ and $\gamma$ are adjustable hyperparameters, $c_i$ represents the category number within the aspect sentiment label, and $\tilde{y}_i$ denotes the probability associated with the class $i^{th}$ belonging to the aspect sentiment label.

#### 6) OUTPUT LAYER

To address both aspect sentiment classification and target detection tasks simultaneously, the output of the model was divided into two layers, as shown in Figure 2. The first focuses on representations related to aspect sentiments, whereas the second focuses on target detection. A unified function was employed to derive a single loss value that encompassed both subtasks to optimize the model parameters. Given the strong interrelation between the two subtasks, they were jointly trained. This indicates that they were simultaneously optimized during training. By sharing all parameters of the framework, the model can capture the dependencies and relationships between aspect sentiment detection and target detection.

$$Loss = \sum_{i=1}^{N} Loss_{s^i} + Loss_{t^i} \tag{8}$$

N represents the number of tuples that must be trained, and $Loss_{s^i}$ and $Loss_{t^i}$ indicate the two loss values for the $i^{th}$ training pair.

## V. EXPERIMENTS

This section explores the datasets, model parameters, evaluation approach, and cutting-edge methods used for the comparative analysis.

### A. DATASET

The data used in this study were obtained from two (2) distinct restaurant datasets: SemEval 2016 (Res16) Task 5 [39], and SemEval 2015 (Res15) Task 12 [40]. These datasets are widely acknowledged as benchmarks for various subtasks within the ABSA. However, it should be noted that although the opinion targets were annotated in these datasets, the corresponding opinion terms associated with these targets were not provided. This study adopted the opinion term annotations from [20] to address this limitation. Each review sentence contains an opinion with its corresponding aspect (opinion target), aspect category (aspect), sentiment polarity (sentiment), and opinion word (opinion term). Each data instance contained the original sentence and a list of sentiment quads (opinion target, aspect category, sentiment polarity, and opinion term) separated by ####. Table 1 provides a breakdown of the statistical information for both the datasets.

**TABLE 1. Statistics of Res15 and Res16 from two restaurant experiment datasets.**

| Datasets | | Sentences | Sentiment | | | | Implicit Target (NULL) | Explicit Target |
|---|---|---|---|---|---|---|---|---|
| | | | Neg | Neu | Pos | Total | | |
| Res15 | Train | 1041 | 396 | 48 | 1257 | 1701 | 332 (20%) | 1369 (80%) |
| | Test | 535 | 305 | 37 | 453 | 795 | 218 (27%) | 577 (73%) |
| Res16 | Train | 2117 | 877 | 125 | 2293 | 3295 | 729 (22%) | 2566 (78%) |
| | Test | 544 | 176 | 40 | 583 | 799 | 179 (22%) | 620 (78%) |

Table 1 presents a comprehensive overview of the statistics for Res15 and Res16, which were derived from the two (2) restaurant datasets. Aspect pertains to the number of aspect categories detected within the dataset, whereas sentiment indicates the number of implied sentiments expressed in opinions. An implicit target (NULL) refers to the presence of an implicit target in a sentence. On the other hand, explicit targets signify the number of direct-opinion targets explicitly expressed in a sentence.

### B. MODEL PARAMETERS

BERT was used as the embedding model for the ATCAD model. The number of Bi-LSTM hidden units was 250, the dropout rate was specified as 0.5, the contextual syntactic embedding dimension value was 232, and L2 regularization with a coefficient of 1e−4 was applied. The Adam algorithm was employed for optimization, with a learning rate of 2e−5 and a coefficient $\beta$ of 0.4. The performance of the model was assessed using the F1 score as a criterion to ensure accurate representation of its ultimate performance.

### C. STATE-OF-THE-ART METHODOLOGIES FOR COMPARISON

To assess the proposed model comprehensively, we conducted a comparative analysis using state-of-the-art methods. This enabled us to evaluate the effectiveness and performance of the approach in relation to leading approaches in the field. The following approaches represent state-of-the-art methods employed for benchmarking the ATCAD performance in TASD tasks:

- Baseline-1-f_lex [18] adopted a comprehensive natural language processing pipeline encompassing several sequential steps. These include tasks such as syntactic parsing, part-of-speech (POS) tags, partial semantic parsing, and integration of lexical-semantic information. These strategies were harnessed to extract various linguistic features explicitly designed to address the TASD task challenges.
- TAS-BERT [11]: A model for simultaneously identifying targets, aspects, and sentiments that uses the BERT model to represent the interrelations between targets and aspects precisely. This model was purposefully tailored to the TASD task and its associated tasks, using the advantages of the BERT model. TAS-BERT enhances the aspect and sentiment detection accuracy and performance by effectively capturing intricate connections.
- MEJD [19]: The MEJD combines pre-trained BERT, Bi-LSTM, and GACN modules, while incorporating POS-tagged information and a virtual POS-TAG to represent implicit opinions.
- GAS [26]: GAS introduced a novel methodology centered on a unified generative framework for TASD tasks. This task was framed as a text-generation challenge by marking the sentences in the original dataset with the intended sentiment components. Sequencing-to-sequence learning trains a generation model to understand and forecast the correlation between the sentence input and annotated components of sentiments.
- PARAPHRASE [20] introduced an end-to-end paraphrase modelling approach to predict sentiment quads. It combines annotated sentiment components with a preconstructed template, creating a natural language as the target sequence. The TASD task is solved by employing Seq2Seq modelling to predict aspect sentiment quads, similar to a text generation issue.
- LEGO-ABSA [27] introduced an innovative multitask framework that utilized a prompt-based approach, guiding the generation process with prompts and specifically emphasizing the TASD task.
- Seq2Path [28]: Seq2Path is a TASD-specific method that employs the Seq2Seq model to generate sentiment tuples, represented as paths in a tree structure. Transforming the task into a path generation problem enables the model to iteratively predict the aspects, target terms, opinion terms, and sentiments of each path. This approach enhances the interpretability and meaningfulness of sentiment analysis results in TASD.
- MVP [29] presented a method known as multi-view-proofing (MVP) that aims to enhance aspect-sentiment tuple prediction in TASD tasks. This was achieved by incorporating multiple views or perspectives of input data through prompts. Leveraging prompts from different angles improves the accuracy and reliability of aspect-sentiment tuple predictions, particularly within the context of TASD.
- SENER [30]: Sentiment Element Named Entity Recognition (SENER) focuses on identifying named sentiment-related entities. Its primary goal is to recognize named entities associated with sentiments. SENER enhances sentiment analysis by incorporating sentiment element recognition within the ABSA framework, thereby providing deeper insights into sentiment-bearing entities. This method contributes to a more comprehensive understanding of sentiment aspects and fosters a more accurate sentiment analysis of textual data.
- SimCPD [31]: SimCPD is a framework that uses contrastive prompts to detect a target aspect sentiment. The process involves extracting target aspects from the text, creating contrastive prompts with positive and negative examples for each aspect, training a sentiment classification model using these prompts, and subsequently employing the model for sentiment analysis of new texts by incorporating contrastive prompts.

## VI. RESULTS

Analysis of the overall performance of the proposed ATCAD model revealed promising results. ATCAD incorporates a contextual syntactic algorithm that focuses on detecting target aspect sentiments and addressing the complex relationships between multiple opinions in sentences. ATCAD is designed to effectively capture both syntactic and semantic features, particularly when the opinion targets are implicitly expressed.

The results of our study demonstrate that ATCAD outperforms the existing methods, as evidenced by achieving the highest F1 score compared to the methods listed in Table 2 for both benchmark datasets, Res15 and Res16. Notably, it surpasses the existing methods by achieving the highest F1 score 71.17 Res15 and 76.04 Res16. These findings highlight the potential of the model to significantly enhance the field by enhancing syntactic information through the incorporation of contextual syntactic embedding, while simultaneously addressing the capabilities of pre-trained BERT models to capture complex semantic significance.

A comprehensive comparison of the performances of several top-performing methods in the TASD task is presented in Table 2. Notably, the ATCAD model distinguished itself by consistently achieving high-performance results for Res15 and Res16 datasets. It surpassed the performance of the other models by a considerable margin, with performance improvements ranging from 3.28% to 5.97%. This

**TABLE 2. Comparison results on Res15 and Res16 restaurant datasets for the TASD task: F1 scores are reported.**

| Methods | Authors | Res15 Macro-F1 | Res16 Macro-F1 |
|---|---|---|---|
| Baseline-1-f_lex | Brun and Nikoulina [18] | - | 38.10 |
| TAS-BERT | Wan, et al. [11] | 57.51 | 65.89 |
| MEJD | Wu, et al. [19] | 57.76 | 67.66 |
| GAS | Zhang, et al. [26] | 60.63 | 68.31 |
| PARAPHRASE | Zhang, et al. [20] | 63.06 | 71.97 |
| LEGO-ABSA | Gao, et al. [27] | 62.3 | 71.8 |
| Seq2Path | Mao, et al. [28] | 65.20 | 72.10 |
| MVP | Gou, et al. [29] | 64.74 | 72.76 |
| SENER | Lee and Kim [30] | 63.04 | 71.27 |
| SimCPD | Ke, et al. [31] | 59.31 | 68.95 |
| ATCAD | | **71.17** | **76.04** |

outstanding performance of the ATCAD model on the Res15 and Res16 datasets underscored its robust ability to analyze and classify sentiment in restaurant-related data accurately. This demonstrates its effectiveness in capturing the nuances and complexities of text, thus enabling accurate predictions in the TASD task. Detecting targets, aspects, and corresponding sentiments in aspect-based sentiment analysis (ABSA) was challenging. Existing methods encounter difficulties primarily owing to the sparsely labelled data for ABSA and the complex interplay between the different elements of opinions.

An additional challenge arises when a review contains an implicit target. Recent studies on ABSA often struggle to extract implicit opinions from the aspects and sentiments of implicit and explicit opinions [11], [19], [26]. Moreover, the syntactic structure of implicit opinions is inherently ambiguous, and differs from that of explicit opinions. This further complicated the ABSA task, which required distinguishing and capturing nuanced implicit opinion targets embedded in text. ATCAD started with the proposed contextual syntactic algorithm, which prioritizes the extraction of part-of-speech (POS) tag features from the dependency parser, specifically related to the opinion term. This approach allows the model to obtain opinion-related contexts, enhancing its capacity to understand and analyze opinions within the text, especially when the opinion target is implicit.

### A. EFFECTIVENESS ANALYSIS OF CONTEXTUAL SYNTACTIC RELATION LEVEL

The exploration of target context-dependency relations focused on understanding how the span of surrounding words containing opinions affected the model's performance. The aim was to determine the optimal range of context words by analyzing these dependency relations when extracting the target-related information. This analysis is vital to distinguish between capturing sufficient contextual information and filtering noisy and irrelevant data. The comparative findings are presented in Table 3. The insights gained can increase the accuracy and relevance of sentiment analysis and aspect-detection tasks in the model design process.

**TABLE 3. Results of dependency relation level and opinion type.**

| Dependency Relation Level | Res15 | | | Res16 | | |
|---|---|---|---|---|---|---|
| | Both | Explicit | Implicit | Both | Explicit | Implicit |
| L1 | **71.17** | 72.87 | 56.69 | **76.04** | 77.15 | 65.82 |
| L2 | 68 | 72.89 | 45.61 | 75.99 | 76.69 | 57.95 |
| L3 | 68.71 | 72.95 | 43.96 | 73.81 | 76.79 | 58.76 |
| L4 | 69.99 | 71.3 | 43.33 | 74.98 | 75.47 | 57.36 |

Table 3 presents the performance of the ATCAD model in capturing both explicit and implicit opinions across different dependency relation levels for Res15 and Res16 datasets. The best results, indicated in bold font, are based on the F1 scores. The results underscored the model's effectiveness in extracting essential opinion elements, particularly implicit opinions. The ATCAD model demonstrated promise in understanding and extracting opinion elements from textual data, which is essential for the TASD task. Notably, the ATCAD model outperformed current state-of-the-art results, particularly for the Res15 dataset. This superiority could be attributed to the significant proportion of opinions with implicit targets in the Res15 dataset. Furthermore, the ATCAD model achieved notable results in extracting implicit targets for both Res15 and Res16 datasets. In addition, it demonstrated proficiency in identifying the opinion types. The ATCAD model captured implicit opinions and accurately classified them based on the opinion type. This comprehensive approach enhanced the model's effectiveness in understanding and analyzing opinion-related information in textual data.

### B. COMPARATIVE PERFORMANCE ANALYSIS

A comprehensive comparison of the performance of the ATCAD model against several state-of-the-art methods on the Res15 and Res16 benchmark datasets for the TASD task revealed its superior effectiveness. The results demonstrate that ATCAD achieved the highest F1 scores, with 71.17 for Res15 and 76.04 for Res16, significantly surpassing the performance of the other methods. For example, the TAS-BERT model by Wan et al. [11] achieved F1 scores of 57.51 and 65.89 for Res15 and Res16, respectively, whereas the MEJD model by Wu et al. [19] achieved scores of 57.76 and 67.66. Similarly, the PARAPHRASE model by Zhang et al. [20] and LEGO-ABSA model by Gao et al. [27] reported lower F1 scores than ATCAD. Notably, the best-performing method before ATCAD, Seq2Path by Mao et al. [28], achieved an F1 scores of 65.20 and 72.10. This clear margin of improvement, ranging from 3.28% to 5.97%, highlights ATCAD's superior ability of ATCAD to capture syntactic and semantic features, particularly when handling implicitly expressed opinion targets. These results underscore the robustness and effectiveness of the ATCAD model in advancing state-of-the-art aspect-based sentiment analysis.

## VII. CONCLUSION

This study introduced a novel joint learning framework called Aspect-Target-Context-Aware Detection (ATCAD) for TASD tasks, incorporating a Contextual Syntactic approach. The ATCAD model demonstrated its effectiveness in capturing explicit and implicit opinions within textual data, surpassing existing state-of-the-art models in the TASD task, particularly in identifying implicit opinions. Focusing on contextual syntactic relations allows for a deeper understanding of opinion terms and their associated contexts, proving crucial in capturing the complexities of opinion expression, especially when the text does not explicitly mention opinion targets. The analysis of different dependency relation levels highlighted the importance of considering a range of surrounding words when extracting target-related information, offering valuable insights for future model designs, and aiding in the delicate balance between context and noise in opinion detection. In the subsequent phase, this research will design a model capable of handling implicit and explicit opinions separately, and subsequently integrate the results. This approach acknowledges inherent differences in the structures and characteristics of implicit and explicit opinions in textual data.

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**MOHAMMAD RADI** received the B.Sc. degree (Hons.) in computer science from QOU, Palestine, and the M.Sc. degree from Universiti Utara Malaysia (UUM), Malaysia. He is currently a Researcher with Universiti Kebangsaan Malaysia (UKM). His research interests include natural language processing, machine learning, text and web mining, and sentiment analysis.

**NAZLIA OMAR** received the B.Sc. degree (Hons.) from UMIST, U.K., the M.Sc. degree from The University of Liverpool, U.K., and the Ph.D. degree from the University of Ulster, U.K. She is currently an Associate Professor with the Center for AI Technology, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia. Her main research interests include natural language processing and computational linguistics.

**WANDEEP KAUR** received the bachelor's degree from Multimedia Universiti, Malaysia, the master's degree from Universiti Teknologi Malaysia, and the Ph.D. degree in sentiment analysis and opinion mining from Universiti Malaya. She has been a Senior Lecturer with the Faculty of Information Science and Technology, National University of Malaysia, since 2020. She has published articles in numerous journals and has a keen interest in the research areas of natural language processing, machine learning, and deep learning (data analytics) using social media data. Her research area has expanded to include AI in healthcare and education.