Semantic-syntactic graph network for aspect-based sentiment analysis

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Article Info

Article history:

Received May 30, 2025
Revised Dec 26, 2025
Accepted Jan 25, 2026

Keywords:

Aspect-based sentiment analysis
Deep learning
Graph neural network
Semantic-syntactic fusion
Sentiment classification
SentSemSynNet

ABSTRACT

Aspect-based sentiment analysis (ABSA) is a fine-grained sentiment analysis task that identifies sentiment polarities toward specific aspects within a sentence. While conventional models have achieved progress, they often neglect to jointly consider both semantic context and syntactic structure, limiting performance in complex linguistic scenarios. Nevertheless, most existing graph convolutional network (GCN)-based approaches have recently focused on either semantic or syntactic information individually, leading to suboptimal sentiment classification accuracy. Hence, this work aims to design an effective ABSA model that simultaneously captures both semantic relationships and syntactic dependencies for enhanced aspect-level sentiment analysis. For solving issues of GCN-based approaches, this work proposed a model called sentiment semantic syntactic network (SentSemSynNet), which constructs a unified graph by integrating semantic and syntactic features and applies graph neural networks to learn rich, aspect-specific representations. The model was evaluated on the SemEval2014 restaurant and laptop datasets. It achieved 88.25% accuracy and 82.95% macro-F-score for restaurant, and 84.52% accuracy and 80.26% macro-F-score for laptop. The model's unique integration of both semantic and syntactic importance through a unified graph structure improved sentiment detection accuracy.

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1. INTRODUCTION

Sentiment analysis, also known as opinion mining, is a subfield of natural language processing (NLP) that focuses on identifying and categorizing opinions expressed in text. It seeks to determine whether the expressed sentiment is positive, negative, or neutral. Sentiment analysis has become a crucial component in various real-world applications such as product reviews, social media monitoring, and customer feedback systems [1]–[4]. While traditional sentiment analysis evaluates the overall sentiment of a sentence or document, it often overlooks the fact that sentiments can vary across different aspects of a single entity. This leads to the more fine-grained task of aspect-based sentiment analysis (ABSA). ABSA aims to detect the sentiment expressed toward specific aspects or attributes of an entity mentioned in a sentence [5]–[7]. For example, in the review, "The screen is bright, but the battery life is disappointing," there are two aspects: screen and battery life. A general sentiment classification might incorrectly label the sentence as neutral due to the conflicting sentiments. ABSA, however, correctly identifies that the sentiment towards screen is positive, while the sentiment towards battery life is negative.

Moreover, a critical challenge in ABSA lies in the need to understand both semantic and syntactic relationships in a sentence [8], [9]. Semantic information helps capture the meaning of words and their contextual usage, while syntactic information focuses on grammatical structure and the relationships between different parts of a sentence. For instance, in the sentence, “Although the performance of the laptop is impressive, the design feels outdated,” the model must semantically understand that “performance” and “design” are aspects, and syntactically determine which sentiment words apply to which aspects. For example, when considering a sentence, “The camera quality of this phone is excellent,” it is respective aspect is camera quality, and the model will predict as positive. Similarly, for another sentence, “The battery drains too quickly,” it is respective aspect is battery and the ABSA model will predict as negative. In many cases, a single sentence contains multiple aspects, each with its own sentiment. This makes overall sentiment classification insufficient for tasks like opinion summarization or product improvement. For example, in the sentence, “The display is stunning, but the speakers are mediocre,” treating this as a single sentiment would mislead decision-makers. Instead, ABSA captures both aspects as display being positive and speakers as negative. To address such complexity, it is crucial to isolate and analyze the polarity of each aspect independently. ABSA frameworks do this by linking opinion words (e.g., “stunning” and “mediocre”) with their respective aspects based on both syntactic dependencies and semantic similarities. This approach ensures that the sentiment assigned to each aspect is precise, enabling more effective sentiment analysis.

Also, in recent years, deep learning (DL) approaches have become the dominant paradigm for ABSA [10]. Models such as long short-term memory (LSTM) [11], convolutional neural network (CNN) [12], and transformers like bidirectional-encoder-representations from transformers (BERT) [13] have demonstrated strong performance due to their ability to capture rich semantic context and learn hierarchical features. These models have replaced manual feature engineering and rule-based systems by learning directly from data. However, DL models often struggle with structural understanding, particularly when it comes to long-range dependencies and complex sentence structures. They may ignore syntactic importance, leading to misclassification of sentiments associated with specific aspects. To address this, graph-based DL models have been introduced, leveraging graph convolutional networks (GCNs) [14], [15] to encode syntactic dependencies using dependency parsing trees. These models allow tokens to interact based on their grammatical relationships, rather than linear order alone, significantly improving aspect-sentiment alignment. Despite their success, many existing graph-based approaches tend to focus exclusively on either semantic or syntactic information, resulting in suboptimal performance when the two forms of information are not jointly considered.

To overcome this limitation, this proposes a unified architecture called sentiment semantic syntactic network (SentSemSynNet). This model seamlessly integrates deep semantic representations from BERT with temporal modeling through bidirectional long short-term memory (BiLSTM) and syntactic structure using a two-layer GCN. The use of BERT captures word meaning in context, BiLSTM models the word-order and sequence dynamics, and GCN propagates syntactic dependencies. By combining these components, SentSemSynNet achieves a holistic understanding of both meaning and structure, enabling more accurate sentiment classification for each aspect. The contributions of this work are as follows.

This work proposes a novel hybrid model, SentSemSynNet, that integrates BERT, BiLSTM, and GCN to jointly model semantic and syntactic information. The SentSemSynNet model identifies aspect-specific sentiment by capturing deep context and grammatical structure. The SentSemSynNet architecture outperforms existing ABSA and GCN approaches for ABSA datasets in terms of accuracy and macro-F-score. The manuscript is organized in the following manner, section 2 discusses existing ABSA approaches, section 3 presents the SentSemSynNet for ABSA, section 4 discusses the results achieved by SentSemSynNet and it compares with existing approaches presented in literature survey, and finally section 5 presents the conclusion and future work.

2. LITERATURE SURVEY

This section discusses the existing ABSA approaches presented in recent years for sentiment analysis. Huang *et al.* [16] presented an aspect-level sentiment-analysis approach, called context-position-aware sentiment analysis (CPA-SA) where main focus was to achieve the aspect-specific contextual-location information. In their work, two asymmetrical context-position weight-functions were designed, wherein the first weight function adjusted contextual word weights according to aspect word positions in sentences and the second weight function improved the sentiment polarity judgement. Further, in their work, they used multiple and single sentence-level bidirectional gated recurrent unit (BiGRU) for extracting the impact of context-related relationship of every sentence in dataset on basis of aspect-sentiment polarity. Moreover, they presented a loss function for handling class imbalance issues. Evaluations were conducted considering SemEval datasets, where considered Restaurat2016, Restaurant2015, Restaurant2014, and Laptop2014. Findings show that the CPA-SA approach achieved 89.02%, 79.61%, 75.18%, and 82.64% accuracy for

Restaurat2016, Restaurant2015, Restaurant2014, and Laptop2014 datasets respectively. Lu *et al.* [17] presented an approach called heterogenous-graph neural-network (HGNN), where they considered interactive aspect contexts and words for encoding sentence sequence data for parameter sharing. The main aim of HGNN was to encode syntax dependency-tree, encode few of part-of-speech (PoS) tags and encode previous sentiment-dictionary for sentiment prediction. Evaluations were conducted on five SemEval datasets, where findings show that HGNN approach achieved 87.92%, 80.37%, 74.08%, 81.91%, and 77.29% for Restaurat2016, Restaurant2015, Restaurant2014, Laptop2014, and Twitter2014 datasets respectively.

Lin and Joe [18] presented an approach on basis of mechanism of global and masked attention, called local-global context-focus (LGCF). In their work, they used previous presented approaches called context-features dynamic-weight and context-feature dynamic mask [19], for assigning text-vector weights on basis of distance from aspect-term. Further, proposed an approach which utilized masked-attention approach for intercepting local embedding within global embedding and then evaluated aspect-term position and finally reordered weights on basis of aspect-position and assigned a global embedding on basis of its respective subscripts, making the model to extract more features and provide a noise free approach. Using the following approach, the LGCF approach learnt both local and global features, providing better sentiment analysis performance. Evaluations were conducted on eight datasets, which included Restaurant2016, Restaurasnt2014, Laptop2014, Twitter2014, and multi-aspect multi-sentiment (MAMS) (camera, car, phone, television, and t-shirt) data. For MAMS data, the LGCF achieved 97.24%, 98.26%, 97.59, 91.61%, and 93.86% accuracy for camera, car, phone, television, and t-shirt data respectively. For SemEval data, achieved 91.87%, 85.52%, 81.29%, and 75.69% for Restaurant2016, Restaurant2014, Laptop2014, Twitter2014 respectively. Zhao *et al*. [20] presented an approach called as structure-dependency tree-based graph convolutional network (SDTGCN) approach, which explored structured syntactic dependency-graph construction considering PoS tags, sentiment knowledge, position information, and dependencies distance for assigning random edge-based weights among nodes. Using the graph construction, the connection among the important words and aspect nodes increases, providing better sentiment analysis. In their work, used node dependency distance and PoS tags for discovering connection among important nodes without considering direct node dependency. Further, the graph nodes were aggregated on basis of their information for attaining accurate aspect representation. Evaluations were conducted on five SemEval datasets, which included Twitter2014, Restuarant2014, Laptop2014, Restaurant2015, and Restaurant2016, where achieved 76.25%, 83.82%, 78.64%, 83.21%, and 91.53% accuracy respectively.

Gu *et al.* [21], for solving issues of GCN, which fail to consider specific aspects in sentence for sentiment analysis, presented a model called syntax-aware graph convolutional network (SAGCN). The SAGCN mode first utilized aspect-specific features in contextual information, and further incorporated external sentiment-knowledge for improving GCN model capability for understanding sentiment information. Further, in SAGCN, a point-wise convolution-transformer (PCT) and multi-head self-attention (MHSA) approach were utilized for capturing semantic information of sentences. In SAGCN, both the syntactic and semantic sentence information were considered. Evaluations were conducted on SemEval2014 dataset, where achieved 77.97%, 97.53%, and 83.06% accuracy for Twitter2014, Restaurant2014, and Laptop2014 dataset respectively. Song *et al.* [22] presented an approach called knowledge-guided heterogenous graph convolutional network (KHGCN), for overcoming issues of BERT. The KHGCN merged sub-word vectors using dynamic weights approach, which is considered in BERT embedding-layer. Further, heterogenous graphs were built for fusing various feature relationship among words and GCN was utilized for identifying context-specific syntactic features. Also, by knowledge-graph embedding, the KHGCN approach learnt more features from different sources. Using the following knowledge information, the syntactic, semantic and knowledge extracted features were aggregated providing a feature-fusion approach for sentiment analysis. The KHGCN was evaluated using Restaurant2016, Restaurant2015, and Laptop2014 dataset, where achieved 91.07%, 85.42%, and 80.87% accuracy respectively for ABSA.

Chen *et al.* [23], for solving issues of understanding of dependency relations between contextual words, this work presented a model called syntactic semantic graph convolutional network (SSGCN), which utilized semantic information and syntactic weight matrix for obtaining text-semantic representations. In this work an attention model was introduced for obtaining specific aspect-hidden context vectors. The SSGCN approach improved text-representations and evaluations were conducted using Restaurat2016, Restaurant2015, Restaurant2014, and Laptop2014, where achieved 89.77%, 81.18%, 82.96%, and 75.86% accuracy respectively. Jiang *et al.* [24], for solving issues of context-awareness, less accuracy, presented a model called deep context-aware sentiment analysis model (DCASAM), which integrated deep BiLSTM and densely connected graph convolutional network (DGCN), which captured contextual variations and dependencies. The deep BiLSTM efficiently captured sequential dependency, whereas the DGCN utilized densely connected structures for capturing intricate connection in data. Using the following, the DCASAM achieves higher accuracy. Evaluations were conducted on Twitter2014, Laptop2014 and Restaurant2014 datasets, where achieved 78.27%, 81.7%, and 87.16% accuracy. Basha and Shivappa [25], presented an approach called modified latent Dirichlet allocation optimized BERTLSTM for ABSA (MOL-ABSA), which utilized a modified-latent Dirichlet-allocation for extraction of aspects from sentence, an optimized BERT (O-BERT) model was used for sentiment classification and LSTM was used for improving classification accuracy. Evaluations were conducted on SemEval2014 and a collected hospital data, where findings showed 85.26%, 81.19%, and 87.53% accuracy for Restaurant2014, Laptop2014, and hospital dataset respectively.

Hu and Li [26] presented a model called bi-channel graph convolutional network (BIC-GCN) for solving issues of syntactic tree approaches as they introduce noise and affect overall performance. The BIC-GCN also solved issue of single graph convolutional network (SGCN) approaches as they fail to aggregated syntactic and semantic structural node information, affecting sentiment classification. In their work, a phrase-structure tree was introduced which transformed the data to structure phrase matrix. The adjacent matrix of structure phrase matrix and dependent syntactic-tree were merged to form initial GCN for enhancing syntactic information. The semantic feature representation was achieved using MHSA and GCN and were then fused for achieving a dual-channel complementary-learning feature. Evaluations were conducted on Twitter2014, Laptop2014, and Restaurant2014, where achieved 78.27%, 81.70%, and 87.16% accuracy respectively.

Han [27] presented syntactic-masked graph convolutional network (SM-GCN) approach for understanding syntactic-structure information, for effectively predicting sentiment analysis. The SM-GCN approach utilized syntactic data and GCN for learning every aspect weight in sentence and its related connection in complete sentence. By incorporation of syntactic-mask matrix, the SM-GCN provides key segments, which is required for sentiment analysis, thereby improving sentiment classification accuracy. Also, the model utilized abstract-graph structure of GCN for integrating next node information by utilizing transfer matrix from fused syntactic masked matrix for improving performance. Evaluations were conducted on SemEval2014 datasets, where achieved 77.24%, 80.86%, and 86.31% accuracy for Twitter2014, Laptop2014, and Restaurant2014 datasets respectively. The complete summary of literature survey is presented in Table 1.

From the extensive literature survey, it is evident that numerous approaches have been proposed for ABSA using DL and graph-based models. However, a critical observation across most of the works is the limited integration of both syntactic and semantic information in a unified manner. Several models have emphasized either syntactic or semantic cues, leading to suboptimal performance in complex sentence structures. For instance, SDTGCN [20] focuses primarily on syntactic dependency graphs without effectively incorporating rich semantic context. Similarly, SAGCN [21] improves upon syntactic feature extraction but only partially integrates semantic knowledge through external sentiment resources. While KHGCN [22] and SS-GCN [23] attempt to combine multiple sources of information, their fusion mechanisms are either simplistic or loosely integrated, resulting in limited synergy between syntax and semantics. Models like SM-GCN [27] and BIC-GCN [26] focus on refining syntactic structures but still lack comprehensive semantic modeling, which is crucial for capturing the nuanced meaning of aspect terms in varying contexts. To address this gap, this work proposed SentSemSynNet, a hybrid model that effectively combines deep semantic features from BERT, sequential dependencies via BiLSTM, and syntactic structures using a two-layer GCN. By unifying these components, SentSemSynNet ensures robust aspect-sentiment alignment and improves classification accuracy, outperforming models that isolate syntactic or semantic representations. This comprehensive integration marks a significant advancement in ABSA, tackling limitations identified in existing works such as [20]–[22], [27]. The complete method of SentSemSynNet is discussed in the next section.

Table 1. Literature survey summary

Ref	Model name	Datasets used	Accuracy (%)
[16]	CPA-SA	Restaurant2016, Restaurant2015, Restaurant2014, and Laptop2014	89.02, 79.61, 75.18, 82.64
[17]	HGNN	Restaurant2016, Restaurant2015, Restaurant2014, Laptop2014, and Twitter2014	87.92, 80.37, 74.08, 81.91, 80.29
[18]	LGCF	Restaurant2016, Restaurant2014, Laptop2014, Twitter2014, and MAMS (camera, car, phone, television, and t-shirt)	91.87, 85.52, 81.29, 75.69; MAMS: 97.24, 98.26, 97.59, 91.61, 93.86
[20]	SDTGCN	Twitter2014, Restaurant2014, Laptop2014, Restaurant2015, and Restaurant2016	76.25, 83.82, 78.64, 83.21, 91.53
[21]	SAGCN	Twitter2014, Restaurant2014, and Laptop2014	77.97, 97.53, 83.06
[22]	KHGCN	Restaurant2016, Restaurant2015, and Laptop2014	91.07, 85.42, 80.87
[23]	SS-GCN	Restaurant2016, Restaurant2015, Restaurant2014, and Laptop2014	89.77, 81.18, 82.96, 75.86
[24]	DCASAM	Twitter2014, Laptop2014, and Restaurant2014	78.27, 81.70, 87.16
[25]	MOL-ABSA	Restaurant2014, Laptop2014, and Hospital dataset	85.26, 81.19, 87.53
[26]	BIC-GCN	Twitter2014, Laptop2014, and Restaurant2014	78.27, 81.70, 87.16
[27]	SM-GCN	Twitter2014, Laptop2014, and Restaurant2014	77.24, 80.86, 86.31

3. METHOD

ABSA approaches seek to determine sentiment expressed toward a specific aspect of an entity in a sentence. For example, in review “The battery life of this phone is amazing, but the camera is poor,” the sentiments toward “battery life” and “camera” are different. Hence, there is a requirement for a good ABSA model which captures both semantic context and syntactic relationships from the sentence providing better ABSA prediction. Hence, this work presents a hybrid DL architecture for ABSA, called as SentSemSynNet inspired by works presented by Devlin *et al.* [28].

3.1. Architecture

Figure 1 presents SentSemSynNet architecture, where first it considers input data, which consists of review sentence, specific aspect term and sentiment label. The first stage of SentSemSynNet includes input representation, where BERT is used for converting text input into rich contextual embedding, effectively capturing semantic information [29]. These embeddings are then passed to BiLSTM, allowing SentSemSynNet model to understand sequential word relationships and positional information effectively. Further, grammatical context understanding is handled through graph construction, where syntactic dependency graph of sentence is created [30]. This graph is then fed to two-layer GCN for syntactic-information extraction, allowing SentSemSynNet to learn from grammatical structure and long-range dependencies in sentence. The output is then passed to an aspect-aware aggregation and pooling stage, where mean-pooling is used to generate fixed-length vector representing sentiment toward aspect [31]. This vector is then used in sentiment classification, where SoftMax layer predicts sentiment. Finally, SentSemSynNet performance is evaluated using standard performance metrics used for ABSA.

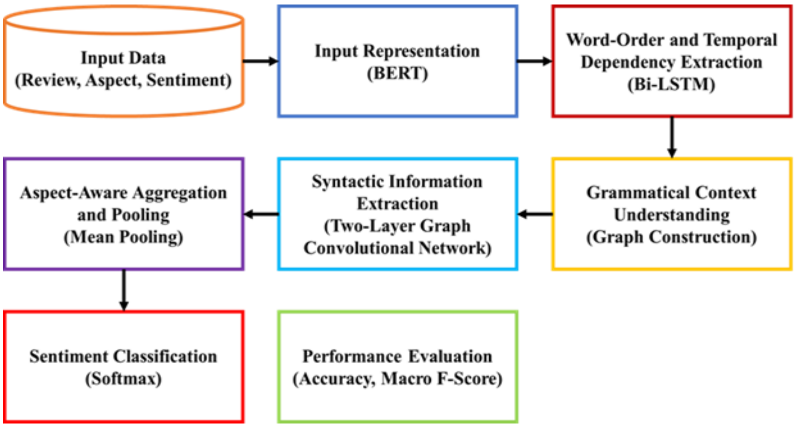

Figure 1. SentSemSynNet architecture

3.2. Input representation

Consider an input from dataset which consists of sentence S which has an aspect term A at a position T, such that $S, A \in T$. Also consider a label for every sentence S denoted as $y \in \{0,1,2\}$, which represents sentiments for sentence S as negative, neutral and positive respectively. As sentence S consists of multiple words, let the words be represented as $w_1, w_2, w_3, \dots, w_n$. In this work, the BERT model has been used to embed input sentence S and aspect A in a way such that it captures rich contextual relevance and semantic information of each word; hence, the first step of the BERT approach is to encode the sentence S. Consider sentence as $S = \{w_1, w_2, w_3, \dots, w_n\}$, which may have one or more aspects being represented as $a = [a_1, a_2, \dots, a_m]$. The input sequence fed into the BERT model is represented by (1).

$$x = [[CLS], w_1, w_2, w_3, \dots, w_n, [SEP], a_1, a_2, \dots, a_m, [SEP]] \quad (1)$$

In (1), $[CLS]$ and $[SEP]$ denotes BERT tokens, which represent classifier token and separator token. The (1) defines how sentence S and aspect A are combine as input using BERT $[CLS]$ and $[SEP]$ tokens, helping model condition meaning of sentence on aspect. The input sentence represented by (1) is then encoded using BERT model Devlin *et al.* [28] as presented in (2).

$$H^0 = BERT(x) \in \mathbb{R}^{L \times d} \quad (2)$$

In (2), L denotes maximum sequence length, d denotes hidden size for BERT model, where this work has considered $d = 768$, $H^0 = h_1^0, h_2^0, \dots h_i^0$ denotes contextualized embedding of token x_i. In this work, the BERT leverages multi-head attention and positional-encoding for encoding deep-semantic features. This lays semantic foundation for SentSemSynNet approach, ensuring aspect-aware understanding. In the BERT model, it is seen that the model fails to capture temporal dependencies and word-order, hence, in this work BiLSTM approach has been utilized to solve this problem.

3.2.1. Sequential modelling using BiLSTM

In NLP, sequential understanding of sentences is often achieved using LSTM networks, which efficiently captures temporal dependencies. However, standard LSTM models are limited in capturing word order from both past and future contexts. Therefore, this work employs a BiLSTM model to better capture both temporal dependencies and contextual word order. In BiLSTM, the output from BERT model, i.e., H^0 is considered as input for reinforcing word-order information and capturing temporal dependencies in both directions; hence, this work computes forward and backward LSTM hidden states, modelling and understanding sentence flow in both directions. The forward and backward LSTM hidden states are evaluated using (3) and (4) respectively.

$$\overrightarrow{h_t}, \overrightarrow{c_t} = \overrightarrow{LSTM}(h_t^0, \overrightarrow{c_{t-1}}) \tag{3}$$

$$\overleftarrow{h_t}, \overleftarrow{c_t} = \overleftarrow{LSTM}(h_t^0, \overleftarrow{c_{t+1}}) \tag{4}$$

In (3), $\overrightarrow{h_t}$ denotes hidden-state at time-step t and $\overrightarrow{c_t}$ denotes cell-state at t in forward direction. The $\overrightarrow{LSTM}$ denotes unit processing sequence from left to right, i.e., from past to future, h_t^0 denotes input word embedding at t, where $h_t^0 \in H^0$ and $\overrightarrow{c_{t-1}}$ denotes cell-state from previous time-step t in forward direction. In (4), $\overleftarrow{h_t}$ denotes hidden-state at t and $\overleftarrow{c_t}$ denotes cell-state at t in backward direction. The $\overleftarrow{LSTM}$ denotes unit processing sequence from right to left, i.e., from future to past and $\overleftarrow{c_{t+1}}$ denotes cell-state from next time-step t in backward direction. Using the forward and backward LSTM hidden states, the final BiLSTM output is achieved by combining both these states, which is represented using (5).

$$h_t^1 = [\overrightarrow{h_t}, \overleftarrow{h_t}] \in \mathbb{R}^{2h} \tag{5}$$

In (5), $h_t^1 \in H^1 \in \mathbb{R}^{L \times 2h}$, where h denotes hidden state of each LSTM direction. The final output of the BiLSTM model retains sequential context and rich local contexts, which enhances the sequential coherence, important for phrases like “only slightly better” or “not very good”. After extraction of the sequential context, it is important to model grammatical structure, hence, in this work, a syntactic dependency graph is built, which is discussed in the next section.

3.2.2. Dependency graph construction

While BiLSTM effectively captures sequential context of sentence, understanding grammatical structure requires deeper syntactic information. Therefore, this work incorporates a syntactic dependency graph to model the grammatical relationships between words. For construction of syntactic dependency graph, every token from sentence S is considered as node, and edges reflect dependency relationship which were parsed using built-in library, SpaCy. Consider graph $G = \{V, E\}$, where $V = \{v_1, v_2, \dots, v_L\}$ represent tokens, E denotes edges and $(v_i, v_j) \in E$ only if a dependency relation between w_i and w_j exists. Hence, from this the adjacency matrix is constructed as presented in (6), which captures relationships between words in dependency parse. In this work, normalization is applied to ensure numerical stability, following the approach proposed in the GCN by Kipf and Welling [29]. Further, in the dependency graph, the degree matrix is evaluated using (7).

In (7), I denotes identity matrix. Further, for normalizing adjacency matrix for stable graph computations, a symmetric normalization has been applied which is represented using (8). Using the (8), the final syntactic graph having word-information, temporal dependency and grammatical context is achieved. The syntactic graph achieved using (8) is critical in recognizing long-distance grammatical relations, i.e., connecting an aspect with its respective modifier word. Moreover, the (8) ensures that information is aggregated and scaled fairly across varying node degrees. Further, the constructed graph is passed on to the proposed GCN approach.

$$A = \begin{cases} 1 \; if \; i = j \; or \; (i, j) \in E \\ 0 \qquad\qquad otherwise \end{cases} \tag{6}$$

$$\widetilde{\mathcal{D}}_{ii} = \sum_j (A + I)_{ij} \tag{7}$$

$$\hat{A} = \widetilde{\mathcal{D}}^{-\frac{1}{2}}(A + I)\widetilde{\mathcal{D}}^{-\frac{1}{2}} \tag{8}$$

3.2.3. Graph convolutional network

In this work, instead of using one layer of GCN, this work has applied two GCN layers for propagating syntactic information across graphs using outputs from BiLSTM and dependency graph construction as initial node features, which thereby allows every word to learn from its syntactic neighbors. The first layer of GCN is evaluated using (9). In (9), σ denotes the rectified linear unit (ReLU) sigmoid activation function and $W^{(1)} \in \mathbb{R}^{2h\times h}$ denotes trainable weights. Further, the second layer of GCN considers input of first layer, which deepens graph feature learning, producing final node representations as H^3. The second layer of GCN is evaluated using (10).

$$H^2 = \sigma\left(\hat{A} \cdot H^1 \cdot W^1\right) \tag{9}$$

$$H^3 = \sigma\left(\hat{A} \cdot H^2 \cdot W^2\right) \tag{10}$$

In (10), W^2denotes trainable weight matrix for second layer of GCN and $W^2 \in \mathbb{R}^{h\times h}$. Using the following GCN approach, allowed each word to incorporate information from syntactically connected words, modeling long-range dependency important for ABSA. Also, the two layer GCN approach made the model structure-aware, improving understanding of how sentiment terms are related to aspects syntactically. Further, for preventing overfitting, a dropout layer was applied after BiLSTM and GCN layers, which randomly zeroed-out features during training. Further, the matrix achieved using second layer of GCN was further passed on to aggregation and pooling layer which further classified the sentiments.

3.2.4. Aspect-aware aggregation, pooling and sentiment classification

For deriving fixed-length sentence representation from H^3, this work performed aspect-aware aggregation and pooling over all token embeddings from the two-layer GCN approach. After the aggregation of all the outputs from the H^3, a mean pooling was applied using (11). In (11), L denotes loss function and $h_i^3 \in H^3$. By using the mean-pooling over all node embeddings from GCN output, this step compresses all relevant features into one-vector, enabling classification. The main aim of classification was to predict sentiment class, i.e., neutral or positive or negative considering aspect. For classification, the pooled-vector v was passed through fully-connected layer (FCL) which followed SoftMax for sentiment classification. In FCL, the pooled-vector v was converted to class logits z for classification using (12).

$$v = \frac{1}{\mathcal{L}}\sum_{i=1}^{\mathcal{L}} h_i^3 \in R^h \tag{11}$$

$$z = W^{fc} \cdot v + b^{fc} \in \mathbb{R}^C \tag{12}$$

In (12), W^{fc} denotes weight of FCL, b^{fc} denotes bias-term for FCL and C denotes classification class, i.e., neutral or positive or negative. Further, the logits z was passed on to SoftMax, where softmax convers logits z into classification probabilities. The SoftMax function is performed using (13). In (13), $\hat{p}_i$ denotes predicted probability of sentiment classification. Finally using the SoftMax function, the final sentiment prediction is performed using (14). In (14), $\hat{y}$ denotes predicted sentiment. In (14), the final prediction is made using $argmax$ over probability distribution. Further, to handle class imbalance issues, a weighted cross-entropy loss was used in (11) and during training. The loss function was evaluated using (15).

$$\hat{p}_i = softmax(z) = \frac{\exp(z_i)}{\sum_{j=1}^{C}\exp(z_j)} \tag{13}$$

$$\hat{y} = arg\max_i(\hat{p}_i) \tag{14}$$

$$\mathcal{L} = -\sum_{i=1}^{C} w_i[y = 1] \cdot \log(\hat{p}_i) \tag{15}$$

$$\theta \leftarrow \theta - \eta \cdot \frac{\partial L}{\partial \theta} \tag{16}$$

In (15), w_i denotes inverse-frequency class weights and y denotes actual sentiment class. The loss function $\mathcal{L}$ assigns higher weights to underrepresented classes. For handling the weight optimizations in the model, this work uses Adam optimizer with weight decay during training which is computed using (16).

In (16), θ includes all model parameters. Form the above approach, it is seen that the SentSemSynNet approach leverages semantic depth of BERT for representing input data, sequential modeling of BiLSTM for understanding word-order and temporal dependency extraction, and the syntactic precision of GCNs to predict aspect-level sentiment effectively. By integrating syntax through dependency graphs, it captures relationships that are often missed by attention alone. In the next section, the results of the SentSemSynNet model are discussed in detail.

4. RESULT AND DISCUSSION

For this study, the SemEval2014 Task 4 dataset was considered. The SemEval 2014 Task 4 dataset is a widely used benchmark for ABSA. It consists of customer reviews from two domains: restaurant and laptop. Each review is annotated with one or more aspect terms and their corresponding sentiment polarities (positive, negative, or neutral). The dataset includes labeled aspect categories (e.g., food, service, price for restaurants; battery, display, and performance for laptops), making it suitable for fine-grained sentiment classification at the aspect level. It is commonly used for training and evaluating ABSA models. The SentSemSynNet model was implanted on a system having Window 11 operating system, with 16 GM RAM. The system considered had AMD Ryzen 5 Processor and was running with graphical processing unit, i.e., 4 GB NVIDA GeForce GTX1650 for faster processing. For execution, the Python environment was used. For evaluation, two standard metrics used for ABSA evaluation were considered, i.e., accuracy and macro-F-score. The accuracy and macro-F-score is evaluated using (17) and (18).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{17}$$

$$Macro - F - score = \frac{\sum_{i=1}^{n} F1-score_i}{n} \tag{18}$$

In (17), TP denotes true positive, TN denotes true negative, FP denotes false positive, and FN denotes false negative. In (18), F1-score is evaluated using (19). In (19), $Precision$ and $Recall$ are evaluated using (20) and (21).

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{19}$$

$$Precision = \frac{TP}{TP+FP} \tag{20}$$

$$Recall = \frac{TP}{TP+Fn} \tag{21}$$

4.1. SentSemSynNetwork performance on SemEval2014 Task 4 dataset

The evaluation results of SentSemSynNet model on SemEval 2014 Task 4 dataset is presented in Figure 2. The findings show effectiveness in ABSA for both laptop and restaurant domains. For restaurant dataset, SentSemSynNet has achieved 88.25% accuracy and 82.95% macro-F-score. For laptop dataset, SentSemSynNet achieved 84.52% accuracy and 80.26 macro-F-score. The findings show that the integration of both semantic and syntactic information using graph-based DL approach improves sentiment classification. Also, the findings show that the SentSemSynNet effectively captures important relationship between context and aspect terms. Further, in the next section, the SenSemSynNet approach is compared with existing approaches.

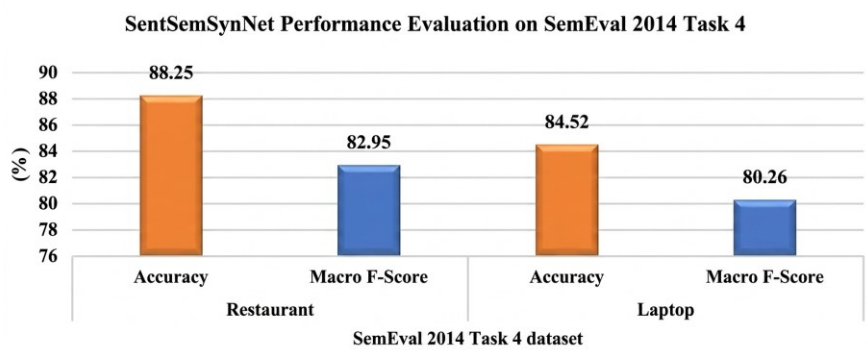

Figure 2. SentSemSynNet performance on SemEval Task 4 dataset

4.2. Comparative study

The comparative results comparing the existing ABSA approaches presented in the literature survey has been compared with proposed SenSemSynNet as presented in Table 2. For restaurant dataset, SentSemSynNet achieved 88.25% accuracy and 82.95% macro-F-score, outperforming SAGCN which achieved 87.53% accuracy and 81.28% macro-F-score and BIC-GCN which achieved 87.16% accuracy and 81.24% macro-F-score. This is because SenSemSynNet approach considered jointly integrating semantic and syntactic features using SentSemSynNet graph-based structure, which allowed for achieving better representation of contextual dependency and sentiment-related information. Further, for laptop dataset, SentSemSynNet achieved 84.52% accuracy and 80.26% macro-F-score, whereas SAGCN achieved 83.06% accuracy and 79.69% accuracy and BIC-GCN achieved 81.70% accuracy and 78.45% macro-F-score. The other approaches liked MOL-ABSA and LGCF achieved better results, but failed to consider integration of syntactic and semantic information at graph-level, which limited their classification accuracy. SentSemSynNet's ability to maintain macro-F-score alongside high accuracy confirms its strength in handling class imbalance and subtle sentiment importance. The results clearly indicate that SentSemSynNet provides better ABSA framework by effectively leveraging both dependency relations and semantic similarity.

Table 2. Performance comparison of SentSemSynNet with existing ABSA models

Ref	Model	SemEval 2014 restaurant		SemEval 2014 laptop	
		Accuracy	Macro F-score	Accuracy	Macro F-score
[16]	CPA-SA	82.64	73.38	75.18	71.5
[17]	Hete-GNN	81.91	73.74	74.08	69.45
[18]	LGCF-CDM-CDW	85.52	79.85	81.29	78.86
[20]	SDTGCN	83.82	76.13	78.64	75.5
[21]	SAGCN	87.53	81.28	83.06	79.69
[22]	KHGCN	-	-	80.87	77.9
[23]	SS-GCN	82.96	74.26	75.86	71.78
[24]	DCASAM	86.7	81.19	80.56	77
[25]	MOL-ABSA	85.26	79.27	81.19	78.52
[26]	BIC-GCN	87.16	81.24	81.7	78.45
[27]	SM-GCN+BERT	86.31	79.2	80.86	76.7
	SentSemSynNet	88.25	82.95	84.52	80.26

5. CONCLUSION

In this work, a novel model called SentSemSynNet was proposed to enhance the performance of ABSA, a subdomain of sentiment analysis that identifies sentiments expressed towards specific aspects in text. Traditional models often fail to effectively integrate semantic and syntactic information in a unified manner, which limits their capacity to correctly capture sentiment importance, especially in complex sentence structures. To overcome this, this work presented a graph-based DL model that simultaneously utilizes syntactic dependencies and semantic associations by constructing a hybrid graph representation of sentences. The SentSemSynNet model was evaluated on the SemEval 2014 Task 4 datasets for restaurant and laptop domains. It achieved 88.25% accuracy and 82.95% macro-F-score on restaurant dataset, and 84.52% accuracy and 80.26% macro-F-score of on lptop dataset. These results surpass existing models such as SAGCN, BIC-GCN, and LGCF, demonstrating that the fusion of semantic and syntactic features significantly enhances sentiment classification accuracy and robustness across datasets. In conclusion, the proposed SentSemSynNet model effectively addresses the limitations of prior ABSA models by integrating deep syntactic structures with semantic meaning, leading to improved aspect-level sentiment classification. Future work will focus on incorporating sarcasm identification, a challenging but critical feature that often alters the true sentiment of a statement, further enhancing the model's real-world applicability.

ACKNOWLEDGEMENT

Authors would like to express our heartfelt thanks to our guide for him unwavering guidance, invaluable insights, and encouragement throughout the research process.

FUNDING INFORMATION

No funding is raised for this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY

Datasets utilized in this research are cited in reference [17].

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