

An explicit multi-aspect sentiment analysis using bidirectional encoder representation transformers

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ABSTRACT

Aspect-based sentiment analysis (ABSA) is a vital natural language processing (NLP) task that extends traditional sentiment analysis by identifying sentiments associated with specific aspects within a sentence. Although recent deep learning (DL) models have improved ABSA performance, most concentrate on extracting only a single aspect and predicting sentence-level polarity, thereby overlooking multiple explicit aspects and their individual sentiments. This reveals a research gap in fine-grained sentiment detection. The main problem addressed in this work is the absence of robust models capable of extracting multiple explicit aspects and accurately predicting aspect-wise polarity. To address this, the primary objective was to design a model supporting multi-aspect extraction and sentiment classification. Accordingly, this work proposes explicit aspect-aware bidirectional encoder representations from transformers (EA-BERT), a BERT-based architecture enhanced with a multi-head attention (MHA) mechanism to capture aspect-specific contextual features and predict their corresponding polarities. The model was trained and evaluated on the SemEval 2014 restaurant (Res2014) and laptop (Lap2014) datasets. EA-BERT achieved accuracies of 90.86% and 90.23% and macro-F-scores of 91.89% and 90.28%, respectively. Experimental comparisons demonstrate that EA-BERT consistently outperforms several recent ABSA models, confirming its effectiveness for multi-aspect sentiment classification.

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1. INTRODUCTION

Sentiment analysis, also referred to as opinion mining, is a fundamental task in natural language processing (NLP) that involves identifying and categorizing emotions, opinions, or attitudes expressed in textual data. It is widely employed across domains such as social media monitoring, customer feedback analysis, and market research to assess public sentiment towards products, services, or events [1], [2]. Traditional sentiment analysis models typically classify entire sentences or documents into broad sentiment categories such as positive, negative, or neutral. However, sentiment often varies within different parts of a single sentence or document, especially when multiple entities or attributes are discussed. This leads to the emergence of aspect-based sentiment analysis (ABSA), a fine-grained sentiment analysis approach that aims to identify sentiment polarities tied to specific aspects or entities mentioned in text [3]. ABSA not only determines what sentiment is expressed but also what the sentiment is directed towards, offering richer and more actionable insights.

ABSA has shown significant value across a range of NLP applications. In customer review mining, for instance, ABSA helps businesses identify strengths and weaknesses of products by evaluating sentiments tied to individual product features [4]. In healthcare, ABSA enables the extraction of patient sentiments towards specific treatments or symptoms from clinical notes [5]. Similarly, in education and tourism, ABSA assists in understanding learner or traveler preferences through feedback on particular services or amenities [6]. Central to ABSA is the concept of aspects—explicit terms or phrases in the text that represent entities or attributes under analysis. These aspects anchor sentiment expressions, allowing models to relate emotional cues to specific targets. For example, in the sentence “The battery life is great, but the screen is dull,” ABSA identifies two aspects, “battery life” and “screen”, and links positive and negative sentiments, respectively. This level of granularity is crucial for sentiment understanding.

Moreover, explicit aspect identification is a key subtask within ABSA. Explicit aspects are terms explicitly mentioned in the sentence (e.g., “keyboard” and “display”), as opposed to implicit aspects, which are inferred. Identifying these explicit aspects improves the accuracy and interpretability of ABSA systems, as it ensures that sentiment is grounded in clear, textually present entities. Moreover, knowing the specific aspect tied to each sentiment allows for more precise sentiment polarity classification and better decision-making support [7]. Despite its importance, much of the current deep learning (DL) research in ABSA focuses on extracting a single explicit aspect and predicting the overall sentiment of the sentence [8], [9]. This simplification overlooks the natural presence of multiple aspects within many real-world texts and fails to provide a complete sentiment picture. Furthermore, limited work has been conducted on evaluating the individual polarity of each aspect, which is critical in applications where actionable insights are required at the aspect level.

To address these limitations, this work proposes a novel DL architecture named explicit aspect-aware bidirectional encoder representations from transformers (EA-BERT). The EA-BERT model is designed to simultaneously extract multiple explicit aspects from a sentence and predict their corresponding sentiment polarities, enhancing the granularity and accuracy of ABSA. By leveraging the powerful contextual representations of BERT, combined with a specialized multi-head attention (MHA) mechanism, EA-BERT enables the identification of aspect-sentiment pairs. This explicit aspect-aware architecture allows the model to distinguish sentiment distributions across aspects, resulting in more accurate aspect-level sentiment classification. The contributions of the work are as follows.

This work proposes a novel EA-BERT architecture for enhanced ABSA, capable of handling multiple explicit aspects within a single sentence. This work integrates BERT-based contextual embeddings with a fine-tuned MHA mechanism to detect aspect-sentiment relationships effectively. This work implements a fusion mechanism that combines both sentence-level and aspect-level features to improve polarity prediction accuracy. This work optimizes aspect-aware attention weights during training to better align with sentiment expressions tied to explicit aspects. This work demonstrates the superior performance of EA-BERT on benchmark datasets (SemEval 2014) through comprehensive experiments and comparison with existing models. The rest of this manuscript is organized as follows: section 2 discusses the literature survey, covering existing approaches in ABSA. Section 3 presents the proposed EA-BERT model in detail. Section 4 provides experimental results and a comparison with baseline methods. Finally, section 5 concludes the work and outlines directions for future research.

2. LITERATURE SURVEY

This section discusses the literature survey, covering existing approaches in ABSA. According to Busst *et al.* [10], aspect extraction in NLP is a critical task, especially when identifying explicit aspects and implicit aspects from user-generated content. Hence, this study presented an ensemble-based bidirectional long short-term memory (Bi-LSTM) that enhanced aspect-extraction accuracy by considering syntactic, semantic, and contextual information using BERT embeddings. The Bi-LSTM was also used for capturing sequential dependency using multiple Bi-LSTM networks. The Bi-LSTM BERT model was evaluated using the FiQA dataset and the SemEval datasets (SemEval 2016 (laptop), SemEval 2015 (restaurant) and SemEval 2014 (restaurant)), where it achieved 94.59%, 95.85%, 87.39%, and 91.28%, respectively. Zhao *et al.* [11] aimed to determine sentiment polarity for specific aspects in a given user text. Also, they overcame limitations of existing graph neural networks (GNN), which include limitations of noisy node representations and overlooked non-adjacent dependencies; hence, this work presented a structured dependency tree-based graph convolutional network (SDTGCN). The SDTGCN model constructed weighted-syntactic graphs considering features like part-of-speech (PoS) tags, sentiment knowledge, and dependency distance for better capture of contextual sentiment cues. Evaluations were conducted on five datasets, i.e., SemEval (SemEval 2014 (laptop and restaurant), SemEval 2015 (restaurant), SemEval 2016 (restaurant)) and the Twitter (now X) dataset, where it achieved 78.64%, 83.82%, 83.21%, 91.53%, and 76.25% accuracy, respectively.

Radi *et al.* [12] presented an aspect-target-context-aware identification approach, called aspect target context aware detection (ATCAD), which integrated contextual cues and syntactic dependencies for enhancing target-aspect sentiment identification. In this work, the head nodes in dependency trees guided the identification of relevant opinion contexts. Further, the approach separated target-aspect detection into opinion-target extraction using a tagging approach and sentiment classification for aspect-sentiment pairs. Evaluations were conducted on two datasets, SemEval 2015 (restaurant) and SemEval 2016 (restaurant), where a macro-F-score of 71.17 and 76.04 was achieved, respectively. Biswas and Poornalatha [13] presented the aspect-based attention model (AAM), which combined pre-trained BERT with an attention-enhanced aspect detection and sentiment analysis. The AAM model was evaluated using SemEval-2014 (restaurant, laptop), where both datasets, trained and tested, achieved 81% accuracy. Liu *et al.* [14] aimed at extracting aspect-opinion-sentiment triplets from text for better sentiment analysis. For addressing limitation of existing methods, which often rely on pipelines or tagging approaches which fall short in the integration of semantic and syntactic relations. Hence, this study introduced syntactic-semantics aspect-sentiment triplet extraction (SynSem-ASTE), a multi-encoder approach that combined semantics and syntax encoding structure for capturing contextual and structural features. A grid-tagging approach was included, which enabled triplet extraction. The SynSem-ASTE was evaluated using SemEval 2016 (restaurant), SemEval 2015 (restaurant), and SemEval 2014 (laptop and restaurant), where it achieved 71.10%, 62.85%, 72.23%, and 59.73% F-score.

Hu and Li [15] focused on aspect-oriented sentiment analysis for identifying sentiment polarity for specific aspects in text. They aimed to address challenges faced by graph convolutional network (GCN) approaches, i.e., limited integration of semantic and syntactic information and syntactic noise. To address the following, a bi-channel graph convolutional network (B-GCN) approach, which combined dependency trees with phrase-structural trees converted to a hierarchical phrase-matrix. This dual representation enhanced syntactic features, while semantic representations were refined considering MHA. The fusion of both channels supported complementary learning. The B-GCN was evaluated using SemEval 2014 (laptop and restaurant) and X datasets, where it achieved 87.16%, 81.7%, and 78.27% accuracy. Han [16], to address the issue of overlooked syntactic structure, which leads to reduced accuracy, a syntactic-masked graph convolutional network (SM-GCN) approach was presented, which integrated syntactic dependencies utilizing a masked matrix and BERT for focusing on key-sentence components. By using GCN principles and fused transfer matrices, the SM-GCN approach enhanced representation learning. The SM-GCN-BERT model was evaluated using SemEval 2014 (laptop and restaurant) and the X dataset, where it achieved 86.31%, 80.86%, and 77.84% accuracy. Zhao *et al.* [17] for solving issues of DL approaches, which struggle to adapt to varying sentiment classes and fail in modelling category information explicitly. Hence, to address the following limitations, this work presented a BERT-based model with class-aware word MHA (BERT-CA-WMA). The BERT-CA-WMA model employed an aspect-projection layer that aligned aspect embeddings with contextual features and integrated sentiment-class information using dynamic attention weighting. Evaluations were conducted using SemEval (SemEval 2016 (restaurant), SemEval 2015 (restaurant), SemEval 2014 (laptop and restaurant)) datasets, where it achieved 89.89%, 83.68%, 90.54%, and 89.72% accuracy. Radi *et al.* [18] for addressing the issue of implicit target in multi-opinion, presented iterative syntactic-guided chain of thought (IS-COT), which combined dependency parsing with a modular prompt, providing iterative reasoning for identifying implicit and explicit sentiments. Evaluations were conducted on SemEval 2015 (restaurant) and SemEval 2016 (restaurant) datasets, where 80.43% and 84.47% F-score was achieved. The summary of the literature survey is given in Table 1.

The reviewed literature presents significant advancements in ABSA, yet each approach demonstrates specific limitations that the proposed EA-BERT seeks to overcome. Busst *et al.* [10] improved explicit and implicit aspect extraction using Bi-LSTM with BERT embeddings, but limited the model to single aspect identification, thereby missing the complexity of multi-aspect sentences. EA-BERT addresses this by extracting multiple explicit aspects in one pass. Zhao *et al.* [11] tackled contextual sentiment with SDTGCN but relied heavily on syntactic graphs, which may introduce noise and overlook deeper semantic patterns. EA-BERT leverages BERT's semantic richness while using attention to focus only on relevant aspects, minimizing noise. Radi *et al.* [12] proposed ATCAD for aspect-target-context detection but separated extraction and classification in a pipeline manner, risking error propagation. EA-BERT unifies these stages for end-to-end learning. Biswas and Poornalatha. [13] utilized BERT with attention but did not provide aspect-wise sentiment classification, which EA-BERT directly supports. Liu *et al.* [14] addressed triplet extraction but lacked focus on explicit aspects, while EA-BERT enhances aspect-level clarity and polarity prediction. Similarly, models like B-GCN [15], SM-GCN [16], BERT-CA-WMA [17], and IS-COT [18] improve syntactic-semantic integration but do not support multi-aspect explicit sentiment evaluation. EA-BERT overcomes these gaps by jointly extracting multiple explicit aspects and predicting individual aspect polarities, offering comprehensive ABSA. In the next section, the EA-BERT model is discussed in detail.

Table 1. Literature survey summary

Ref	Model	Dataset(s) used	Aspect extraction	Explicit sentiment	Accuracy/F1-score (%)
[10]	Ensemble Bi-LSTM	FiQA, SemEval 2016 (laptop), SemEval 2015 and 2014 (restaurant)	Yes	Yes	94.59 (FiQA), 95.85, 87.39, 91.28
[11]	SDTGCN	SemEval 2014 (laptop, restaurant), 2015, 2016 (restaurant), X	Yes	Yes	78.64, 83.82, 83.21, 91.53, 76.25
[12]	ATCAD	SemEval 2015 (restaurant), SemEval 2016 (restaurant)	Yes	Yes	71.17 (F1), 76.04 (F1)
[13]	AAM	SemEval 2014 (restaurant, laptop-combined)	Yes	Yes	81.00
[14]	SynSem-ASTE	SemEval 2016, 2015 (restaurant), 2014 (laptop, restaurant)	Yes	Yes	71.10, 62.85, 72.23, 59.73 (F1)
[15]	Bi-Channel GCN (B-GCN)	SemEval 2014 (laptop, restaurant), X	Yes	Yes	87.16, 81.70, 78.27
[16]	SM-GCN	SemEval 2014 (laptop, restaurant), X	Yes	Yes	86.31, 80.86, 77.84
[17]	BERT-CA-WMA	SemEval 2016, 2015 (restaurant), 2014 (laptop, restaurant)	Yes	Yes	89.89, 83.68, 90.54, 89.72
[18]	IS-COT	SemEval 2015, 2016 (restaurant)	Yes	Yes	80.43, 84.47 (F1)

3. METHOD

The proposed methodology is organized as follows: it begins with an overview of the BERT model, followed by a detailed presentation of the EA-BERT architecture. Subsequently, the SemEval 2014 dataset used for evaluation is discussed. The methodology then explains the representation of text and aspects within EA-BERT, the BERT-MHA layer, and the optimization strategy applied to the MHA layer. Finally, the training process of the EA-BERT model is described.

3.1. Bidirectional encoder representations from transformers

BERT is a deep-language representation model, which was introduced by Devlin *et al* [19]. The BERT model provided a breakthrough in NLP by pre-training deep bidirectional representations from unlabeled text, considering right and left context in all layers. Unlike traditional word-embedding approaches, the BERT model is context-sensitive and helps in modelling word meaning differently depending on the given context. Due to these advantages, the BERT model is suitable for ABSA tasks, where the same word could convey different sentiments depending on the aspect it modifies. The traditional BERT consists of multiple transformer layers having self-attention processes, allowing it to provide weights to the importance of each word in the input sentence. The traditional model is pre-trained on large corpora like BooksCorpus and Wikipedia, which can be fine-tuned using the least changes for specific downstream tasks. In this work, BERT is utilized as a base for extracting syntactic-semantic features for SemEval2014 review texts. The BERT model has been enhanced with an MHA layer and a classifier head for optimizing it for explicit aspect extraction using the SemEval 2014 labelled dataset. This setup provides a model for detecting sentiments linked with aspects directly mentioned in text. In the next section, the EA-BERT architecture is discussed.

3.2. Architecture

In Figure 1, the EA-BERT architecture is presented. In EA-BERT, first, the SemEval2014 ABSA sentiment analysis dataset is considered. The dataset consists of text, aspect, and polarity. First, the text is passed on to the BERT layer, as $x_1, x_2, \dots, x_n$, where n is the sequence length. The BERT layer generates contextualized-embeddings, which are passed on to the BERT multi-head self-attention (MHSA) layer, which captures relationships across different parts of the input and identifies explicit aspect-sentiment pairs. Further, using softmax, the output is passed on to the MHA optimization layer, where the BERT model has been fine-tuned, such that the attention heads extract sentiment relations tied to explicit aspects. Further, the output is passed on to a fusion layer, where the aspect and polarity from the first layer are also used, which helps during training and testing. The fusion approach provides output for the complete text, providing prediction performance, and finally, the aspect and polarity of aspects are evaluated.

3.3. SemEval2014 dataset

The SemEval-2014 task 4 dataset, introduced [20], is a widely used benchmark for ABSA. This work strictly followed the official restaurant and laptop train-test splits without modification. Text preprocessing was conducted using the BERT WordPiece tokenizer, and aspect terms were aligned with tokenized sequences through offset mapping. All input sequences were padded or truncated to a fixed

maximum length, with special tokens [CLS] and [SEP] appended. The maximum sequence length was determined based on dataset statistics [21]–[30].

The dataset comprises two review domains: restaurant (hospitality) and laptop (electronics). Each sentence is annotated with one or more explicit aspect terms and their corresponding sentiment polarities (positive, neutral, or negative), enabling fine-grained sentiment analysis at the aspect level rather than only sentence-level polarity. Let a sentence be denoted as T , its explicit aspect terms as A , and the associated sentiment polarities as P . Accordingly, each dataset instance can be represented as shown in (1).

$$\mathcal{D} = \{(T_i, A_i, P_i)\}_{i=1}^N \quad (1)$$

Where the T_i denotes the sentence i , $A_i \subset T_i$ denotes explicit aspect-terms and $P_i \in \{-1, 0, +1\}$, denotes sentiment label (negative, neutral, and positive). The goal of this work, EA-BERT, is to predict polarity. $\hat{P}_i$ for each aspect A_i withing T_i . Hence, in the next section, the text and aspect representation in the dataset using BERT is discussed in detail.

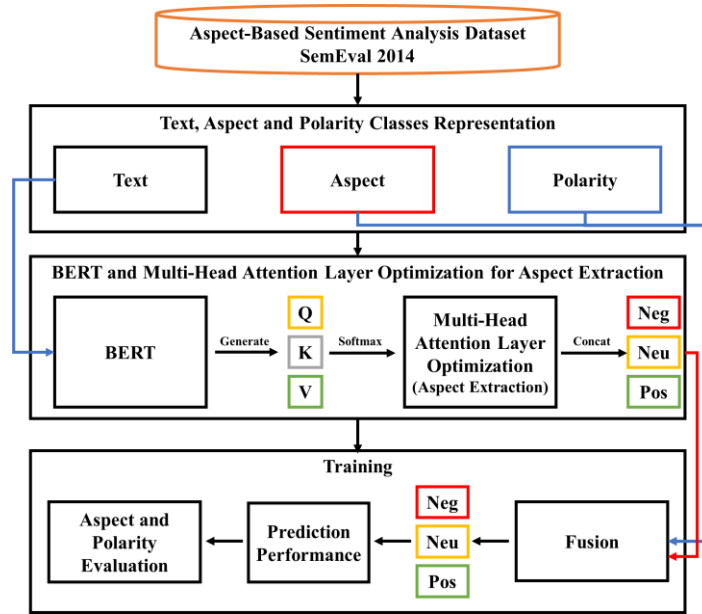


Figure 1. EA-BERT architecture

3.4. Dataset preprocessing, text, and aspect representation in BERT

The official SemEval-2014 restaurant and laptop train/test splits were strictly followed without modification. All sentences were lowercased and tokenized using the BERT WordPiece tokenizer. Maximum sequence length was fixed to 128 tokens. Padding and truncation were applied when necessary. Aspect terms spanning multiple tokens were aligned using the tokenizer offset mapping to construct the aspect mask. M , before passing on to the BERT layer, consider the input sentence. T_i has been tokenized as $x_1, x_2, \dots, x_n$. From this, the input sentence can be represented as (1). In (2), $x_j \in \mathbb{V}$ and $n \leq 128$ (max sequence length). Each token x_j is embedded using BERT using (3). The full embedding matrix for the sentence T_i is achieved as presented in (3). In (5) provides aspect representation as the average of its token embeddings. After the embedding process using BERT, the embeddings are passed onto the MHA layer. In (4), d denotes embedding-dimension in BERT-base, where $d = 768$ and E_j denotes the embedding vector for every token x_j . If $A_i = [x_k, \dots, x_m]$ is aspect-term, then the embedding for aspect is as (5).

$$T_i = [x_1, x_2, \dots, x_n] \quad (2)$$

$$E_j = \text{BERT}_{\text{Embed}}(x_j) \quad (3)$$

$$E_T = [E_1, E_2, \dots, E_n] \in \mathbb{R}^{n \times d} \quad (4)$$

$$E_A = \frac{1}{m-k+1} \sum_{j=k}^m E_j \quad (5)$$

3.5. Multi-head attention layer

In this work, the BERT model uses MHSA for capturing contextualized dependencies. Each attention operates as a query. Q , key K and value V projections. The Q , K and V are represented using (6), (7), and (8) respectively. In (6), (7), and (8), the W^Q , W^K , $W^V \in \mathbb{R}^{d \times d}$ which denotes learnable weights and d_h denotes dimensions per head. Further, the Q , K , and V are passed on to the attention layer, where the softmax is used. The attention process is computed using (9). For h heads, the process computes MHA output using (10). In (10), $head_i = \text{Attention}(Q_i, K_i, V_i)$ and $W^O \in \mathbb{R}^{hd_h \times d}$. In the next section, how the MHA layer has been optimized in the BERT model is discussed.

$$Q = E_T W^Q \quad (6)$$

$$K = E_T W^K \quad (7)$$

$$V = E_T W^V \quad (8)$$

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_h}}\right)V \quad (9)$$

$$\text{MHSA}(E_T) = \text{Concat}(head_1, head_2, \dots, head_h) \cdot W^O \quad (10)$$

3.6. Optimization of multi-head attention layer

This section discusses the optimization process of the MHA layer for explicit aspect-extraction. For fine-tuning MHSA for explicit aspect extraction, this work has optimized attention weights such that they highlight aspect-sentiment regions. Let $H = \text{MHSA}(E_T)$ be output from contextual representation. In this work, in the attention layer, the masked attention for the aspect term is evaluated. For this process, the mask $M \in \{0,1\}^n$ is computed, where $M_j = 1$ if $x_j \in A_i$. Hence, from this the (11) is achieved. Using (11), this work combines aspect embedding. E_A and sentence representation H using (12). Further, the attention scores (polarity) for aspects are computed using (13). In (14), $u \in \mathbb{R}^d$ denotes a learnable context vector. Further, the aspect-aware sentence is represented using (15).

$$H_A = \sum_{j=1}^n M_j \cdot H_j \quad (11)$$

$$Z_j = \tanh(W_z[E_A; H_j] + b_z) \text{ where } j = 1, \dots, n \quad (12)$$

$$\alpha_j = \frac{\exp(u^T Z_j)}{\sum_{k=1}^n \exp(u^T Z_k)} \quad (13)$$

$$R = \sum_{j=1}^n \alpha_j \cdot H_j \quad (14)$$

$$\hat{y} = \text{softmax}(W_c R + b_c) \quad (15)$$

Further, the sentiment for aspect-aware representation is predicted using (15). In (15), $\hat{y} \in \mathbb{R}^3$, i.e., predicted probability for positive, negative, and neutral. Also, similar to output $\hat{y}$, $W_c \in \mathbb{R}^{3 \times d}$ and $b_c \in \mathbb{R}^3$. After prediction, the output is passed on to the training layer, which is discussed in the next section.

3.7. Training

During the training process, this work considers the ground truth label, which is considered as a one-hot vector. $y \in \{0,1\}^3$. From this, the loss function is evaluated as presented in (16). In this work, as multiple aspects. $A_1, A_2, \dots, A_m$ are considered, hence, the loss function is evaluated using (17). Further, during training, in this work, the weights for $\Theta = \{W^Q, W^K, W^V, \dots, W_c, b_c\}$ are updated using the adaptive moment estimation (Adam) optimizer using (18).

$$\mathcal{L}_{ce} = -\sum_{i=1}^3 y_i \log(\hat{y}_i) \quad (16)$$

$$\mathcal{L}_{total} = \frac{1}{m} \sum_{i=1}^m \mathcal{L}_{ce}^i \quad (17)$$

$$\Theta \leftarrow \Theta - \eta \cdot \nabla_{\Theta} \mathcal{L}_{total} \quad (18)$$

To understand how the EA-BERT model operates during testing, Figure 2 illustrates the testing process of the EA-BERT model using a sample sentence: “The screen is bright, and the battery lasts long, but the keyboard feels cheap.” In this sentence, three distinct aspect terms can be identified: “screen” (Aspect 1), “battery” (Aspect 2), and “keyboard” (Aspect 3). During testing, the input sentence is first tokenized and encoded using BERT, which generates contextualized embeddings for each token, effectively capturing the semantic and syntactic importance of the text. These embeddings are then passed through the BERT MHA optimization layer, which is specifically fine-tuned to extract relationships between aspect terms and their surrounding sentiment-bearing context. Through this attention mechanism, the model is able to accurately identify the explicit aspect terms and associate them with their respective sentiment polarities. For example, the model extracts a positive sentiment for “screen” and “battery”, while assigning a negative sentiment to “keyboard”. This fine-grained aspect-level sentiment analysis ensures that the model not only detects sentiment but also precisely links it to the relevant aspect terms within the sentence, thus demonstrating the strength of EA-BERT in handling explicit aspect-sentiment pair extraction.

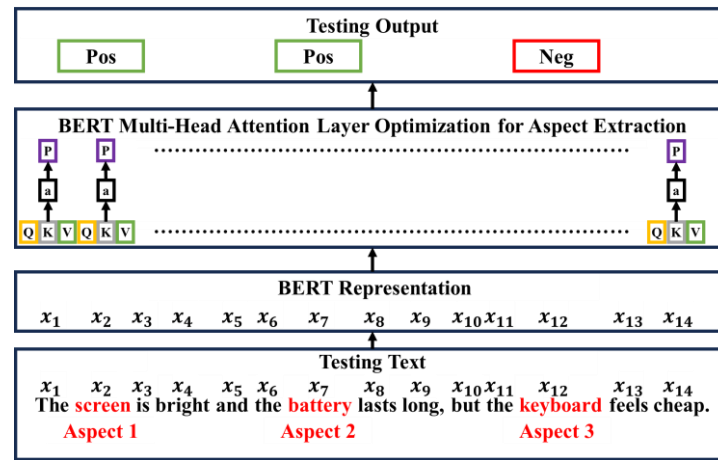


Figure 2. Testing process

Further, for evaluation, two metrics were considered in this study. The two metrics include accuracy and macro-F-score, which the existing approaches discussed in the literature survey have considered for evaluation. The accuracy and macro-F-score are evaluated using (19) and (20), respectively.

$$Accuracy = \frac{1}{N} \sum_{i=1}^N 1(\hat{y}_i = y_i) \quad (19)$$

$$Macro - F1 = \frac{1}{C} \sum_{c=1}^C \frac{2 \cdot Precision, Recall}{Precision + Recall} \quad (20)$$

In (19), N denotes the total number of instances in the test set, $\hat{y}_i$ denotes predicted label for i^{th} instance, y_i denotes true-label for i^{th} instance and $1(\cdot)$ denotes an indicator function, returning 1 if condition is true, and 0 otherwise. In (20), C denotes total number of classes (i.e., 3). Using these two metrics, the EA-BERT model is discussed in result section.

3.8. Intuitive explanation of the optimized multi-head attention layer

While BERT already employs self-attention internally, the proposed EA-BERT introduces an additional optimized MHA layer to explicitly model aspect–sentiment interactions. Unlike standard self-attention, which distributes attention across all tokens uniformly, the optimized MHA layer in EA-BERT is guided by an aspect mask that highlights explicit aspect terms in the sentence. Specifically, each attention head learns to focus on different sentiment-bearing regions surrounding the aspect term. For example, in the sentence “The battery lasts long, but the keyboard feels cheap”, one attention head focuses on the phrase “lasts long” with respect to the battery, while other focuses on “feels cheap” for the keyboard. This enables the model to extract multiple aspect–sentiment pairs simultaneously. Thus, the optimized MHA layer serves as an aspect-aware attention mechanism that strengthens the linkage between explicit aspect tokens and their surrounding opinion expressions, improving multi-aspect sentiment discrimination beyond standard BERT fine-tuning.

4. RESULTS AND DISCUSSION

The EA-BERT model was implemented and executed on a Windows 11 system equipped with an AMD Ryzen 5 processor, 16 GB of RAM, and a 4 GB NVIDIA GeForce GTX 1650 GPU. The model was developed using the Python programming language and run within a Python 3.11 environment. The sample distribution of the SemEval 2014 dataset used for evaluation is presented in Table 2.

Table 2. SemEval 2014 dataset

Dataset	Train			Test		
	Negative	Neutral	Positive	Negative	Neutral	Positive
Laptop	870	464	994	128	169	341
Restaurant	807	637	2164	196	196	728

4.1. Implementation details, hyperparameters, and training configuration

To improve reproducibility, the detailed training configuration of EA-BERT is reported in this section. The base encoder used in all experiments is BERT-base-uncased, consisting of 12 transformer layers, 12 attention heads, and a hidden dimension of 768. The model was fine-tuned end-to-end using the Adam optimizer with linear learning rate warm-up. Early stopping was applied with a patience of 2 epochs based on the validation macro-F-score. Gradient clipping with a norm threshold of 1.0 was used to stabilize training. The detailed hyperparameters are listed in Table 3.

Table 3. Hyperparameter settings of EA-BERT

Parameter	Value
Pretrained model	BERT-base-uncased
Max sequence length	128
Batch size	16
Learning rate	2e-5
Optimizer	Adam
Weight decay	1e-4
Dropout	0.1
Attention heads (MHA layer)	8
Hidden size	768
Epochs	8
Loss function	Cross-entropy
Random seed	{13, 21, 42, 87, 100}

4.2. Aspect extraction

The results presented in Table 4 show the effectiveness of the EA-BERT model in performing aspect-level sentiment analysis, particularly in accurately extracting multiple explicit aspects and predicting their corresponding sentiment polarities. In the first sentence, EA-BERT successfully identified both “Battery” and “Blue Screen” as aspects, assigning a neutral polarity to the battery and a negative polarity to the blue screen issue, thereby correctly deriving the overall negative sentiment. Similarly, in the second sentence, it detected “Software,” “Droid,” and “System” as aspects and appropriately captured the negative sentiment associated with the system crash, maintaining the correct overall polarity. In other examples, such as the third and fourth sentences, EA-BERT demonstrated its capability to handle positive and neutral combinations. For instance, it correctly tagged “Multi-Touch Gestures” and “Tracking Area” as positive, and “External Mouse” and “Gaming” as neutral, producing a valid positive overall sentiment. Likewise, the fourth sentence exhibited high sentiment positivity for “Food” and “Kitchen” and neutrality for “Menu,” again leading to a valid positive classification.

The fifth sentence presented a complex case involving multiple negative aspects, including “Mayonnaise,” “Toast,” and “Bacon,” which were all correctly identified with negative polarity, along with several neutral items, such as “Cheese” and “Omelette.” EA-BERT accurately consolidated these to a negative overall sentiment. Lastly, in the sixth sentence, EA-BERT correctly detected the discomfort associated with “Seats,” while also identifying “Benches” as a neutral aspect, maintaining the negative overall sentiment. These results highlight EA-BERT’s robustness in handling multi-aspect scenarios, its fine-grained polarity classification, and its ability to improve sentiment interpretation beyond the sentence-level label by focusing on individual aspect sentiments.

Table 4. Aspect extraction and polarity prediction

Sentence	Actual label	Predicted aspect	Predicted polarity	Overall polarity
I took it back for an Asus, and the same thing-blue screen which required me to remove the battery to reset.	Battery (Neutral)	Battery, blue screen	Neutral, negative	Negative
When I finally had everything running with all my software installed, I plugged in my Droid to recharge, and the system crashed.	Software (Neutral), System (Negative)	Software, droid, system	Neutral, neutral, negative	Negative
However, the multi-touch gestures and large tracking area make having an external mouse unnecessary (unless you're gaming).	Multi-touch gestures (Positive), tracking area (Positive), external mouse (Neutral), Gaming (Neutral)	Multi-touch gestures, tracking area, external mouse, gaming	Positive, positive, neutral, neutral	Positive
The food is uniformly exceptional, with a very capable kitchen that will proudly whip up whatever you feel like eating, whether it's on the menu or not.	Food (Positive), kitchen (Positive), menu (Neutral)	Food, kitchen, menu	Positive, positive, neutral	Positive
They did not have mayonnaise, forgot our toast, left out ingredients (i.e., cheese in an omelette), kept the food under hot temperatures, and the bacon was so overcooked it crumbled on the plate when you touched it.	Toast (Negative), mayonnaise (Negative), bacon (Negative), cheese (Neutral), ingredients (Negative), plate (Neutral), omelette (Neutral)	Mayonnaise, toast, ingredients, cheese, bacon, plate, omelette	Negative, negative, negative, neutral, negative, neutral, neutral	Negative
The seats are uncomfortable if you are sitting against the wall on wooden benches.	Seats (Negative)	Seats, benches	Negative, neutral	Negative

4.3. Performance evaluation

This section presents a performance evaluation of the EA-BERT model using the SemEval 2014 restaurant (Res2014) and laptop (Lap2014) datasets. The model's performance was assessed using two standard metrics: accuracy and macro-F-score using (19) and (20), which are widely used in ABSA to evaluate both classification correctness and balance across sentiment classes. As shown in Figure 3, the EA-BERT model achieves strong performance on both datasets. For the SemEval Res2014 dataset, EA-BERT attains 90.86% accuracy and 91.89% macro-F-score, indicating that EA-BERT is highly effective in correctly identifying sentiment classes across various explicit aspects in restaurant reviews. On the SemEval Lap2014 dataset, the model achieves 90.23% accuracy and 90.28% macro-F-score, demonstrating its generalizability and robustness across domains, particularly in consumer electronics reviews. These results validate that EA-BERT effectively handles multiple explicit aspects within a sentence and successfully assigns sentiment polarities with high precision and balance. The macro-F-score values, which consider performance across all sentiment classes equally, further indicate the model's strength in maintaining consistent accuracy across both majority and minority classes. This confirms the efficacy of EA-BERT in real-world ABSA scenarios.

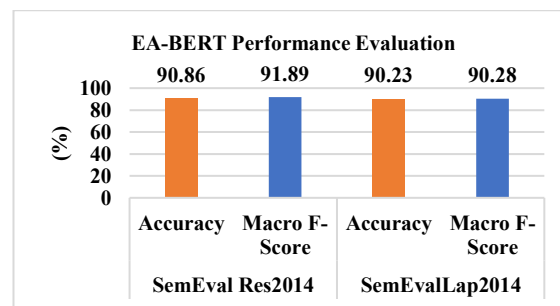


Figure 3. EA-BERT performance on the SemEval 2014 dataset

4.4. Comparative study

The comparative study in Table 5 shows the performance of various recent DL models for ABSA on the Res2014 and Lap2014 datasets. Each of these models provide unique architectural advancement to improve sentiment classification accuracy and macro-F-score. The SDTGCN model [11] leveraged structured dependency tree-based GCNs to model syntactic relations and contextual cues more effectively than

traditional GCNs, achieving 83.82% accuracy and 76.13% macro-F-score on Res2014 and 78.64% accuracy and 75.5% macro-F-score on Lap2014. However, its performance is limited by potential noise in graph construction and inadequate aspect-specific sentiment focus. The SynSem-ASTE model [14] and its variants (BERT, RoBERTa, and DeBERTa-based) aimed to extract aspect-sentiment triplets by combining syntactic and semantic information. These models improved contextual understanding but still underperform in sentiment classification, particularly on the Lap2014 dataset, where macro-F-scores remain under 64%, highlighting difficulties in generalizing to different domains. The binary channels graph convolutional network (BIC-GCN) model [15] improves sentiment classification by integrating BIC-GCNs with hierarchical syntactic structures, achieving 87.16% accuracy and 81.24% macro-F-score on Res2014. Similarly, SM-GCN + BERT [16] incorporates masked syntactic dependencies into BERT, obtaining competitive results with 86.31% accuracy and 79.2% macro-F-score on Res2014.

Despite these advancements, the proposed EA-BERT surpasses all prior models, achieving 90.86% accuracy and 91.89% macro-F-score on Res2014, and 90.23% accuracy and 90.28% macro-F-score on Lap2014. EA-BERT outperforms due to its capability to extract multiple explicit aspects from a sentence and evaluate sentiment polarity for each aspect individually, rather than relying on a single-aspect representation. This granular approach enables more precise sentiment detection and enhances classification performance, especially in sentences with complex aspect-opinion structures. Thus, EA-BERT addresses the limitations of existing models by offering fine-grained, aspect-level polarity classification, resulting in more accurate and balanced ABSA outcomes.

Table 5. Comparative study

Ref	Year	Model	SemEval Res2014		SemEvalLap2014	
			Accuracy	Macro F-score	Accuracy	Macro F-score
[11]	2024	SDTGCN	83.82	76.13	78.64	75.5
[14]	2024	SynSem-ASTE	-	72.23	-	59.73
		BERT + SynSem-ASTE	-	72.23	-	59.73
		RoBERTa + SynSem-ASTE	-	74.67	-	63.13
		DeBERTa + SynSem-ASTE	-	74.73	-	63.37
[15]	2025	BIC-GCN	87.16	81.24	81.7	78.45
[16]	2025	SM-GCN + BERT	86.31	79.2	80.86	76.7
	Proposed	EA-BERT	90.86	91.89	90.23	90.28

4.5. Robustness and statistical validation

To evaluate the robustness of EA-BERT, experiments were repeated using five different random seeds {13, 21, 42, 87, 100}. For each configuration, accuracy and macro-F1 score were recorded and averaged. Standard deviation (SD) was computed to assess stability. The low SD values indicate that EA-BERT exhibits stable performance across different random initializations in Table 6.

Table 6. Robustness evaluation over multiple runs

Dataset	Metric	Mean (%)	SD
Res2014	Accuracy	90.86	± 0.41
Res2014	Macro-F1	91.89	± 0.37
Lap2014	Accuracy	90.23	± 0.46
Lap2014	Macro-F1	90.28	± 0.39

4.6. Statistical significance testing

To verify whether the observed improvements are statistically significant, paired t-tests were conducted between EA-BERT and the strongest baseline (BIC-GCN) on both datasets. For each test, five paired runs were used. The null hypothesis assumes no significant difference between models. The results show that EA-BERT achieves statistically significant improvements with $p < 0.01$ on both the restaurant and laptop datasets for macro-F-score, confirming that the performance gains are not due to random chance.

4.7. Failure cases and error analysis

Although EA-BERT demonstrates strong performance for explicit aspect extraction, certain limitations are observed. The model struggles in sentences where implicit aspects are present without explicit mention, e.g., “It heats very quickly” (implicit aspect: battery/processor). Overlapping sentiment expressions occur, such as mixed opinions toward closely located aspects. Sarcastic or figurative language appears, where

sentiment is not lexically expressed. Long-distance dependencies exceed the fixed context window. These cases reveal that EA-BERT primarily depends on explicit aspect annotations and sentiment cues and may require complementary syntactic or commonsense reasoning mechanisms for improved implicit aspect handling.

4.8. Computational cost and training time

The EA-BERT model was trained on an NVIDIA GTX 1650 GPU (4 GB VRAM). For the restaurant dataset, the average training time was approximately 32 minutes, while for the laptop dataset, it was approximately 29 minutes. Inference time per sentence was approximately 4.2 ms, making the model suitable for near real-time applications. Compared with graph-based models such as BIC-GCN and SDTGCN, EA-BERT exhibits lower preprocessing overhead, as it does not require dependency parsing or graph construction, but incurs moderate computational cost due to fine-tuning BERT and the additional MHA layer.

4.9. Limitation

Despite its effectiveness, EA-BERT has the following limitations: it relies on explicit aspect annotations and does not directly handle implicit aspects. Its performance depends on the quality of annotated aspect terms. The additional MHA layer increases computational complexity compared to vanilla BERT. It may not generalize optimally to domains with highly informal or noisy language without retraining. These limitations highlight the need for future extensions toward implicit aspect modelling and domain adaptation.

5. CONCLUSION

This research focused on enhancing the performance of ABSA, a sub-domain of sentiment analysis that provides fine-grained sentiment insights by associating sentiments with specific aspects within a sentence. While traditional sentiment analysis methods offer only sentence-level polarity, ABSA enables a deeper understanding by identifying sentiments linked to distinct features or components of a product or service. However, many existing DL models are limited by their focus on a single explicit aspect and insufficient evaluation of aspect-level polarity, which reduces the accuracy and completeness of sentiment interpretation. To address these research gaps, the proposed work introduced EA-BERT, a novel model designed to extract multiple explicit aspects from user-generated content and predict their corresponding polarities. The methodology leverages BERT to generate context-rich sentence embeddings, followed by an optimized MHA mechanism that selectively emphasizes aspect-specific contextual features. To enhance reproducibility and transparency, detailed preprocessing steps, hyperparameter configurations, and training protocols were incorporated, and official SemEval-2014 dataset splits (restaurant and laptop domains) were strictly followed. The EA-BERT model was trained and evaluated on the SemEval-2014 datasets, achieving accuracy scores of 90.86% and 90.23%, and macro-F-scores of 91.89% and 90.28% for the restaurant and laptop datasets, respectively. Robustness experiments conducted across multiple random seeds demonstrated stable performance, and statistical significance testing confirmed that the improvements over baseline models were not due to chance. These results significantly outperform several state-of-the-art models, including SDTGCN, SynSem-ASTE, BIC-GCN, and SM-GCN. The findings validate that EA-BERT effectively captures multiple explicit aspects and their associated sentiments, leading to more accurate and comprehensive ABSA. Nonetheless, the model exhibits limitations when handling implicit aspects, sarcastic expressions, and long-range sentiment dependencies, which are identified as directions for future research. Overall, the proposed EA-BERT framework demonstrates strong potential for improving fine-grained sentiment understanding in practical applications. Future research will explore several extensions of EA-BERT. First, graph-based syntactic encoders such as dependency-aware GCNs will be integrated with the optimized MHA layer to jointly model structural and semantic dependencies. Second, implicit aspect detection mechanisms will be incorporated using weak supervision and contrastive learning. Third, EA-BERT will be evaluated on multilingual datasets and cross-domain benchmarks, including social media reviews and healthcare feedback. Finally, lightweight model compression and knowledge distillation will be investigated to enable deployment on resource-constrained devices.

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C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
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CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

No dataset is utilized in this research. The source code, trained models, and experiment scripts will be made publicly available upon acceptance of the manuscript. Until then, they can be shared upon reasonable request.

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