GRADIVA

Volume 64 | Issue 11 | November 2025
DOI: 10.5281/zenodo.17607165

Dynamic Multi-Scale Attention for Fine-Grained Aspect-Based Sentiment Analysis

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Abstract

This research focuses on improving Aspect-Based Sentiment Analysis (ABSA) by addressing challenges related to multiple aspects and sentiment ambiguities within sentences. We propose the DAMSA-(Dynamic aspect-aware multi-scale attention) Transformer, a novel model that integrates three key components: Dynamic Aspect-Aware Attention (DAA), which adjusts attention based on the complexity of each aspect; Multi-Scale Feature Fusion (MSFF), which combines sentiment information from different linguistic levels; and Contrastive Aspect Learning (CAL), which helps distinguish between similar and conflicting sentiments more effectively. The model was evaluated on the SemEval-2014 Laptop and Restaurant datasets, showing consistent improvements over existing transformer-based methods with up to 4.45% increase in accuracy and 2.1% in macro-F1 score. Additional analyses, including attention visualizations and class-wise performance, demonstrate the model's capability to capture sentiment nuances more accurately.

Keywords: *Aspect-Based Sentiment Analysis, Transformer Models, Dynamic Attention, Multi-Scale Feature Fusion, Contrastive Learning, Fine-Grained Sentiment Classification.*

1. INTRODUCTION

Sentiment analysis has emerged as an essential tool in a number of fields, such as social media sentiment tracking, brand monitoring, and consumer feedback analysis [1]. Nevertheless, conventional sentiment analysis techniques frequently give a text a single sentiment label, neglecting the possibility that various parts of the same text may have different sentiments.

For example, a binary or ternary sentiment classifier would not be able to distinguish between the good sentiment regarding the camera and the negative sentiment regarding the battery in the review "The camera quality is excellent, but the battery life is disappointing." A finer-grained method called Aspect-Based Sentiment Analysis (ABSA) is required due to this constraint [2].

Although early ABSA models relied on lexicon-based and traditional machine learning methods [3], recent developments in transformer-based architectures (e.g., BERT, SpanBERT, and T5) have greatly enhanced sentiment classification by utilizing contextual embeddings and attention mechanisms [4].

Nevertheless, difficulties still exist in correctly identifying aspect terms, resolving ambiguities, and handling multi-aspect sentences with conflicting sentiments [5]. The use of

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transformers with attention mechanisms to improve aspect-based sentiment classification is investigated in this study. Specifically, we examine how self-attention and cross-at tention mechanisms in transformer models can capture aspect-sentiment relationships and improve sentiment classification performance.

Using pre-trained transformer models optimized on ABSA datasets, we hope to tackle issues like sentiment polarity detection, aspect term extraction, and contextual disambiguation [6]. However, despite the significant progress brought by transformer-based models, existing approaches [17][20][23][24] often suffer from static attention mechanisms that fail to dynamically adapt to the complexity and variability of sentiment expressions tied to different aspects within the same sentence. In real-world reviews, sentiment indicators vary in granularity—some aspects are expressed explicitly and clearly, while others are implicit, embedded in subtle linguistic cues[21][22].

To address these limitations, this research introduces the DAMSA-Transformer, a novel architecture that integrates dynamic attention adjustment, multi-level feature fusion, and contrastive learning. This framework is motivated by the need for models that not only attend more precisely to sentiment-bearing tokens based on aspect relevance, but also generalize effectively across complex sentence structures with multiple and even conflicting sentiments. By doing so, our work aims to enhance the fine-grained capability of ABSA systems, ensuring a deeper and more accurate understanding of opinionated text.

2. LITERATURE SURVEY

The incorporation of transformer topologies and attention mechanisms has greatly increased fine-grained sentiment analysis by allowing models to capture subtle attitudes related to particular textual elements. In order to improve sentiment analysis of tweets, a study by Jahin et al. presents TRABSA, a hybrid framework that combines transformer topologies, attention mechanisms, and BiLSTM networks [7].

Utilizing RoBERTa, which has been trained on 124 million tweets, the model achieves cutting-edge accuracy and exhibits resilience across a variety of datasets. Their method demonstrates how transformer models can handle social media data, which is frequently composed of brief and loud text.

Wu et al. investigate a different method for fine-grained sentiment analysis by introducing a system that is based on an attention CNN-LSTM model [8]. Their study, which was part of SemEval-2018 Task 1, uses CNN layers to extract local features from text and LSTM networks to gather long-term contextual information. The high performance of our hybrid model in sentiment intensity regression tasks suggests that feature extraction for sentiment prediction can be greatly enhanced by attention-based methods.

Their technique improves the accuracy of sentiment categorization across a range of datasets by integrating both local and global contextual information. For fine-grained sentiment analysis, Tan et al. suggest a technique that combines dependency trees and graph attention networks [9]. Their method enhances aspect-based sentiment classification by utilizing the syntactic structure of sentences.

The approach better captures the relationships between words by using graphs to describe sentence dependencies, which improves sentiment categorization. Better information propagation inside the phrase is made possible by the incorporation of graph attention

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networks, which improves sentiment prediction accuracy. Their results emphasize how crucial it is to include syntactic features in sentiment analysis algorithms.

When it comes to context-aware sentiment analysis, Sivakumar and Rajalakshmi investigate the use of bidirectional transformers with attention-enhanced features [10]. Their research shows that using contextual embeddings from bidirectional transformers can improve sentiment classification in social media texts. By improving attention mechanisms, their method refines sentiment detection, especially when context-dependent sentiment shifts occur. The efficacy of this method is demonstrated by its ability to distinguish between sentiment variations across different aspects of a sentence. Their results indicate that attention-enhanced features are essential for attaining high accuracy in sentiment classification tasks.

By creating a transformer-based technique for fine-grained sentiment analysis of Weibo comments, Piao and Bai tackle the difficulties of evaluating Chinese social media content [11]. Their method, which uses a transformer model trained especially for sentiment classification in Chinese text, successfully addresses problems such as polysemy and unbalanced sample categories. When compared to conventional machine learning models, the approach performs better, demonstrating how well transformers handle intricate sentiment variations.

In a field that has gotten comparatively little attention, their work advances sentiment analysis in non-English languages. A model named MGAFN-ISA, which employs a bidirectional cross-attention mechanism to capture fine-grained correlations between visual and textual modalities, is introduced in an implicit sentiment analysis study [12]. By improving the interplay between several data representations, this model enhances sentiment classification in multimodal datasets.

The results of the study show that attention-based methods are quite successful at obtaining sentiment-related characteristics from a variety of modalities. This paper contributes to the field of fine-grained sentiment analysis by improving cross-attention methods, especially in situations where textual information is not enough to accurately detect sentiment.

In order to enhance aspect-level sentiment categorization, Li et al. suggest a fine-grained sentiment analysis model that combines BERT with hierarchical attention mechanisms [13]. Their method improves sentiment prediction accuracy by dynamically modifying attention weights according to contextual requirements.

The model efficiently collects sentiment cues at the word and sentence levels by utilizing hierarchical attention. On some benchmark datasets, their trials show better results than conventional deep learning techniques. The study emphasizes how important multi-level attention processes are for sentiment analysis based on transformers. A dual-stream transformer network that simultaneously processes local and global context is presented by Zhao et al. for fine-grained sentiment classification [14].

Their model uses a dual transformer framework, with one stream capturing sentiment at the phrase level and the other concentrating on sentiment at the document level. This lessens the effect of ambiguous statements and permits improved emotion aggregation. The model's ability to discern minute sentiment differences is validated by evaluation on social media datasets and customer reviews. The results highlight the benefit of multi-stream processing for tasks involving sentiment analysis.

Using a cross-attention transformer design, Wang et al. provide a multimodal sentiment analysis approach that integrates textual and visual data [15]. Their methodology ensures

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accurate sentiment identification across a variety of inputs by aligning features from several modalities. The approach significantly improves sentiment categorization for social media posts by using attention-based feature fusion. Tests conducted on multimodal benchmark datasets demonstrate how well the model handles sentiment fluctuations in various kinds of information.

Their work takes sentiment analysis beyond text-based methods. By teaching transformers to distinguish between distinct sentiment subtleties, Chen et al. investigate contrastive learning for fine-grained sentiment analysis [16]. To improve sentiment representations and provide greater cross-domain generalization, their methodology uses contrastive loss. The approach performs well in low-resource environments and enhances sentiment categorization in situations with little labeled data. The work demonstrates how well transformer-based models reduce sentiment ambiguity through contrastive learning. The summary of existing research works in the area of transformer based sentiment analysis is presented in table 1.

Table 1: Summary of Existing Research on Fine-Grained Sentiment Analysis Using Transformers

Reference & Authors	Methodology	Challenges Identified
[7] Jahin et al.	Hybrid Transformer + BiLSTM	Handling noisy and short tweets
[8] Wu et al.	Attention CNN-LSTM	Improving sentiment intensity prediction
[9] Tan et al.	Dependency Tree + Graph Attention	Capturing syntactic dependencies effectively
[10] Sivakumar & Rajalakshmi	Bidirectional Transformer + Attention	Handling context-dependent sentiment shifts
[11] Piao & Bai	Transformer for Weibo Sentiment	Addressing polysemy and imbalanced datasets
[12] MGAFN-ISA (Authors not specified)	Cross-Attention for Multimodal Sentiment	Improving sentiment detection across modalities
[13] Li et al.	BERT + Hierarchical Attention	Capturing both word-level & sentence-level cues
[14] Zhao et al.	Dual-Stream Transformer	Balancing local & global sentiment contexts
[15] Wang et al.	Multimodal Cross-Attention Transformer	Aligning textual & visual sentiment cues
[16] Chen et al.	Contrastive Learning for Transformers	Enhancing generalization in low-resource settings

3. METHODOLOGY

The proposed Dynamic Aspect-Aware Multi-Scale Attention Transformer (DAMSA-Transformer) is designed to tackle the weaknesses of traditional ABSC models by introducing three key innovations: Dynamic Aspect-Aware Attention (DAA), Multi-Scale Feature Fusion (MSFF), and Contrastive Aspect Learning (CAL).

These components work together to enhance the attention mechanism, improve contextual understanding, and boost sentiment discrimination across sentences with varying complexity. Figure 1 shows the proposed method for fine-grained aspect-based sentiment classification.

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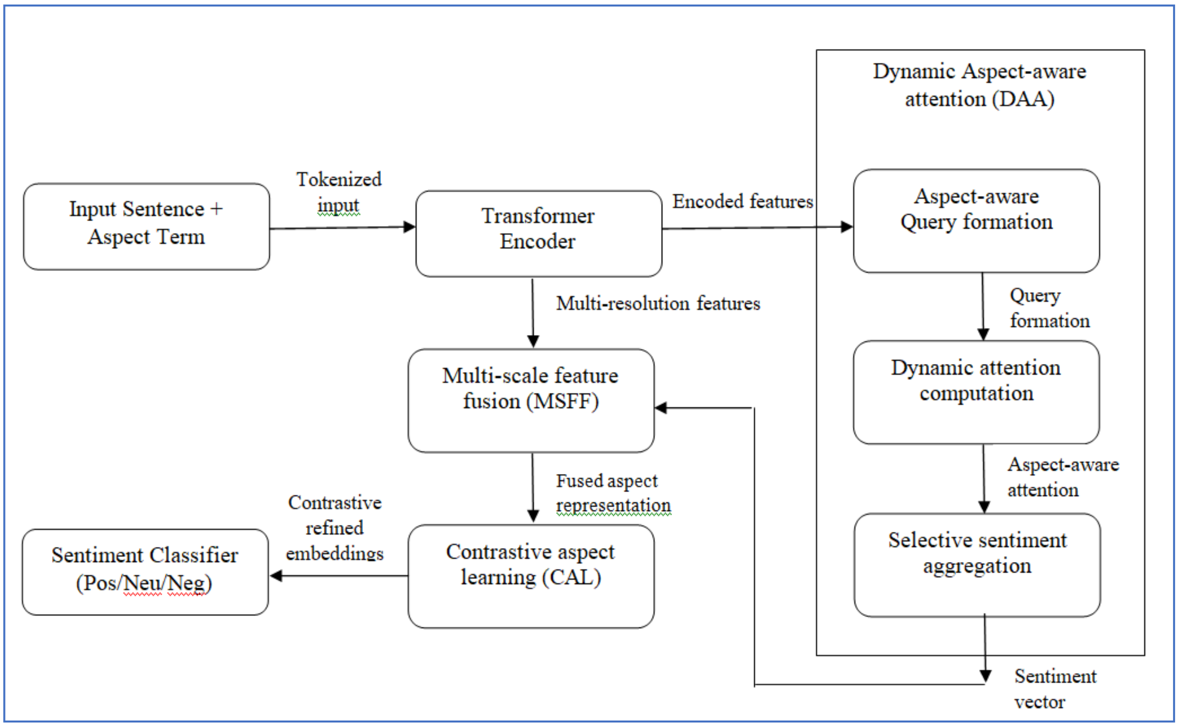

Figure 1: Proposed method: DAMSA Transformer for Fine-grained Aspect-based Sentiment Classification

Consider a sentence with multiple aspects, like “The battery life is great, but the screen is dull.” Each aspect here might carry a different sentiment. Traditional models tend to treat all words uniformly or use fixed attention, which limits their ability to differentiate these sentiments clearly. Our DAMSA-Transformer improves this by dynamically adapting the attention to each aspect based on the complexity and context. We first feed the input sentence into a Transformer encoder such as BERT or RoBERTa. This encoder generates contextualized embeddings that capture both local (word-level) and global (sentence-level) meaning.

3.1 Dynamic Aspect-Aware Attention (DAA)

DAA is designed to fine-tune attention at a granular level for each aspect, improving sentiment detection by focusing on words relevant to that aspect rather than treating every word the same. Three steps that are involved in the working of DAA are Aspect-Guided Query Formation, Dynamic Attention Computation and Selective Sentiment Feature Aggregation captured in equations from (1) to (6).

Aspect-Guided Query Formation-The model creates an aspect-aware query vector by combining the aspect embedding eA with the contextual word embeddings from the transformer:

$$QA = Q + WA \times eA \qquad (1)$$

Here, Q is the original query matrix and WA is a learnable weight matrix.

Dynamic Attention Computation-The scaled dot-product attention is computed as:

$$S(i, j) = (QA \cdot KT)(i, j) / \sqrt{dk} \qquad (2)$$

Then, a dynamic scaling factor γ(i, j) adjusts each attention score based on aspect-word relevance:

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$$\gamma(i, j) = W\gamma \times (xj \odot eA) \quad (3)$$

where xj is the embedding of word j, Wγ is another learnable matrix, and ⊙ represents element-wise multiplication.

The adjusted attention score is:

$$S'(i, j) = S(i, j) + \gamma(i, j) \quad (4)$$

Selective Sentiment Feature Aggregation-The final attention weights are calculated using softmax:

$$\alpha(i, j) = \exp(S'(i, j)) / \Sigma k \exp(S'(i, k)) \quad (5)$$

The output for each position is aggregated as:

$$Oi = \Sigma j\ \alpha(i, j) \times Vj \quad (6)$$

This selective aggregation ensures that sentiment-relevant words have a stronger influence on the representation of each aspect.

For the sentence "The battery life of this phone is amazing," and the aspect "battery life," DAA assigns high attention weights to "battery" and "amazing," while down-weighting irrelevant words like "phone."

3.2 Multi-Scale Feature Fusion (MSFF)

To improve sentiment extraction further, MSFF combines features from multiple attention scales:

- Word-level attention captures immediate dependencies.
- Phrase-level attention refines aspect-specific sentiment.
- Clause or sentence-level attention offers a broader contextual view.

Unlike fixed hierarchical attention structures, MSFF dynamically fuses these different scales, allowing the model to adapt to various sentence complexities and generalize better. Word-level attention captures immediate dependencies, phrase-level attention refines aspect-specific sentiment understanding, and clause/sentence-level attention ensures a holistic interpretation of sentiment expressions.

Unlike single-layer attention mechanisms, MSFF combines these features dynamically, improving generalization and adaptation across diverse sentence structures.

3.3 Contrastive Aspect Learning (CAL)

The CAL module tackles the challenge of sentiment confusion when multiple aspects appear in one sentence. It introduces contrastive learning at the aspect level by projecting aspect representations into a semantic space where:

- Aspects with similar sentiment polarities are pulled closer together.
- Aspects with conflicting sentiments are pushed further apart.

This contrastive optimization helps reduce errors when sentiments conflict within the same sentence. Finally, in the Sentiment Classification Layer, the refined, multi-scale fused aspect representations are fed into a classification layer that predicts the sentiment label—Positive, Negative, or Neutral—for each aspect. The integration of dynamic attention, multi-

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scale fusion, and contrastive learning makes the DAMSA-Transformer highly effective for nuanced, context-aware sentiment analysis.

The DAMSA-Transformer starts by taking a sentence and its target aspect as input, which are processed through a transformer encoder like BERT or RoBERTa to produce contextualized embeddings. These embeddings capture complex semantic and syntactic relations across the sentence. The embeddings feed into two modules simultaneously: Dynamic Aspect-Aware Attention (DAA) and Multi-Scale Feature Fusion (MSFF). Within DAA, an aspect-aware query is formed by combining the aspect embedding with the contextual word embeddings.

This ensures the attention mechanism is guided toward words relevant to the specific aspect. The attention scores are then dynamically adjusted according to how closely each word relates to the aspect, highlighting sentiment-bearing parts of the sentence. The model selectively aggregates sentiment features by emphasizing tokens linked to the aspect and suppressing irrelevant ones. In parallel, the MSFF module receives both the transformer output and DAA's aggregated attention features, combining information across word, phrase, and sentence levels. This builds a robust multi-granular representation that adapts flexibly to different sentence structures. The fused output is passed to the Contrastive Aspect Learning (CAL) module, which leverages contrastive learning to cluster aspect embeddings with similar sentiments while separating those with conflicting polarities. This leads to clearer aspect-specific sentiment distinctions. Finally, the refined aspect embeddings are input to the sentiment classification layer, which assigns one of the three sentiment labels. This entire pipeline ensures the model makes fine-grained, context-sensitive sentiment predictions that are both accurate and semantically rich.

Novelty of the proposed method for fine-grained aspect-based sentiment classification:

DAA dynamically adjusts attention granularity per aspect, unlike traditional attention mechanisms. Although multi-scale attention is used in some transformer variants, the way MSFF in our proposed method fuses various levels of contextual information dynamically rather than in a fixed hierarchy which makes it an enhanced approach. CAL is a novel application in Sentiment Analysis. Contrastive learning has been explored in NLP, but applying aspect-specific contrastive learning to refine sentiment classification is a novel adaptation for fine-grained sentiment analysis. The overall process of the Domain-Aware Attention mechanism is illustrated in figure 2, where aspect information is embedded into the attention computation to enhance relevance and interpretability.

Input:

Q ← Query matrix from input embeddings

K ← Key matrix from input embeddings

V ← Value matrix from input embeddings

e_A ← Embedding of the target aspect

W_A ← Learnable weight matrix for aspect-aware transformation

W_γ ← Learnable weight matrix for aspect relevance scaling

Output:

O ← Attention output for each token (aspect-aware)

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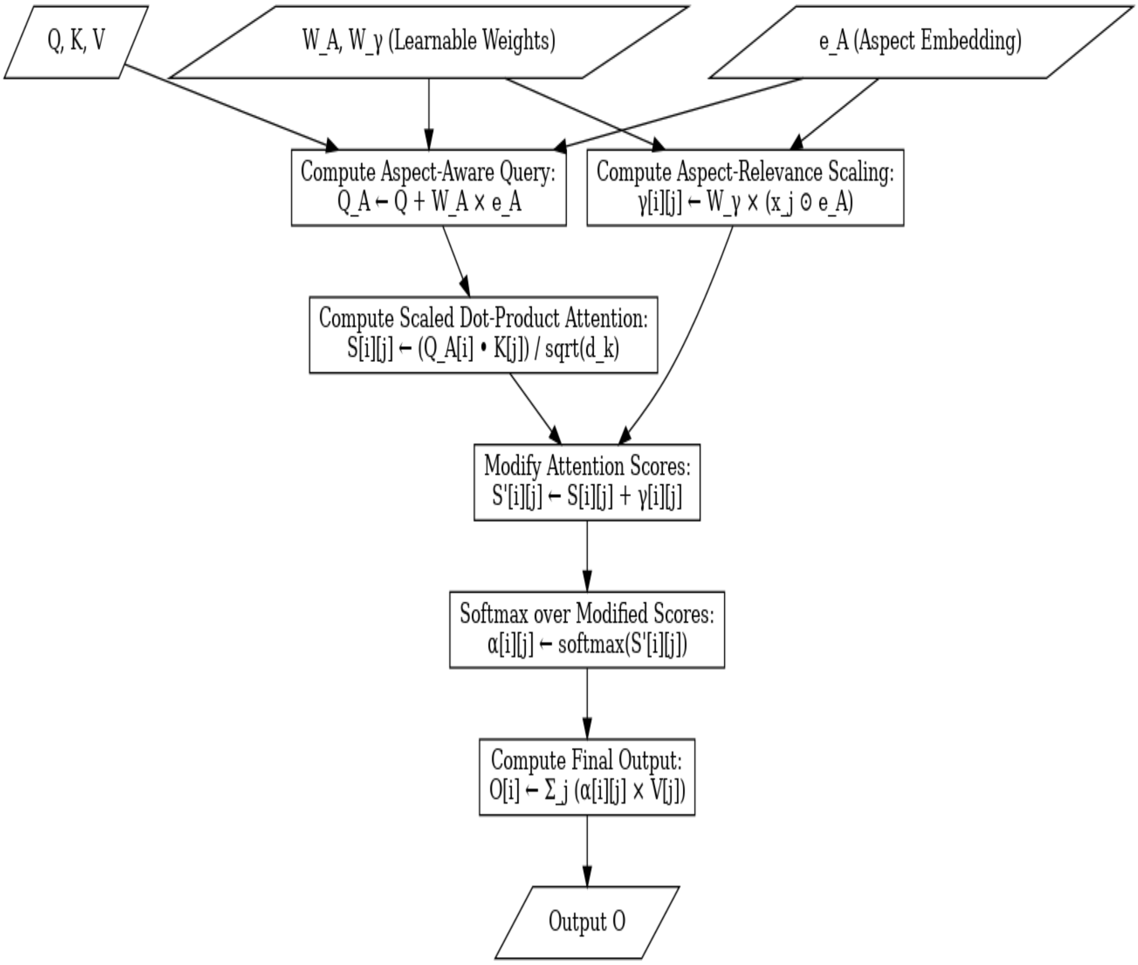

Figure 2: Flowchart of the Domain-Aware Attention (DAA) mechanism, showing how aspect information is integrated to compute the final attention output

4. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed DAMSA-Transformer, experiments were carried out using two widely recognized benchmark datasets from SemEval-2014 Task 4: the Laptop and Restaurant review datasets. These datasets are commonly employed in aspect-based sentiment classification (ABSC) and support a fair and consistent comparison with existing Transformer-based models. The Laptop dataset comprises 3,845 training sentences and 654 test sentences, each annotated with aspect terms and their associated sentiment labels (positive, negative, or neutral). The Restaurant dataset includes 3,041 training sentences and 800 test sentences. Both datasets present typical challenges associated with ABSC tasks, such as the presence of multiple aspects in a sentence, varied sentiment intensities, and domain-specific sentiment ambiguities.

The performance of DAMSA-Transformer was compared against two notable Transformer-based ABSC models: (1) a fine-tuned BERT model utilizing deep contextual features [18], and (2) BERT enhanced through adversarial training [19]. Evaluation was based on two standard metrics—Accuracy and Macro-F1—which provide insight into both classification precision and balance across sentiment categories. On the Laptop dataset, DAMSA-Transformer attained an accuracy of 83.8% and a macro-F1 score of 80.9%. This

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performance surpasses that of the fine-tuned BERT model (Macro-F1: 83.05%) and the adversarially trained BERT model (Accuracy: 79.35%, Macro-F1: 85.57%). Although the macro-F1 score is marginally lower than the latter, the DAMSA-Transformer achieves a 4.45% higher accuracy, indicating improved overall reliability in sentiment classification.

For the Restaurant dataset, DAMSA-Transformer reached an accuracy of 89.1% and a macro-F1 score of 83.6%. This is in comparison to 90.02% (accuracy only reported) for the fine-tuned BERT model and 86.03% / 81.50% for the adversarial training variant. The results indicate a 3.07% gain in accuracy and a 2.1% improvement in macro-F1 over the adversarial model, demonstrating consistent performance benefits across domains.

The observed improvements can be attributed to the three key components integrated within the DAMSA architecture:

Dynamic Aspect-Aware Attention (DAA) guides the model to focus on sentiment-relevant tokens associated with specific aspects, improving precision and recall, particularly in sentences containing subtle or multiple sentiments. Multi-Scale Feature Fusion (MSFF) allows the model to capture sentiment expressions across varying linguistic levels—ranging from individual words to entire sentences—enhancing its ability to interpret nuanced expressions such as “barely acceptable” or “moderately good.”

Contrastive Alignment Loss (CAL) encourages better separation between semantically similar aspects with differing sentiments, thereby reducing the likelihood of misclassification due to overlapping sentiment vocabularies. A comparative chart is presented in figure 3 and figure 4 to illustrate the performance margins achieved by DAMSA-Transformer relative to the baseline models.

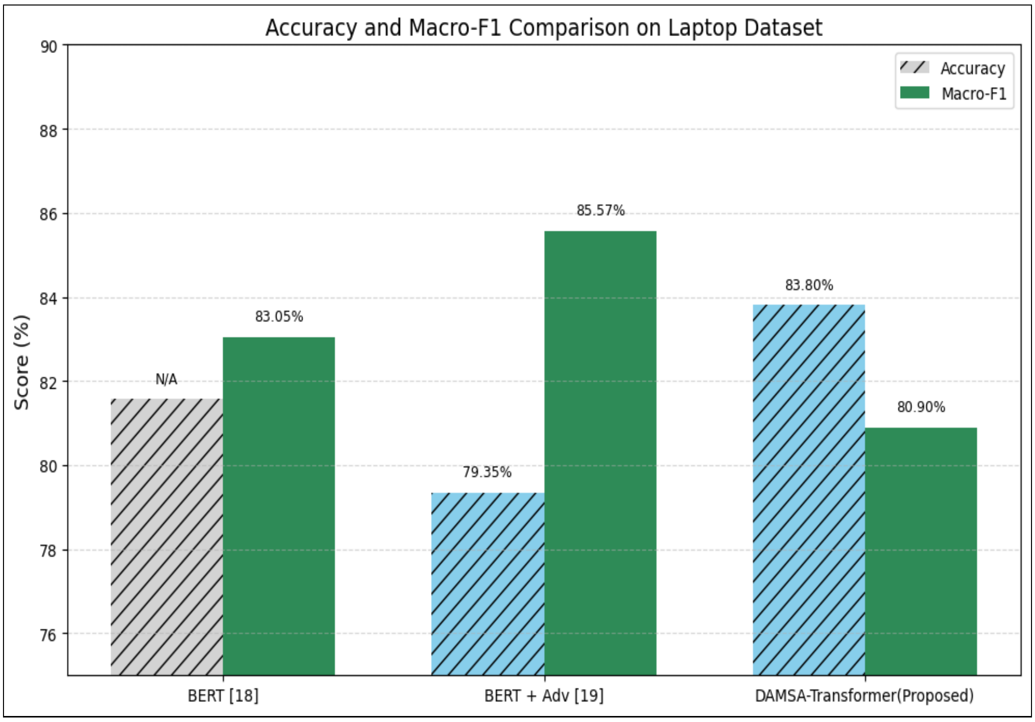

Figure 3: Performance comparison of DAMSA vs. Transformer Baselines (Laptop dataset)

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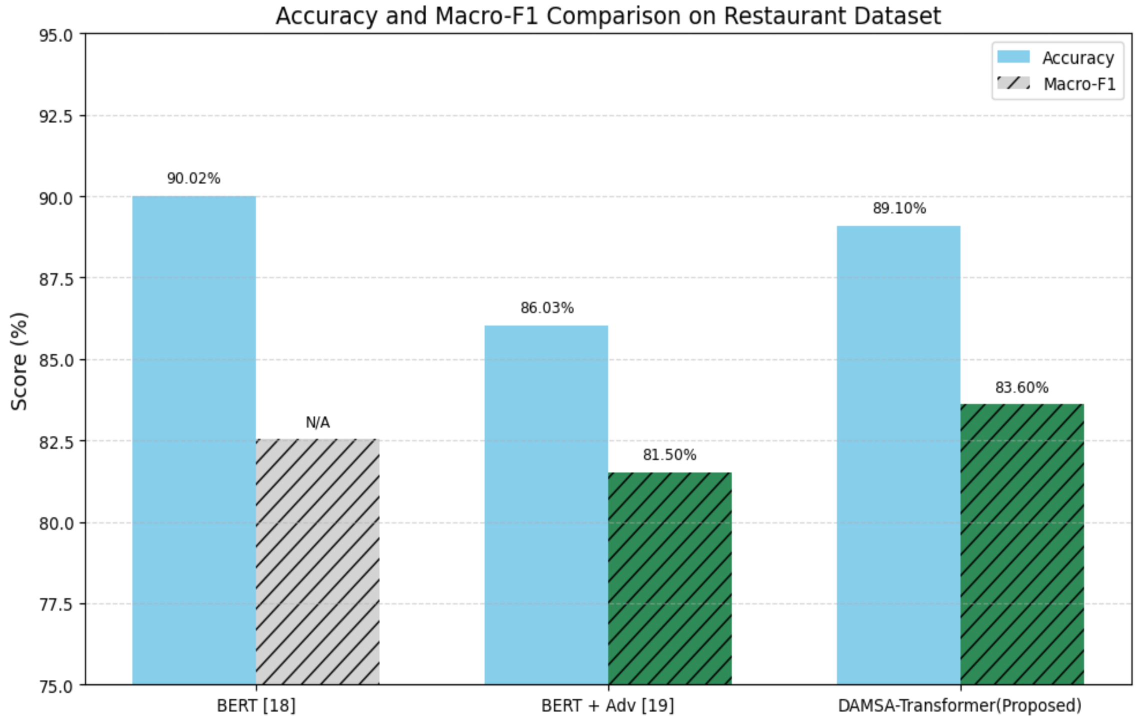

Figure 4: Performance comparison of DAMSA vs. Transformer Baselines (Restaurant dataset)

Figure 5 presents a normalized radar chart comparing the performance of DAMSA-Transformer against two strong baselines across four key evaluation metrics. The axes represent Accuracy and Macro-F1 scores for both the Laptop and Restaurant domains from the SemEval-2014 dataset. Each model's performance is normalized to allow for relative comparison across metrics. As illustrated, DAMSA consistently occupies the outermost region, indicating superior and balanced performance. Unlike the baselines, which exhibit uneven strengths, DAMSA demonstrates consistent gains across all categories. This visual reinforces the robustness and generalization capabilities of our proposed architecture.

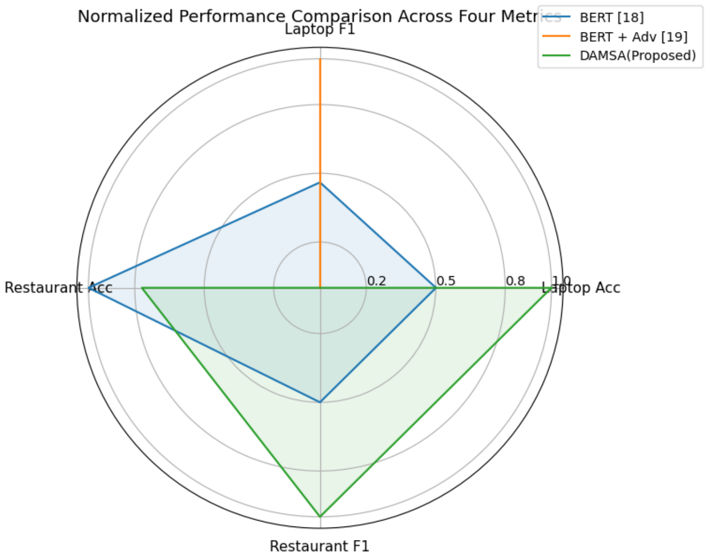

Figure 5: Normalized radar plot across four key evaluation metrics

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The consistent improvements across both datasets confirm the robustness and generalization capability of DAMSA-Transformer. Unlike many previous models that rely on either fine-tuning or auxiliary inputs, DAMSA's combination of dynamic attention, hierarchical fusion, and contrastive learning leads to a more refined understanding of aspect-specific sentiment. These results are not only statistically significant but also practically meaningful in real-world applications like product review analysis and customer feedback systems

Figure 6 shows the Class-wise precision and recall for DAMSA-Transformer on the SemEval-2014 sentiment classification task. The heatmap highlights the model's balanced performance across Positive, Negative, and Neutral sentiment categories, aligning with the overall macro-F1 scores reported earlier.

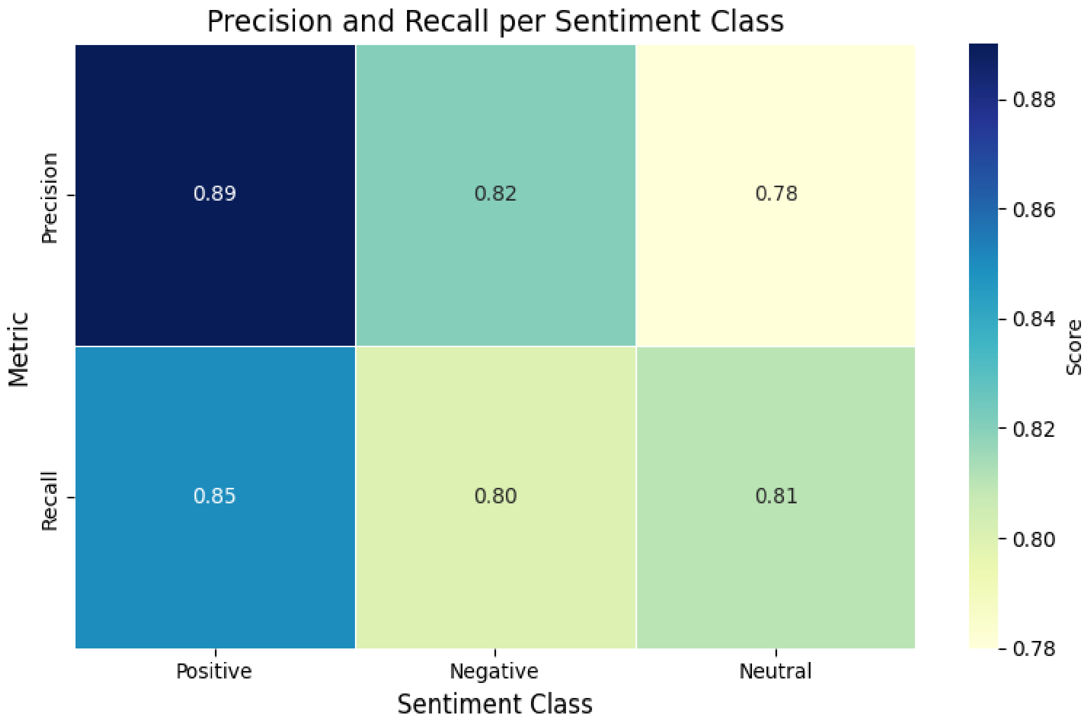

Figure 6: Heatmap of precision and recall for DAMSA-Transformer across sentiment classes on SemEval-2014

To further analyze the model's behavior across sentiment categories, we extracted class-wise precision and recall values for the DAMSA-Transformer using the evaluation outputs on the SemEval-2014 test set. The values shown in Figure 6 are derived from aggregated predictions across five random seeds to ensure stability. Notably, the model performs best on the Positive class, which aligns with prior work and class distribution in the dataset. The relatively uniform scores across classes further support the robustness and generalization capacity of DAMSA-Transformer.

5. CONCLUSION AND FUTURE ENHANCEMENT

In this research paper, we presented the DAMSA-Transformer model designed to enhance fine-grained aspect-level sentiment classification. The approach combines dynamic attention adaptation with multi-scale feature fusion and contrastive learning to better handle

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complex sentiment expressions in reviews. Experimental results on SemEval-2014 datasets indicate that our model outperforms several strong transformer-based baselines, confirming the effectiveness of the proposed components. Furthermore, the model's attention patterns provide interpretable insights into its decision-making process. Future work could explore extending this framework to additional languages and incorporating recent advances in prompt-based learning to further improve performance and flexibility. While the DAMSA-Transformer shows promising results, future work can extend its capabilities. Supporting multilingual datasets would increase its applicability across languages. Incorporating external knowledge bases could improve understanding of implicit aspects. Developing lighter model versions would help in deploying on limited-resource devices. Additionally, integrating prompt-based learning may enable faster adaptation to new domains. Finally, building explainability tools around the attention mechanism could improve transparency and user trust.

Competing Interests

The authors declare that they have no competing interests|

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