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# MAMS-Enriched: Structural and Graph-Based Representations for Aspect-Based Sentiment Analysis

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Abstract—Aspect-Based Sentiment Analysis (ABSA) re-mains challenging in sentences containing multiple aspects with conflicting sentiment polarities, where models must correctly associate opinion expressions with their corresponding targets. Although recent ABSA research has predominantly focused on increasingly complex neural architectures, comparatively limited attention has been directed toward the structural quality and linguistic richness of dataset representations. Ex-isting benchmark datasets, including MAMS, provide aspect-level sentiment annotations but lack explicit syntactic and relational information required for structure-aware learning and interpretable graph-based modeling. This paper introduces MAMS-Enriched, a syntax-enhanced and graph-oriented ex-tension of the MAMS dataset for Aspect-Based Sentiment Analysis. The proposed resource augments each sentence with token-level Part-of-Speech (POS) tags, dependency relations, aspect-relative distance features, lexical sentiment priors, and aspect-indicator representations generated through an auto-mated enrichment pipeline integrating spaCy, VADER, and BERT-based token alignment. Each aspect term is transformed into an independent graph instance with bidirectional depen-dency connectivity, enabling direct compatibility with graph-learning frameworks such as PyTorch Geometric. To evaluate the effectiveness of the enriched resource, experiments were conducted using lightweight BiLSTM and Graph Convolutional Network (GCN) models under enriched and ablation settings. Experimental results demonstrate that the enriched dataset improves representation quality and predictive performance. In particular, BiLSTM accuracy improved from 47.18% to 67.12%, corresponding to an absolute improvement of 19.94 percentage points after enrichment. Ablation analysis further confirms the importance of dependency structure, where removal of dependency relations reduced GCN accuracy from 52.25% to 46.41%. Multi-seed evaluation additionally demonstrates con-sistent performance stability and reproducibility across random initializations. The findings demonstrate that direct structural enrichment significantly improves dataset quality for aspect-level sentiment analysis while enhancing interpretability, graph compatibility, and experimental consistency. The proposed resource provides a reusable foundation for future research in syntax-aware and graph-based ABSA systems.

Keywords— Aspect-Based Sentiment Analysis, ABSA Datasets, Dependency Parsing, Graph Neural Networks, Graph Convolutional Networks, Syntax-Aware Sentiment Analysis, Structural Enrichment, PyTorch Geometric

## I. Introduction

Aspect-Based Sentiment Analysis (ABSA) aims to iden-tify sentiment polarity toward specific target aspects within a sentence rather than assigning a single sentiment label to the entire text. For example, in the sentence “The food was excellent but the service was terrible” the sentiment associated with ”food” is positive, whereas the sentiment toward ”service” is negative. This fine-grained sentiment understanding is particularly important in do-mains such as customer review analysis, recommendation systems, and opinion mining applications [1], [2].

Recent advances in deep learning and transformer-based language models have improved ABSA performance. Architectures based on BERT and graph neural net-works have demonstrated strong capability in learning contextual sentiment representations [3]–[5]. Transformer-based and attention-driven architectures have additionally demonstrated strong effectiveness in fine-grained senti-ment modeling [24], [26], [31], [33]. In particular, syntax-aware Graph Convolutional Networks (GCNs) have shown that dependency structures can improve relational rea-soning between aspect terms and opinion expressions [6], [7]. However, despite rapid architectural progress, most existing benchmark datasets still provide only aspect-level polarity annotations while lacking syntactic and relational information required for structure-aware learning.

Widely used datasets such as SemEval-2014 Task 4 and the MAMS benchmark provide valuable resources for eval-uating ABSA systems [8], [9]. Nevertheless, these datasets do not include token-level Part-of-Speech (POS) tags, dependency structures, lexical sentiment priors, or graph-ready representations. Consequently, models must implic-itly infer linguistic structure during training, increasing computational complexity and reducing interpretability, particularly in adversarial multi-aspect settings where conflicting sentiment polarities coexist within the same sentence [10], [11].

Recent studies increasingly emphasize the importance of syntactic structure in improving aspect-level senti-ment reasoning. Dependency-guided approaches, graph attention networks, and syntax-aware transformers have demonstrated that linguistic structural information im-proves robustness and interpretability in ABSA tasks [6], [12]–[15]. However, most prior work remains strongly model-centric, focusing on architectural innovation while less attention has been given to enriching the dataset representation itself.

This work adopts a data-centric perspective by in-troducing MAMS-Enriched, a syntax-enhanced extension designed for graph-based learning of the MAMS dataset. The proposed resource augments the original corpus with token-level POS tags, dependency relations, aspect-relative distance encoding, lexical sentiment scores, and aspect-indicator representations generated through an au-tomated enrichment pipeline integrating spaCy, VADER, and BERT-based token alignment [3], [16]. Each aspect term is converted into an independent graph instance with bidirectional dependency edges, enabling direct compat-ibility with graph-learning frameworks such as PyTorch Geometric.

To evaluate the effectiveness of the enriched dataset, experiments were conducted using lightweight BiLSTM and Graph Convolutional Network (GCN) models un-der enriched and ablation settings. Experimental results demonstrate that enriched representations improve repre-sentation quality and downstream sentiment classification performance. Multi-seed evaluation additionally confirms the experimental consistency and stability of the proposed enrichment framework.

The main contributions of this work are summarized as follows:

1. A syntax-enhanced extension of the MAMS dataset incorporating POS tags , dependency relations, lex-ical sentiment priors, aspect-distance encoding, and aspect-indicator features.
2. An automated enrichment pipeline integrating syn-tactic parsing, lexical sentiment analysis, contextual embedding alignment, and graph construction.
3. Experimental validation demonstrating substantial performance improvements after structural enrich-ment, including multi-seed reproducibility analysis and ablation studies.
4. A reusable dataset representation supporting dependency-based graph learning for future ABSA research

## II. Related Work

### A. Aspect-Based Sentiment Analysis Datasets

Benchmark datasets have played a central role in the development of Aspect-Based Sentiment Analysis (ABSA) systems. Early resources such as the SemEval-2014 Task4 restaurant and laptop datasets established standard eval-uation settings for aspect extraction and sentiment classi-fication tasks [8]. Subsequent datasets, including Twitter-based sentiment corpora and restaurant review collections, expanded ABSA evaluation toward more challenging real-world scenarios [17], [18].

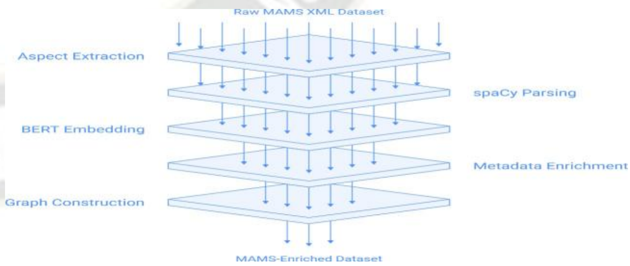


Fig. 1. Overall structural enrichment pipeline for MAMS-Enriched.

Among existing resources, the MAMS dataset intro-duced a more difficult adversarial setting in which multiple

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aspects with conflicting sentiment polarities coexist within the same sentence [9]. This property significantly increases the complexity of aspect-level sentiment reasoning and exposes limitations in models that rely primarily on surface-level semantic correlations.

Recent multilingual and dimensional ABSA resources further indicate that dataset design remains an active re-search direction, especially for improving domain coverage, label expressiveness, and benchmark reliability [44], [45]. Despite their importance, most ABSA datasets provide only aspect terms and sentiment labels while omitting syntactic and relational information. As a result, graph-based and syntax-aware models must independently re-construct linguistic structure during training, increasing

preprocessing overhead and reducing reproducibility.

B. Syntax-Aware Sentiment Modeling

Recent research has demonstrated that syntactic struc-ture plays an important role in aspect-level sentiment rea-soning. Dependency-based approaches improve the ability of models to capture long-range relationships between aspect terms and opinion expressions [6], [19].

Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) have become widely adopted for syntax-aware ABSA because dependency trees can naturally be represented as graph structures [4], [5]. Several studies have shown that dependency-guided graph propagation improves relational reasoning and reduces sentiment ambiguity in multi-aspect sentences [6], [7], [12]. Hybrid architectures integrating contextual embeddings with graph-based representations have also demonstrated strong performance improvements. Additional studies incorporating graph attention, transformer fusion, and syntax-enhanced contextual learning further reinforce the importance of structural representations in ABSA [25], [34], [35], [50]. Syntax-aware transformer frameworks and relation-aware graph attention mechanisms further high- light the importance of linguistic structure in improv-ing interpretability and sentiment disambiguation [13], [14]. However, most existing approaches remain primar-ily model-centric, emphasizing architectural complexity rather than improving the dataset representation itself.

Recent syntax-enhanced and dependency-aware ABSA studies continue to demonstrate the importance of struc-tural modeling in aspect-level sentiment classification [46], [47].

C. Data-Centric and Structural Enrichment Approaches Recently, increasing attention has been directed toward

data-centric AI methodologies that emphasize improving dataset quality and representation instead of continuously increasing model complexity. Within ABSA, this perspec-tive motivates the integration of linguistic, positional, and lexical information directly into token representations.

Several studies have explored the incorporation of ex-ternal knowledge sources such as sentiment lexicons, syn-tactic priors, and dependency-aware attention mechanisms [20], [14]. Recent works have also explored data augmenta-tion, auxiliary sentence construction, and prompt-guided graph attention mechanisms for improving aspect-level sentiment learning [32], [49]. Other approaches integrate structural features through auxiliary learning tasks or multi-view architectures [21]. Although these methods improve sentiment reasoning, they often require increas-ingly complex training pipelines and large computational resources.

In contrast, structurally enriched datasets remain com-paratively underexplored in ABSA research. Existing benchmarks rarely provide graph-ready representations, token-level syntactic annotations, or deterministic prepro-cessing pipelines compatible with graph-learning frame-works.

The present work addresses this gap by introducing a reusable enriched version of the MAMS dataset that explicitly integrates syntactic, positional, lexical, and aspect-centric information within a unified representation framework.

Unlike prior syntax-aware ABSA studies that primarily emphasize architectural innovation, the proposed work focuses on dataset-level structural enrichment through reusable graph-oriented representations. This data-centric perspective improves experimental consistency while re-ducing preprocessing redundancy across downstream ABSA experiments.

III. Dataset Construction and Enrichment Framework

A. Source Dataset

The proposed resource is constructed using the Multi-Aspect Multi-Sentiment (MAMS) dataset, a benchmark specifically designed for challenging Aspect-Based Senti-ment Analysis scenarios [9]. Unlike conventional ABSA datasets, MAMS ensures that each sentence contains mul-tiple aspects with conflicting sentiment

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polarities, thereby

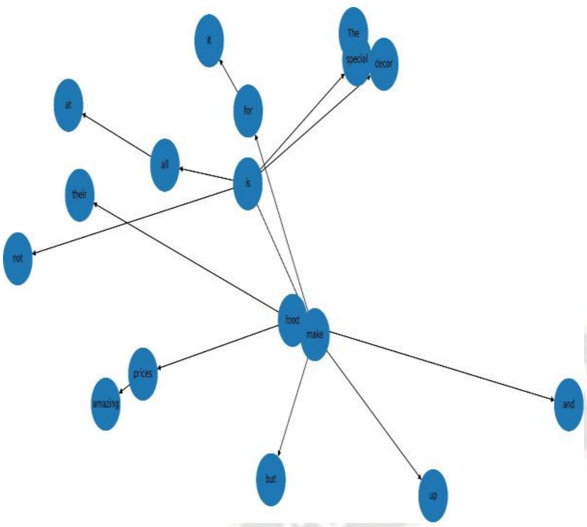


Fig. 2. Dependency-based graph representation generated from an enriched MAMS sentence.

creating adversarial conditions for aspect-level sentiment classification.

Each instance in the corpus contains sentence text, aspect terms, character-level aspect spans, and sentiment polarity labels. The dataset consists of restaurant-domain reviews annotated using three sentiment categories: positive, neutral, and negative. Following preprocessing, the corpus used in this study contains 4,297 training sentences, 500 validation sentences, and 500 test sentences.

Although MAMS provides high-quality aspect annotations, it lacks structural information such as dependency relations, Part-of-Speech (POS) tags, lexical sentiment priors, and graph-compatible representations. Consequently, models must implicitly infer these relationships during training, increasing preprocessing complexity while limiting interpretability.

### B. Motivation for Structural Enrichment

Recent syntax-aware ABSA studies demonstrate that linguistic structure improves aspect–opinion association and relational reasoning [6], [7], [12]. However, most benchmark datasets provide only raw text and sentiment labels, forcing downstream models to repeatedly reconstruct syntactic structure during experimentation.

This study adopts a data-centric perspective by embedding structural information directly into the dataset representation itself. The objective is to reduce preprocessing variance, improve reproducibility, and provide graph-oriented representations that can be readily utilized by both sequential and graph-based learning frameworks.

The enrichment process integrates POS tags, dependency relation encoding, aspect-relative distance weighting, lexical sentiment priors, and aspect-indicator representations within unified token-level features.

### C. Linguistic Annotation Pipeline

The enrichment process follows a deterministic multi-stage pipeline illustrated in Fig.1.

1) XML Parsing: The original XML files are parsed to extract sentence text, aspect spans, and sentiment polarity annotations.

2) Syntactic Processing: Sentences are processed using spaCy to generate tokenization, POS tags, dependency relations, and syntactic head indices. Each token is as-sociated with its textual content, POS label, dependency relation, and character-level position.

3) Dependency Graph Construction: Tokens represent graph nodes while dependency relations form graph edges. For every dependency edge (u, v), an inverse edge (v, u) is additionally introduced to support bidirectional message propagation during graph learning.:

4) Contextual Embedding Alignment: Semantic token representations are obtained using BERT embeddings [3]. Since BERT utilizes subword tokenization while spaCy generates word-level dependency structures, di-rect integration produces alignment inconsistencies. To address this issue, token-level alignment is performed using character-offset mappings. Subword embeddings corresponding to the same spaCy token are averaged to produce unified token-level semantic representations.

5) Lexical Sentiment Injection: Each token is assigned a lexical sentiment prior using the VADER sentiment analyzer [42]. Compound polarity scores provide lightweight lexical grounding that complements contextual semantic representations. Lexicon-based sentiment priors have previously demonstrated effectiveness in improving sentiment-aware contextual representations [37], [42].

### D. Structural Feature Representation

Each token is represented using a structurally enriched feature vector combining semantic and syntactic information.

The representation combines contextual embeddings, POS identifiers, dependency identifiers, aspect-relative distance scores, lexical sentiment priors, and aspect-indicator values within a unified token-level feature vector.

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Aspect-relative distance weighting is computed using:

$$f(d_i) = \frac{1}{|i - m| + 1}$$

TABLE I

Statistics of the MAMS-Enriched Dataset

| Attribute | Value |
|---|---|
| Training sentences | 4,297 |
| Validation sentences | 500 |
| Test sentences | 500 |
| POS categories | 17 |
| Dependency relation types | 45 |
| Sentiment classes | 3 |
| Graph structure | Bidirectional dependency graph |
| Storage format | PyTorch Geometric (.pt) |

E. Aspect-Specific Graph Generation

A major characteristic of the proposed framework is the creation of independent graph objects for every aspect term within a sentence. Rather than processing an entire sentence as a single sentiment instance, the framework generates aspect-specific graph representations that local-ize sentiment reasoning around the target aspect.

This design substantially reduces sentiment leakage in adversarial multi-aspect sentences where conflicting opinion expressions coexist. Each graph object contains a node feature matrix, dependency connectivity structure, and sentiment label. The generated graph structures are fully compatible with PyTorch Geometric [41] and related graph-learning libraries.Fig. 2 presents an example dependency-based graph representation constructed from an enriched MAMS sentence.

F. Dataset Statistics and Resource Serialization

The framework preserves the original corpus while expanding structural representation quality. Table. I sum-marizes the final dataset characteristics.

To improve reproducibility and eliminate preprocessing variance, all graph objects are serialized into reusable .pt files containing precomputed embeddings, dependency graphs, and structural metadata. The resulting resource provides deterministic preprocessing, reusable structural annotations, and direct compatibility with graph-learning frameworks.

IV. Experimental Setup and Validation

A. Evaluation Objective

The experimental evaluation was designed to determine whether explicit structural enrichment improves aspect-level sentiment classification performance independent of architectural complexity. Rather than proposing a novel neural architecture, the experiments focus on validating the effectiveness of the enriched dataset representation itself.

where i denotes the token index and m represents the midpoint of the target aspect span. This weighting mechanism assigns larger importance to tokens located closer to the target aspect while gradually reducing the influence of distant tokens.

Distance-aware weighting strategies have previously demonstrated effectiveness in localizing aspect-specific contextual information in ABSA tasks [22], [23].

Two primary research questions are investigated:

1. Does structural enrichment improve performance in lightweight sequential models lacking explicit syntactic awareness?

2. Which structural components contribute most sig-nificantly to aspect-level sentiment reasoning?

TABLE II

Training Parameters

| Parameter | Value |
|---|---|
| Optimizer | Adam |
| Learning Rate | 0.0001 |
| Batch Size | 32 |
| Loss Function | Cross-Entropy |
| Epochs | 30 |
| Hardware | NVIDIA GPU |

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To answer these questions, experiments were conducted using both sequential and graph-based learning settings under enriched and ablation configurations.

B. Experimental Models

A lightweight BiLSTM model was used as the sequential baseline, while a Graph Convolutional Network (GCN) was employed to validate compatibility with dependency-based graph learning.

Each token acts as a graph node, while dependency relations form bidirectional graph edges. The graph representation enables aspect–opinion interaction modeling through explicit structural connectivity.

The experiments primarily validate the structural qual-ity and graph compatibility of the proposed dataset rather than introducing architectural innovation.

C. Experimental Configurations

Three major evaluation settings were constructed:

1) BiLSTM_Raw_105: The sequential baseline utilizes semantic token representations without structural enrich-ment.

2) BiLSTM_Enriched_105: The same BiLSTM archi-tecture is trained using syntax-enhanced token represen-tations incorporating syntactic and lexical metadata.

3) GCN_Enriched_105: The GCN model operates over dependency-based graph structures generated from the enriched dataset.

To further analyze feature contribution, three ablation configurations were evaluated:

GCN_No_Syntax removes syntactic and positional metadata, GCN_No_POS removes only Part-of-Speech identifiers, and GCN_No_DEP removes dependency relation encoding while retaining the remaining structural features. These experiments isolate the relative contribution of individual enrichment components.

D. Training Configuration

All experiments were implemented using PyTorch and PyTorch Geometric under identical training settings to ensure fair comparison.

Dropout regularization and label smoothing were additionally employed in selected experiments to improve generalization under adversarial sentiment conditions.

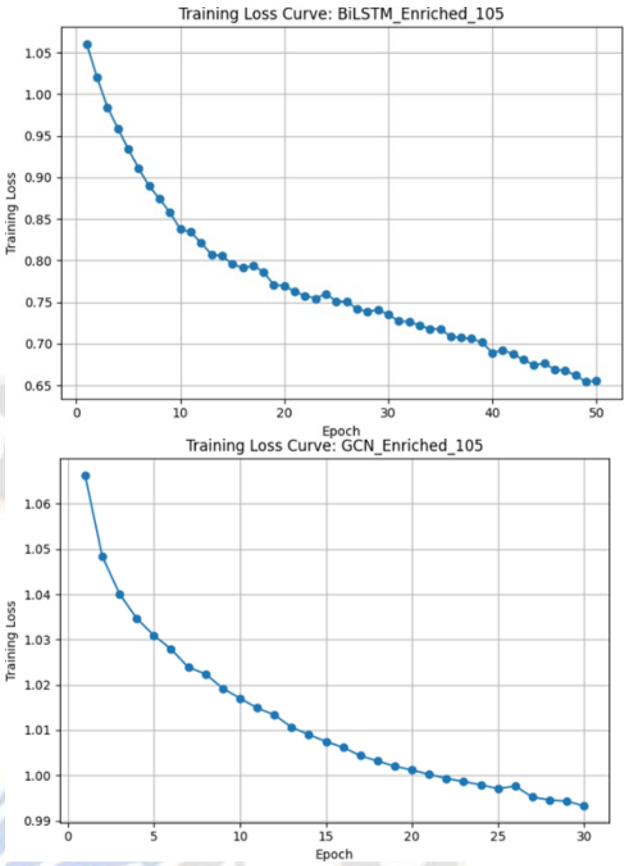


Fig. 3. Training loss curves for (top) BiLSTM and (bottom) GCN models using the enriched MAMS representation.

E. Multi-Seed Evaluation

To ensure experimental reliability and reduce randomness-induced variance, all major experiments were evaluated across multiple random seeds. The reported results correspond to the mean and standard deviation obtained from repeated executions. Multi-seed evaluation improves statistical stability and provides stronger evidence regarding the effectiveness of the proposed enrichment framework. Performance was evaluated using Accuracy and Macro-F1 score. Multi-seed evaluation has increasingly become standard practice for improving reproducibility and reducing variance in neural NLP experiments [43], [44].

Macro-F1 was included because adversarial multi-aspect sentiment datasets frequently exhibit class imbalance and polarity ambiguity.

F. Visualization and Structural Analysis

Several visualization artifacts were generated to analyze structural characteristics and model behavior, including dependency-tree visualizations, graph construction diagrams, training loss curves, confusion matrices, and

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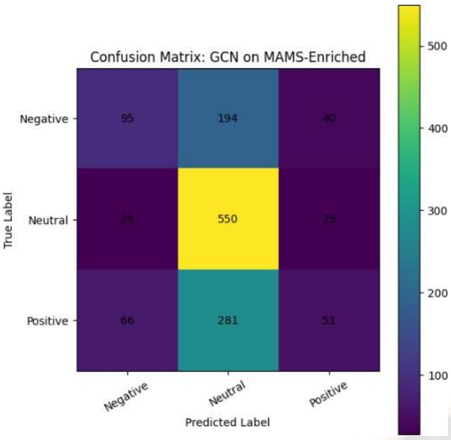


Fig. 4. Confusion Matrix obtained from the GCN evaluation on MAMS-Enriched.

architecture representations. These visualizations provide interpretability regarding syntactic connectivity, graph topology, convergence stability, and class-level prediction behavior. Fig. 3 and Fig. 4 present the training loss and confusion matrix obtained during evaluation. Visualization-based interpretability has become increasingly important in graph-based NLP systems and syntax-aware sentiment analysis research [26], [36]

## V. Results and Discussion

### A. Quantitative Performance Analysis

Table. III summarizes the averaged multi-seed evaluation results obtained under enriched and ablation settings. The sequential baseline trained using raw semantic representations achieved only 47.18% accuracy and 0.3000 Macro-F1, indicating that lightweight sequence models struggle under adversarial multi-aspect sentiment condi-tions. After incorporation of the enriched features, the same BiLSTM architecture improved substantially to 67.12% accuracy and 0.6431 Macro-F1, corresponding to an absolute improvement of 19.94 percentage points in

accuracy.

These findings suggest that explicit enrichment improves representation quality even without increasing architectural complexity.

### B. Contribution of Structural Features

The enrichment process integrates syntactic, positional, lexical, and aspect-centric information directly into token representations. The strong improvement observed in the enriched BiLSTM configuration indicates that structural metadata compensates for the limitations of purely sequential contextual learning. Similar observations regarding the importance of structural and contextual feature fusion have also been reported in recent transformer-enhanced ABSA frameworks [36], [47].

The results further suggest that enriched represen-tations improve aspect–opinion alignment in sentences containing conflicting sentiment polarities. Dependency relations and aspect-relative distance weighting help localize sentiment propagation toward the correct target aspect while reducing interference from unrelated opinion expressions.

In addition, the relatively small standard deviation values across repeated executions confirm that the enrichment pipeline produces stable and reproducible performance gains independent of random initialization.

### C. Ablation Analysis

To evaluate the contribution of individual structural components, ablation experiments were conducted under multiple feature-removal settings. Fig. 5 presents the performance variation observed under enriched and feature-removal configurations.

Among all configurations, removing dependency information produced the largest performance degradation. The GCN_No_DEP setting reduced accuracy to 46.41% and Macro-F1 to 0.2841, substantially lower than the fully enriched graph representation.

Similarly, removing the entire syntactic feature suite in the GCN_No_Syntax configuration reduced performance to 46.26% accuracy and 0.2896 Macro-F1. These results indicate that dependency-aware structural connectivity is the primary contributor to effective fine-grained sentiment understanding.

However, removing only POS information produced comparatively minor degradation. The GCN_No_POS configuration achieved 52.02% accuracy, remaining close to the fully enriched setting. This finding indicates that dependency connectivity plays a more influential role in relational sentiment modeling than isolated categorical POS identifiers.

Overall, the ablation analysis identifies dependency structure as the most influential component within the proposed enrichment framework.

### D. Training Stability and Visualization Analysis

Training curves remained stable throughout optimization and showed consistent convergence behavior across experimental settings. Prior studies involving hierarchical

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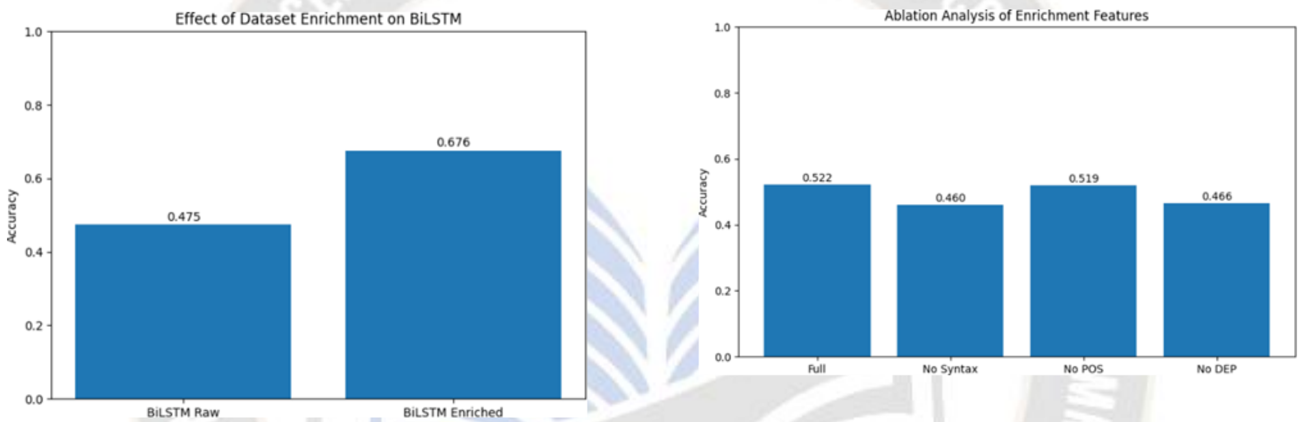
attention, graph convolution, and tree-structured semantic modeling have similarly reported the importance of structurally coherent representations for stable optimization behavior [27]–[30]. Loss values decrease consistently without significant oscillation, indicating that the enriched representations provide informative and structurally coherent learning signals.

Confusion matrix analysis further shows improved separation between positive and negative sentiment classes after enrichment. Most remaining ambiguity occurs within the neutral class, which is consistent with the inherent difficulty of neutral sentiment prediction in adversarial ABSA datasets.

TABLE III

Performance Comparison Across Enriched and Ablation Configurations

| Model | Accuracy | Macro-F1 |
|---|---|---|
| BiLSTM_Raw_105 | 0.4718 ± 0.0025 | 0.3000 ± 0.0068 |
| BiLSTM_Enriched_105 | 0.6712 ± 0.0043 | 0.6431 ± 0.0058 |
| GCN_Enriched_105 | 0.5225 ± 0.0031 | 0.4134 ± 0.0057 |
| GCN_No_Syntax | 0.4626 ± 0.0037 | 0.2896 ± 0.0181 |
| GCN_No_POS | 0.5202 ± 0.0011 | 0.4061 ± 0.0009 |
| GCN_No_DEP | 0.4641 ± 0.0016 | 0.2841 ± 0.0040 |




(a) BiLSTM Ablation Analysis

(b) GCN Ablation Analysis

Fig. 5. Ablation analysis across enriched and feature-removal configurations for BiLSTM and GCN models.

The dependency-tree and graph visualizations additionally confirm that aspect–opinion relationships are successfully encoded through bidirectional syntactic connectivity. Together, the experimental findings demonstrate that the proposed enrichment framework improves predictive performance while also enhancing structural transparency, graph compatibility, and reproducibility for Aspect-Based

Sentiment Analysis research.

## VI. Conclusion and Future Work

This paper introduced MAMS-Enriched, an enriched resource and graph-oriented extension of the MAMS dataset for Aspect-Based Sentiment Analysis. The proposed framework augments conventional aspect-level sentiment data with token-level syntactic, positional, lexical, and aspect-centric metadata to generate reusable graph-ready representations suitable for both sequential and graph-based learning.

The enrichment pipeline integrates Part-of-Speech tags, dependency relations, aspect-relative distance encoding, lexical sentiment priors, and aspect-indicator representations within a unified preprocessing framework. In addition, a BERT–spaCy token alignment mechanism was introduced to ensure consistency between contextual embeddings and dependency-based graph structures.

Experimental validation demonstrated that the enriched representation improves representation quality under adversarial multi-aspect sentiment conditions. Multi-seed evaluation showed that the enriched BiLSTM configuration outperformed the raw semantic baseline, while ablation analysis identified dependency relations as the most influential structural component. The generated graph representations additionally proved compatible with dependency-aware learning frameworks such as Graph

Convolutional Networks.

The proposed resource improves dataset usability and reproducibility for future syntax-aware ABSA research. Overall, the findings demonstrate that explicit structural enrichment represents an effective data-centric strategy for improving robustness and interpretability in aspect-level sentiment analysis. Recent surveys further indicate that reproducibility, structural interpretability, and mul-tilingual generalization remain important open challenges in ABSA research [46], [48].

Future work will focus on extending the enrichment framework to additional ABSA domains, including laptops and product reviews, as well as multilingual and code-mixed sentiment datasets. Further improvements may include dynamic dependency refinement, discourse-aware graph construction, and integration with lightweight ex-plainability frameworks for interpretable sentiment rea-soning. The proposed resource may also support future research on reproducible and structurally grounded graph-

based sentiment analysis.

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