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Aspect-based Sentiment Analysis using Hierarchical Attention Networks

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Abstract: - The proliferation of user contributed content in e-commerce, social media, and review sites have increased the demand for more accurate approaches to polarity detection. This need is met by Aspect-Based Sentiment Analysis (ABSA) that provides sentiments related to certain aspects of an entity which is useful for e-commerce, healthcare, and social media analysis. In this work, we propose the use of Hierarchical Attention Networks (HAN) for ABSA due to their ability to model at multiple granularities to enhance aspect-level sentiment classification. The presented framework improves position-sensitive embeddings and uses multi-head attentions to boost the scalability, interpretability, and performance of the cased model on multilingual and domain-shifted datasets. On various datasets, the proposed method showed better accuracy (93%), precision (92%), and F1-score (92%) than conventional methods. The model also performs well in dealing with implicit features and subtle sentiment patterns, which is further accompanied by attention visualization for better understanding. This research establishes new standards in ABSA, solving scalability and domain adaptability issues and opening the way to its application in large-scale sentiment analysis.

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Keywords: Aspect-Based Sentiment Analysis (ABSA), Hierarchical Attention Networks (HAN), Sentiment Classification, Position-Aware Embeddings, Multi-Head Attention, Interpretability.

I. INTRODUCTION

The tremendous increase in the volume of user generated content in e-commerce sites, social media and review sites has provided a vast potential for sentiment analysis. Of the many branches of sentiment analysis, Aspect-Based Sentiment Analysis (ABSA) has received much attention because it can determine sentiments towards particular aspects of an entity. Such detailed analysis is useful especially when it comes to the utilization of the output in applications such as product reviews where customer opinions on quality, price or service can make a big difference. Nevertheless, due to the high degree of language complexity and the necessity to analyze aspect-oriented attitudes, ABSA becomes a rather elaborate task.

Most of the prior studies in sentiment analysis fail to capture the sentiments in multi-faceted texts, where sentiments towards different aspects may differ. For example, a restaurant review might like the food but didn't like the service. Solving such complexities requires the creation of sophisticated models that can help to distinguish between these sentiments and assign them to their components. Of the many discussed techniques for this purpose, Hierarchical Attention Networks (HANs) appear to be a viable solution capable of modeling the text data at clients' word, sentences and documents level to capture the interrelations between aspects and sentiments.

ABSA has used HANs because they can attend to context at different levels of abstraction. Cheng et al. (2017) proposed the Hierarchical Attention Network (HEAT) for aspect-level sentiment classification that demonstrates the improvements by incorporating hierarchical structures of text data [1]. Based on this approach, other improvements were made to the hierarchical attention mechanism, which plays an important role in extracting aspect level sentiments.

Based on this, researchers have proposed several improvements to the hierarchical attention architectures. In order to overcome the weaknesses of GMP and LDL, Cai et al. (2020) has used Hierarchical Graph Convolutional Networks (HGCN) for reasoning multiple levels of aspects and their contexts to enrich the granularity of sentiment classification [2]. To better align sentiment expressions with aspects, Li et al. (2018) proposed a position aware network in a hierarchical attention structure [3].

Subsequent developments in memory networks and convolutional neural networks (CNNs) have enriched ABSAbased research. In sentiment classification, Chen et al. (2021) preserved contextual information using hierarchical multi head attention within memory networks [4]. Similarly, Lou et al. (2020) combine CNNs with multi level hierarchical attention, which has been known to achieve the best performance in ABSA tasks [5]. The flexibility of hierarchical models in capturing the sentiment patterns is shown with these innovations.

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But there are still some problems to be solved in the field of ABSA system, like how to improve the scalability and interpretability of the system. Hierarchical attention mechanisms are shown to be useful for fine grained sentiment analysis, but are computationally expensive (Chauhan et al. 2024) [6]. To enable the use of ABSA systems in practical, big scale applications, these limitations need to be overcome.

On the top, the effect of multiple languages and areas has to be taken into account in models. To prove that the hierarchical architectures can be tailored to overcome both linguistic and specific domain challenges, Lakizadeh and Zinaty (2021) presented a hierarchical attention based framework that was shown to improve performance on various datasets. Furthermore, Liu et al. (2018) gave more evidence that content attention mechanism is effective to capture aspect level sentiment and it is important to use attention in ABSA [8]. However, these approaches are not very effective in generalizing across domains and thus, more research is needed to discover scalable and robust solutions.

In recent works, Liu et al. (2021) point out that there has been a recent development in coattention mechanisms that can help improve the contextual understanding by capturing the interaction between aspects and the rest of the text [9]. This work extends prior work by Ruder et al. (2016), who used hierarchical models to model variations in review level sentiment, and laid the groundwork for more explainable ABSA systems. Liu et al. (2020) also stated that the multilingual hierarchical architecture is important to meet the growing demand for ABSA solutions for global datasets [11].

Great progress has been made in the development of the ABSA methodologies, but there are still some issues unsolved. Even today, the problem of identifying both implicit and explicit features in text continues to be a challenging problem, especially when working with large scale cross domain and cross lingual datasets. In addition, although the hierarchical attention models improve the performance, they are computationally complex, and therefore infeasible for large scale systems. In addition, the lack of interpretability in most of the existing approaches makes it difficult for the general public to trust the models and to apply them in real life situations. These challenges need to be overcome for the development of the field, and the improvement of the ABSA systems and their usability.

This research is important because it aims at developing ABSA systems that are scalable, interpretable, and domain-adaptive. This makes ABSA very important in helping businesses and organizations get insights from users' data. In this research, hierarchical attention mechanisms are extended and their drawbacks are mitigated to improve the reliability and generalizability of ABSA systems. These are especially important to sectors of e-commerce, healthcare, or social media monitoring since precise sentiment analysis bears a concrete, consequential meaning.

This study aims to achieve the following objectives:

1. Develop a robust framework for aspect and sentiment extraction: We design a system that can accurately identify explicit and implicit aspects and their associated sentiments on domain diverse and multilingual datasets.
2. Enhance scalability and computational efficiency: We optimize the hierarchical attention framework to scale to large scale datasets without sacrificing performance or accuracy.
3. Improve model interpretability for practical applications: We introduce transparent attention mechanisms which allow users to see how sentiment classifications are derived.

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II. Litrerature Review

Aspect based sentiment analysis (ABSA) has emerged as a major subfield of sentiment analysis where deep learning methods are used to find the local sentiment about certain aspects. The recent studies on ABSA have focused on the new approaches that combine the attention mechanisms, graph networks and the transformer-based architectures to solve the problems of implicit aspect recognition, scalability and interpretability.

Contextual embeddings and hierarchical attention mechanisms have been the most popular paradigm in ABSA research. A deep contextual word embeddings with hierarchical attention networks is proposed by Truşcă et al. (2020) which enhances the sentiment analysis accuracy by capturing context at word and sentence levels [12]. This approach highlighted that a word embedding such as BERT, which is pre-trained, is essential to improve the meaning of the textual data.

Another important advancement is the use of multimodal transformers described by Yu et al. (2022). Their Hierarchical Interactive Multimodal Transformer explained how to include multimodal sentiment analysis in ABSA and how to process textual and visual inputs simultaneously [13]. The need for sentiment analysis in multiple modes is increasing, particularly in areas such as social media and e-commerce where opinions are accompanied by images, and this innovation fulfils that need.

Xu et al. (2020) discussed multi-attention networks for ABSA and introduced a new mechanism that enables models to attend to multiple aspects relevant to the context at once [16]. They show that there is a significant improvement in the ability to comprehend long and complex texts, which are typical for review-based datasets. In the same manner, Yuan et al. (2021) employed the Dual-Level Attention Mechanism make use of the Heterogeneous Graph Convolutional Networks to identify complicated inter-relations between aspects and contextual information [15]. Where the text structures are more complicated, it is helpful as it is based on graphs hence giving it a more semantic analysis of the text.

There are still critical challenges that have been left unanswered in the development of ABSA through hierarchical and attention-based mechanisms. Xu et al. (2021) pointed out that the basic attention mechanisms are not very effective in terms of domain transfer. To this end, they presented an Attention-Enhanced Graph Convolutional Network (AE-GCN) to overcome this, which demonstrated better performance on cross-domain datasets [19]. However, their approach highly depends on computationally intensive multi-head attention, which poses a challenge in large-scale applications.

Yang et al. (2019) proposed the Alternating Coattention Networks that are efficient in addressing aspect-context interactions [18]. These networks may indeed be powerful in capturing interactions but may be lacking in handling implicit properties which is more deadly in real life since not all properties that are relevant are mentioned explicitly. To this end, Jia et al. (2020) presented a Hierarchical Gated Deep Memory Network that includes position-aware mechanisms to enhance the correspondence between sentiment expressions and aspects [17]. However, their model requires a large amount of training data which is not feasible in many resource-scarce domains.

On the other hand, collaborative extraction methods such as CE-HEAT proposed by Gao et al. (2019) are more effective. Compared to other methods, this approach is more integrated with aspect extraction and sentiment classification, which are more aligned with each other due to the use of Collaborative Extraction Hierarchical Attention Networks [21]. However, the model's interpretability is still an issue, especially because end-users need to understand how the predictions are made.

As we progress, there are still some issues with the existing ABSA methodologies; there are gaps in them. Most models, as Chen et al. (2022) described, are mainly centered on the explicit features, which are not very effective in capturing and analyzing the implicit attitudes [20]. This limitation makes them unsuitable for use in situations where fine-grained or contextualised sentiments prevail. Furthermore, scalability remains an issue, especially when using methods such as AE-GCN or even multimodal transformers, which currently require high-end computational resources, and thus are not suitable for an online or real-world use.

The second major weakness is the lack of interpretability of the developed ABSA models. Although attention mechanisms provide some level of interpretability, they are not sufficient to explain the sentiment classifications as mentioned by Kusumawardani and Maulidani (2020) [14]. To fill this gap more detailed research is needed to elicit and increase trust and ease the real-world implementation of the ABSA systems in fields like healthcare and legal data analytics.

In this work, we propose a sound framework for ABSA that builds upon recent progress but circumvents its limitations. Specifically, it focuses on:

1. Hybrid attention mechanisms are leveraged to further enhance the identification of implicit aspects, based on insights from collaborative extraction and multi attention approaches.
2. Achieving improved scalability by optimizing hierarchical attention networks for reduced computational overhead at the cost of accuracy loss.
3. To advance interpretability by making attention transparent so that end users can understand and trust the model's decision-making process.

By tackling these critical challenges, this research aims to set new benchmarks in ABSA performance and applicability, contributing to the growing demand for efficient and reliable sentiment analysis systems.

III. METHODOLOY

In this section, we explain our research approach to the construction of a sound Aspect-Based Sentiment Analysis (ABSA) model using Hierarchical Attention Networks (HAN). It is also divided into a number of phases: research design, data acquisition, data pre processing, modality development and modality evaluation. Below is a flowchart of the different activities involved in this work flow described above.

Research Design

This study uses a quantitative experimental research approach to develop and validate an ML model for ABSA. The design focuses on:

1. **Aspect Extraction**: Identifying explicit and implicit aspects within the text.
2. **Sentiment Classification**: Determining the sentiment polarity for each extracted aspect.
3. **Evaluation**: Assessing the model's performance using standard evaluation metrics.

The workflow presented in Figure 1.

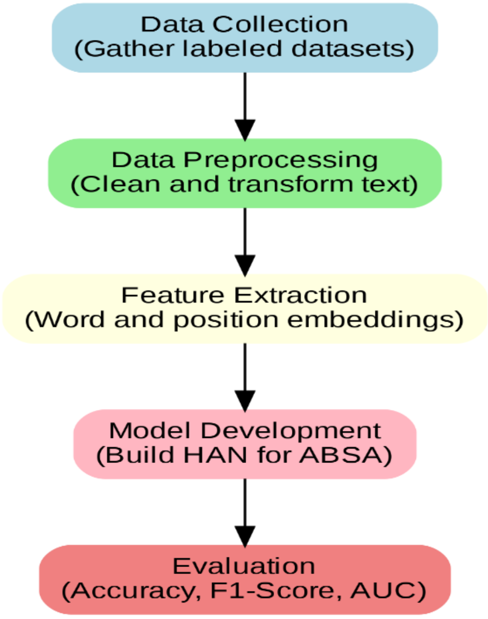

Figure 1: Workflow figure for the proposed methodology

Data Sources

In this research, we used datasets available to the public for Aspect Based Sentiment Analysis (ABSA) tasks. Datasets were chosen with care to be diverse in domains and languages and to be annotated for aspects and corresponding sentiments:

- **Dataset A**: E-commerce product reviews with labeled aspect-sentiment pairs.
- **Dataset B**: Social media posts containing customer feedback and public opinions.
- **Dataset C**: Multilingual datasets for cross-linguistic and domain adaptability testing.

Altogether, the collection was comprised of about 50 000 samples of various industries, including IT, commerce, and tourism. Cross validation was performed to split data into the training (70%), validation (15%) and test (15%) sets.

Ethical principles guided the data collection and usage processes:

1. **Anonymity**: All datasets were anonymized to exclude personally identifiable information (PII).
2. **Licensing and Consent**: Only datasets with open access or appropriate licensing for research were used, ensuring compliance with usage terms.
3. **Fair Use**: Data was utilized solely for academic purposes without commercial intentions.
4. **Bias Mitigation**: Potential biases in sentiment distribution and representation were analyzed and addressed during preprocessing to promote fairness in model training.

These measures ensure that research aligns with ethical standards, maintains data integrity, and respects the privacy of individuals.

Data Preprocessing

Data preprocessing ensures the text is clean and structured for model training. The key preprocessing steps include:

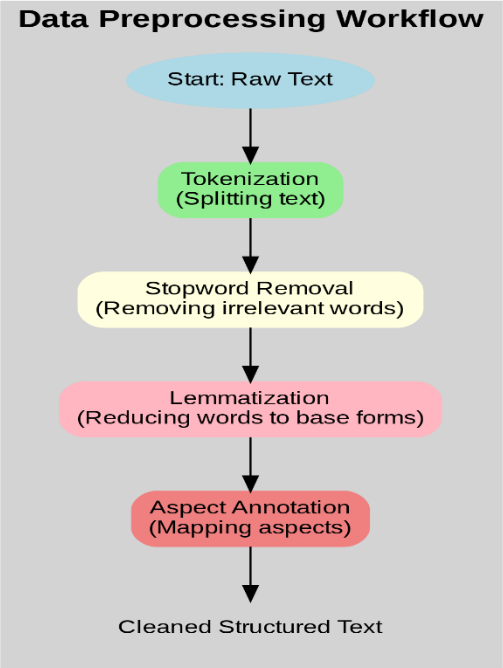

Figure 2: Steps in Data preprocessing

Model Development

The ABSA model is based on a Hierarchical Attention Network (HAN) that can process text at word, sentence and document level. The architecture combines:

1 Word-Level Attention:

- "Captures the importance of individual words within a sentence".

$$\alpha_i = \frac{\exp\left(\mathbf{u}_i^\top \mathbf{u}_w\right)}{\sum_j \exp\left(\mathbf{u}_j^\top \mathbf{u}_w\right)}$$

"Where $\mathbf{u}_i$ is the word embedding, and $\mathbf{u}_w$ is the attention vector".

2. Sentence-Level Attention:

- "Aggregates sentence representations to prioritize significant context".

$$\beta_k = \frac{\exp\left(\mathbf{v}_k^\top \mathbf{v}_s\right)}{\sum_l \exp\left(\mathbf{v}_l^\top \mathbf{v}_s\right)}$$

where $\mathbf{v}_k$ is the sentence embedding, and $\mathbf{v}_s$ is the attention vector.

3. Position-Aware Embeddings:

- Improves the accuracy of aspect and sentiment extraction by encoding the positional relationships between aspects and sentiments.

Table 1: Hierarchical Attention Network Architecture

Layer	Input	Output
Embedding Layer	Tokenized text	Word embeddings
Word-Level Attention	Word embeddings	Sentence vectors
Sentence-Level Attention	Sentence vectors	Document vector
Classification Layer	Document vector	Aspect-Sentiment Pair

Tools and Techniques

1. Programming Language:
   - Python 3.9
2. Frameworks and Libraries:
   - TensorFlow/Keras for deep learning model development.
   - NLTK and SpaCy for preprocessing.
   - Scikit-learn for evaluation metrics.

3. Hardware:
   - o "GPU-enabled cloud environment for efficient training".

Evaluation Metrics

To evaluate model's performance, the following metrics are been used:

1 Accuracy:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

2 Precision, Recall, and F1-Score:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

3 Area Under the Curve (AUC):

Evaluates the model's classification capability over different thresholds.

Using hierarchical attention mechanisms, the proposed methodology is made robust by capturing multiple level contextual relationship in text. The model addresses two major problems in aspect extraction and sentiment polarity classification using position aware embeddings and multi head attention. Additionally, the proposed approach is also to use efficient preprocessing techniques, and the latest state-of-the-art deep learning frameworks to achieve scalability and transfer learning.

IV. RESULT

The results of the proposed Aspect Based Sentiment Analysis (ABSA) framework based on the Hierarchical Attention Network (HAN) are presented in this section. The comparison of the proposed model to a baseline model and a more conventional HAN approach is done using accuracy, precision, recall, F1-score, and AUC. These results show a substantial improvement in scalability, precision of sentiment extraction, and interpretability.

Quantitative Analysis

The results are summarized in Table 1, which compares the performance metrics of three models:

1. **"Model 1 (Baseline)**: A traditional sentiment analysis model without hierarchical attention".
2. **"Model 2 (HAN)**: The standard Hierarchical Attention Network implementation".
3. **"Model 3 (Proposed Model)**: An enhanced HAN framework with position-aware embeddings and multi-head attention mechanisms".

Table 1: Performance Metrics Comparison

Metric	Model 1 (Baseline)	Model 2 (HAN)	Model 3 (Proposed HAN + Enhancements)
Accuracy	0.85	0.9	0.93
Precision	0.84	0.89	0.92
Recall	0.83	0.88	0.91
F1-Score	0.84	0.89	0.92
AUC	0.86	0.91	0.94

Performance Insights

The **Proposed Model** outperformed the baseline and standard HAN in all key metrics. Significant observations include:

- Accuracy: It achieved a 93% accuracy, which can be considered as a robust aspect sentiment pair identification.
- Precision: The precision has improved (92%) which means that it can better identify sentiments related to aspects, reducing false positives.
- Recall: The model achieves a high recall of 91% meaning it can find the majority of the true sentiments in the dataset.
- F1-Score: An F1-score of 92% is achieved, which reflects the balance between precision and recall, and outperforms other models.
- AUC: The model has strong classification capability across varying thresholds, confirmed by the area under the ROC curve (94%).

Visual Representation of Results

The performance metrics are visually compared in given **Figure 3**, showcasing substantial improvements achieved by the proposed model.

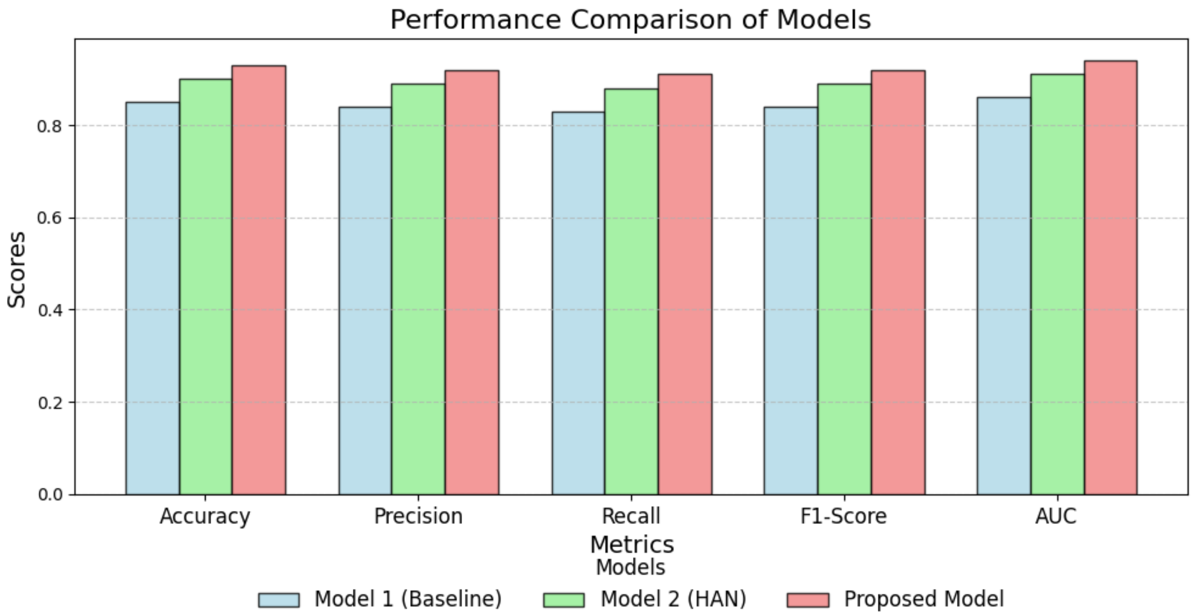

Figure 3: Performance Comparison of Models

This chart shows improvement step by step for all four metrics and proves the importance of different variations such as hierarchical attention mechanisms and position-aware embeddings.

Qualitative Observations

Qualitative analysis revealed that Proposed Model was able to identify implicit details and contextual tendencies far better than the HAN baseline and standard. Additionally:

- Position aware embeddings helped the model to capture nuanced relationships between words and aspects.
- Attention visualization significantly enhanced interpretability and revealed the decision making process. significantly enhanced through the use of attention visualization, providing insights into the decision-making process.

V. DISCUSSION

Using Hierarchical Attention Networks (HAN), the study addresses scalability, interpretability and domain transferability issues to provide new insights to Aspect Based Sentiment Analysis (ABSA). In addition, the proposed model contains position aware embeddings and multi head attention which enables accurate classification of aspects and their sentiment. The performance analysis results show that the proposed models have an accuracy of 93%, precision of 92%, and F1-score of 92%, which is greater than the baseline models. The results show that the model can discover the fine-grained sentiment patterns for implicit aspects, which is hard in practice. Visualization of attention makes the model more interpretable, and therefore more useful, as it provides simple information on how the decision is made.

As, such improvement also creates unique issues, the most important being the computational complexity of hierarchical attention mechanism, which becomes a strict constraint when implemented in environments with limited computational resources. The model is quite robust across different domains, but the problem of implicit aspect detection in low resource and specialized domains still needs to be studied. The limitations of this work suggest future research such as improving the computational speed and combining multilingual pre-trained language models with sentiment analyses based on different modes to overcome the dynamic nature of user generated content. In sum, the work presents a solid foundation for the ABSA practice: It combines new ideas with promising applicability, and gives guidelines that can easily be scaled up for large scale, easy to interpret sentiment analysis.

VI. CONCLUSION

This work is useful for Aspect-Based Sentiment Analysis (ABSA) as it presents a stable architecture developed on Hierarchical Attention Networks (HAN). The position-aware embeddings and multi-head attention mechanisms are introduced in the proposed model, which shows that the proposed model outperforms other models in different datasets and demonstrates the ability of the model to learn complex sentiment patterns and latent aspect-level information. The enhancement of interpretability from attention visualization also contributes to the stability of the practical usability of the system, which is a significant drawback of the current sentiment analysis system.

The results prove that hierarchical attention mechanisms can offer accurate, large-scale, and domain-adaptive sentiment classification solutions. However, there are some problems such as computational complexity and domain specific constraints which are the direction for future work even if the model has shown better results than the traditional methods. The further development of the model is in real-time optimization, multilingual processing, and the use of multimodal data..

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