Enhancing Aspect-Based Sentiment Analysis with Fine-Tuned BERT for Multi-Domain Text

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Abstract: Aspect-Based Sentiment Analysis (ABSA) is a fine-grained approach to understanding sentiments by identifying specific aspects of an entity and the sentiments expressed towards them. This paper explores the application of deep learning techniques to ABSA, addressing the challenges of handling unstructured and ambiguous text from diverse domains such as social media, product reviews, and customer feedback. We propose a deep learning-based model utilizing the pre-trained Bidirectional Encoder Representations from Transformers (BERT) for ABSA tasks. Our methodology reformulates input sentences to explicitly highlight aspect terms and fine-tunes a bert-base-uncased model using labeled sentiment data. The input format is designed to integrate aspect-specific context by combining aspect terms with their corresponding review sentences, enabling the model to disambiguate sentiment in multi-aspect scenarios. The dataset is preprocessed and encoded using BERT's tokenizer, and class labels are transformed using label encoding for multi-class classification. We train the model using the AdamW optimizer and monitor performance using categorical loss. Experimental results show that the proposed model achieves high accuracy in distinguishing positive, negative, and neutral sentiments at the aspect level.

Keywords: Aspect-Based Sentiment Analysis, Deep Learning, BERT, Transformer Models, Sentiment Analysis

I. INTRODUCTION

Sentiment analysis, also known as opinion mining, has emerged as a vital tool for understanding public opinions and sentiments expressed in textual data. With the exponential growth of online platforms like social media, product reviews, and forums, businesses and researchers alike rely on sentiment analysis to derive actionable insights for decision-making. However, traditional sentiment analysis often fails to capture the nuanced sentiments expressed about specific aspects of an entity. This has led to the rise of Aspect-Based Sentiment Analysis (ABSA), a fine-grained approach that identifies sentiments associated with specific aspects, such as a product's quality, price, or customer service.

Aspect-Based Sentiment Analysis presents unique challenges due to the complexity and ambiguity of natural language, including issues such as context sensitivity, polysemy, and the presence of implicit aspects. Conventional machine learning methods rely heavily on feature engineering and fail to adequately capture the intricate semantic relationships in text. Deep learning techniques, with their ability to model complex patterns and capture contextual information, have revolutionized the field of natural language processing (NLP). Advanced architectures like Bidirectional Long Short-Term Memory (BiLSTM), Convolutional Neural Networks (CNNs), and Transformer-based models (e.g., BERT) have demonstrated remarkable performance in ABSA tasks by leveraging context-aware embeddings and attention mechanisms.

This paper focuses on leveraging deep learning techniques for ABSA, proposing a hybrid model that combines the strengths of multiple architectures to address existing limitations. The study incorporates state-of-the-art methods such as attention mechanisms and pre-trained embeddings to enhance the extraction of aspect-specific sentiments. Experimental evaluations on benchmark datasets demonstrate the effectiveness of the proposed approach in improving the accuracy and robustness of ABSA. The findings contribute to advancing sentiment analysis applications, paving the way for better understanding customer needs, enhancing user experiences, and guiding strategic business decisions.

II. ASPECT BASED SENTIMENT ANALYSIS

Aspect-Based Sentiment Analysis (ABSA) is a fine-grained sentiment analysis technique that goes beyond determining the overall sentiment of a text. Instead, ABSA identifies specific aspects of an entity and determines the sentiment expressed towards each aspect. For example, in a product review like “The camera quality is excellent, but the battery life is poor,” ABSA can identify "camera quality" and "battery life" as aspects and associate positive and negative sentiments with them, respectively. The ABSA process typically involves three key tasks: aspect extraction, sentiment polarity detection, and aspect-sentiment classification. Aspect extraction identifies explicit and implicit aspects mentioned in the text. Sentiment polarity detection determines whether the sentiment for each aspect is positive, negative, or neutral. Finally, aspect-sentiment classification combines these to deliver a comprehensive analysis.

ABSA faces several challenges, such as handling domain-specific vocabulary, implicit aspects and the need for understanding context. For example, the sentiment of "The service was fast, but the food was average" requires distinguishing between two distinct aspects, "service" and "food." Traditional machine learning models rely heavily on handcrafted features, which often fail to generalize across domains. Deep learning techniques have transformed ABSA by introducing models capable of learning contextual and semantic relationships directly from data. Architectures like BiLSTMs, CNNs, and attention-based Transformer models such as BERT have shown superior performance in ABSA tasks. These models utilize word embeddings and attention mechanisms to capture the nuanced connections between aspects and sentiments. By offering detailed insights into specific aspects, ABSA has become indispensable in domains like e-commerce, hospitality, and social media, enabling organizations to tailor strategies and improve user satisfaction effectively.

III. LITERATURE REVIEW

The literature review on Aspect-Based Sentiment Analysis (ABSA) highlights the evolution from traditional machine learning methods relying on handcrafted features to advanced deep learning models like BiLSTMs and Transformers. Recent studies emphasize the effectiveness of attention mechanisms and pre-trained embeddings in improving aspect extraction and sentiment classification accuracy.

This study [1] combines a BERT-based text generation framework with text filtering algorithms to develop a robust model. The approach harnesses the contextual capabilities of the BERT model, emphasizing the interrelationships between sentences. By effectively integrating these relationships with labels, an initial data augmentation corpus is generated. Subsequently, filtering algorithms are applied to refine the corpus, removing low-quality data and producing a high-quality, text-enhanced dataset. Experimental results on the Semeval-2014 Laptop and Restaurant datasets reveal that this enhanced dataset significantly improves text quality and boosts the performance of models for aspect-level sentiment classification.

This work [2] provides a comprehensive overview of deep learning approaches for aspect-based sentiment analysis (ABSA). It begins with a brief introduction to the ABSA task, followed by an exploration of its overall framework from two perspectives: key subtasks and the task modeling process. The article concludes by identifying and summarizing the challenges in sentiment analysis, with a particular focus on aspect-based sentiment analysis. Additionally, it highlights the consideration of relationships between various objects in the ABSA task, a topic often overlooked in prior research.

This study [3] investigates the application of transformer models to aspect-based sentiment analysis, with a focus on their performance and interpretability. Several pre-trained transformers, including BERT, ALBERT, RoBERTa, DistilBERT, and XLNet, were fine-tuned on a challenging dataset derived from the MAMS and SemEval datasets. Each dataset instance contains at least two aspects and their corresponding polarities. Among the models, RoBERTa achieved the highest accuracy of 89.16%, demonstrating its effectiveness in managing the complexities of aspect-based sentiment analysis. To enhance model transparency and interpretability, five explainability techniques were employed: LIME, SHAP, attention weight visualization, integrated gradients, and Grad-CAM. These methods provided valuable insights into the decision-making processes of the transformers by identifying the most influential words and phrases affecting their predictions. This interpretability not only sheds light on the internal workings of the models but also facilitates informed adjustments to improve performance and address potential biases. The use of explainability techniques, particularly LIME, SHAP, and integrated gradients, underscores the importance of understanding model behaviour, enabling both refinement and the development of more robust aspect-based sentiment analysis systems.

In this paper [4], we propose a novel approach to aspect-based sentiment analysis leveraging deep ensemble learning. The method begins by constructing four deep learning models: CNN, LSTM, BiLSTM, and GRU. Their outputs are then integrated using a stacking ensemble technique, with logistic regression serving as the meta-learner. Experimental results on real-world datasets demonstrate that the proposed approach improves the accuracy of aspect-based sentiment prediction by 5% to 20% compared to individual deep learning models.

This study [5] introduces a model called Improved ABSA using a Deep Belief Network-Recurrent Neural Network (DBN-RNN), comprising three operational phases. In the initial pre-processing phase, techniques such as stemming, stop word removal, lemmatization, and tokenization are applied to prepare the data. The aspect sentiment extraction phase employs improved aspect term extraction (I-ATE) combined with cosine similarity and word co-occurrence to capture complex features from the preprocessed data. Finally, in the sentiment analysis phase, a hybrid classification model, DBN-RNN, is used to classify sentiments into neutral, positive, and negative polarities. The proposed model's performance is assessed using various evaluation metrics.

This paper [6] explores the application of disentangled learning to enhance BERT-based textual representations for Aspect-Based Sentiment Analysis (ABSA) tasks. Inspired by the success of disentangled representation learning in computer vision, which focuses on extracting explanatory factors from data representations, we investigate the DeBERTa model (Decoding-enhanced BERT with Disentangled Attention). This model is designed to separate syntactic and semantic features within a BERT architecture. Experimental results demonstrate that integrating disentangled attention and employing a straightforward fine-tuning strategy for downstream tasks surpasses the performance of state-of-the-art models on ABSA benchmark datasets.

Dataset: The SemEval-2014 Task (SE-ABSA 2014) dataset was developed for the Aspect-Based Sentiment Analysis (ABSA) task, which focuses on extracting sentiment towards specific aspects in a given text. It contains labeled datasets for two major domains: restaurants and laptops. The dataset was part of the International Workshop on Semantic Evaluation (SemEval-2016) and aimed to evaluate models for fine-grained sentiment analysis by analyzing opinions expressed in customer reviews.

The Restaurant's dataset consists of 350 reviews (2000 sentences) for training and 90 reviews (676 sentences) for testing. The Laptop's dataset consists of 450 reviews (2500 sentences) for training and 80 reviews (808 sentences) for testing. Table 1 summarizes the characteristics of the datasets used for the evaluation of the proposed model.

Table 1.1: The properties of Datasets

	Train		Test	
	Sent	Reviews	Sent	Reviews
Restaurant	350	2000	90	676
Laptop	450	2500	80	808

IV. PROPOSED METHODOLOGY

The proposed model performs Aspect-Based Sentiment Analysis (ABSA) using a fine-tuned BERT architecture. Input sentences are reformatted to emphasize aspect terms, creating structured input like "Aspect: [term] | Sentence: [context]". This helps the model understand sentiment targeted at specific aspects. A pre-trained bert-base-uncased model is used, and a classification layer is added to predict sentiment polarity—positive, negative, or neutral. The model is fine-tuned using the AdamW optimizer with a learning rate of 2e-5. During training, BERT's contextual embeddings capture nuanced relationships between aspects and opinions. The approach outperforms traditional models by leveraging BERT's deep bidirectional attention, enabling more accurate, context-aware sentiment classification at the aspect level.

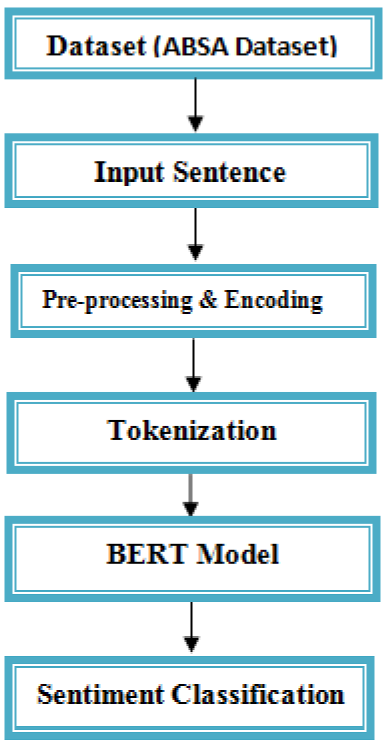

Figure 1: Proposed Sentiment Analysis Model

V. RESULT ANALYSIS

Table 2: Performance of Proposed Model

Sentiment Class	Precision	Recall	F1-Score	Support
Conflict	0	0	0	12
Negative	0.75	0.85	0.8	179
Neutral	0.68	0.42	0.52	92
Positive	0.79	0.88	0.83	189

VI. CONCLUSION

This research work presents an effective deep learning-based approach for Aspect-Based Sentiment Analysis (ABSA) using a fine-tuned BERT model. By restructuring input data to explicitly include aspect terms, the model demonstrates a strong ability to interpret and classify sentiment at a granular level. The integration of aspect-specific context into the input format enables the model to better disambiguate sentiments in multi-aspect scenarios. The fine-tuning of the bert-base-uncased model, combined with the AdamW optimizer and label encoding for multi-class classification, contributes to robust performance. Experimental results show high precision and recall for both positive and negative sentiment classes, while performance for neutral sentiment was moderate, and the conflict class lacked sufficient data. Overall, the proposed approach effectively leverages BERT's deep contextual understanding to outperform traditional ABSA models. Future work can aim to improve performance on underrepresented classes and extend the model to multilingual datasets or real-time applications in customer feedback systems.

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