

## Introduction

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*Current draft: 2/3/26 at 2:37am EDT*

**About me.** I am a Ph.D. student in Computer Science at Old Dominion University (ODU). My interests include applied machine learning, natural language processing, computer vision, and AI for biomedical applications.

## 1 URLs

Here are my links:

- Web Page: [https://www.cs.odu.edu/~cs\\_djaya003/](https://www.cs.odu.edu/~cs_djaya003/)
- GitHub: <https://github.com/dineth99-bit>

## 2 Images

Figure 1 shows an original PNG image of me with no scaling or cropping. The original dimensions are 754 x 1280. Figure 2 shows an example of cropping the image using the `trim`, `clip` options to `includegraphics`.



**Figure 1:** Original PNG

Figure 3 shows the same cropping as Figure 2 but scaled up. It's blurry because the original image (Figure 1 was a low resolution.)

We can insert PDFs into the document in the same way as images. Figure 4 is the first page of an academic paper. I've added the `\frame` command to show where the boundaries are. Figure 5 shows the margins trimmed off so that the text can be larger (scaled up).



**Figure 2:** Cropped PNG - 0.10in from left, 0.5in from bottom, 0.1in from right, 0.25in from top

### 3 Quotation Marks

In my research and software projects, I focus on building *trustworthy* and *robust* machine learning systems. For example, I study how to detect “out-of-distribution” samples and reduce ‘‘hallucinations’’ in LLM-based applications.

### 4 Tables

Table 1 shows a simple example table. Table 2 shows an example confusion matrix from [https://en.wikipedia.org/wiki/Confusion\\_matrix](https://en.wikipedia.org/wiki/Confusion_matrix). This employs rows that span multiple columns (multicol) and columns that span multiple rows (multirow).

**Table 1:** Education Summary

Institution	Program	Result
Old Dominion University	Ph.D. in Computer Science (Student)	OGPA 4.00/4.00
University of Ruhuna	B.Sc. (Hons)	OGPA 3.94/4.00 (First Class)
Vellore Institute of Technology	Certificate in AR/VR and Robotics	Merit
E-soft Metro Campus	Diploma in Information Technology	Merit

**Table 2:** Selected Work Experience (Years by Location)

		Location	
Track		USA	Sri Lanka
	Research	1	0
	Industry/Teaching	0	6



**Figure 3:** Cropped and scaled PNG

## Enhanced Aspect-Based Sentiment Analysis with Integrated Category Extraction for Instruct-DeBERTa

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<sup>¶</sup>NisansaDdS@ecse.mrt.ac.lk, <sup>†</sup>{nadeesha, kushan}@eie.ruh.ac.lk, <sup>‡</sup>{sachintha, kashnika}@emojot.com

### Abstract

Aspect-Based Sentiment Analysis (ABSA) has seen significant advancements with the introduction of Transformer-based models, which have reshaped the landscape of Natural Language Processing (NLP) tasks. This paper introduces enhancements to the Instruct-DeBERTa model which is one of the leading ABSA models for ABSA. It takes a hybrid approach combining the strengths of InstructABSA for Aspect Term Extraction (ATE) and DeBERTa-V3-baseabsa-V1 for Aspect Sentiment classification (ASC). In this work, we enhance Instruct-DeBERTa by introducing category classification through a cosine similarity-based method, comparing aspect embeddings with predefined categories. Also for InstructABSA and DeBERTa-V3-baseabsa-V1, we investigate different configurations by adding a linear layer followed by ReLU activation, incorporation of regularization and optimization of attention heads. These modifications were tailored specifically for the data sets in the hospitality domain. Our empirical evaluations, run on diverse datasets, have shown that these enhancements significantly raise the performance of Instruct-DeBERTa for hospitality domain datasets.

### 1 Introduction

The growing interest in NLP makes ABSA an important building block for sentiment detection and investigation using textual information (Mudalige et al., 2020; Rajapaksha et al., 2020). Unlike traditional approaches to sentiment analysis, where just the estimate of polarity value was estimated, ABSA focuses on fine-grained opinions expressed on some features or attributes offered by products or services (Rajapaksha et al., 2021; Jayasinghe et al., 2021). This is especially important for any business wishing to understand customer feedback better and improve products and services based on the overall opinion of the consumers.

It was only in the most recent years that one witnessed substantial progress in machine and deep learning applied to ABSA methodologies (Rajapaksha et al., 2022; Samarawickrama et al., 2022). Early lexicon-based approaches failed to properly account for context and ambiguity, while later-introduced machine learning models were most of the time heavily reliant on manual feature engineering and lacked generalization across domains. Significant progress has been associated with its application, especially through models such as recurrent neural networks, long short-term memory networks, and convolutional neural networks. But still, capturing long-term dependencies and complex syntactic structures effectively remains hard.

Transformer-based architectures, most notably exemplified by BERT, revolutionized the field by using attention mechanisms to capture contextual relationships from all directions within a sentence. Having advanced their ability to further comprehend complex linguistic patterns and relations, these models set new records on many NLP tasks. In this line of research, state-of-the-art models that emerge are InstructABSA for ATE and DeBERTa-V3-baseabsa-V1 for ASC. The work presented by Jayakody et al. (2024b) introduces Instruct-DeBERTa — a hybrid model that combines the best of InstructABSA (Scaria et al., 2024) in ATE with those of DeBERTa-V3-baseabsa-V1 (Yang et al., 2023, 2021) in ASC. The model was constructed to perform the joint task of aspect extraction and sentiment polarity detection within a single pipeline. Evaluation across the SemEval 2014-2016 restaurant reviews (Res-14, Res-15, and Res16) and the SemEval 2014 laptop dataset (Lap-14), has demonstrated that Instruct-DeBERTa is better by quite a margin than any other model in accuracy and robustness and is hence likely state-of-the-art for the joint task of ATE and ASC.

However, there are always some aspects that

Figure 4: Inserted PDF

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Figure 5: Trimmed PDF