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Aspect-based Sentiment Analysis on Product Reviews using Enhanced Bidirectional LSTM

Seenia Joseph[1*], and Dr.S. Hemalatha[2]

[1*]Research Scholar, Department of Computer Science, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India. seeniajoseph@gmail.com, https://orcid.org/0000-0002-3354-9257

[2]Associate Professor, Department of Computer Science, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India. drhemashanmugam@gmail.com, https://orcid.org/0000-0003-3102-020X

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Abstract

Consumer opinions on purchased products significantly influence the number of purchases on e-commerce platforms. Sentiment analysis of these opinions assists both consumers and companies in making informed decisions. Currently, consumers judiciously evaluate different aspects of a product to guarantee it meets their requirements. Consequently, performing sentiment analysis on various product aspects can aid consumers select the precise product and support companies in meeting on areas that prerequisite upgrading. This study recommends a systematic and expandable method to aspect-based sentiment analysis of user reviews for electrical devices like computers, mobile phones, and headphones. Through an amalgamation of advanced preprocessing, sentence-level segmentation by means of transformer-based models, and similarity-based aspect detection, the system is competent of extracting fine-grained sentiment for each product aspect. A hybrid sentiment classification strategy employing both BERT and VADER certifies robustness and accurateness in sentiment detection, while the structured transformation of data into a multi-label format permits for efficient model training. The proposed Bi-LSTM architecture with an integrated attention mechanism boosts sentiment prediction by concentrating on the utmost pertinent parts of each sentence, directing to better-quality performance across evaluation metrics, including accuracy, precision, recall, and F1-score. The exploration offers a comparative study of the performance of aspect-based sentiment analysis using a standard Bi-LSTM model versus a Bi-LSTM model with an attention mechanism, applied to analyse the reviews of three diverse products. The outcomes explains that the Bidirectional Long Short-Term Memory (Bi-LSTM) model with an attention mechanism outpaces the Bidirectional Long Short-Term Memory (Bi-LSTM) in terms of accuracy, precision, recall, and F1-score. The investigation validates the efficiency of merging NLP techniques and deep learning to deliver understandings from product reviews, presenting beneficial assistance to consumers by aiding to make informed decisions and focus on companies directing to improve their offerings based on targeted feedback.

Keywords: Aspect Based Sentiment Analysis, Attention Mechanism, Aspect Extraction, Customer Reviews, Labelled Dataset, Bi-LSTM.

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*Corresponding author: Research Scholar, Department of Computer Science, Karpagam Academy of Higher Education, Coimbatore, Tamil Nadu, India.

1 Introduction

Demand for technology that permits for the enquiry of product reviews has augmented due to the extensive use of internet applications for the buying of various goods. This could be helpful for both buyers and sellers to make better choices. Future product enhancements can be learnt by customer reviews, according to the corporation selling the products. Consumers can also use product reviews to help them decide whether or not to buy a product. Sentiment analysis is one technique that provides the polarity of reviews as either favourable, negative, or neutral (Sinha & Narayanan, 2023). However, Aspect-Level Sentiment Analysis has emerged as a result of the increasing integration of technology with user needs. This method focuses on finding and analysing particular features or aspects of a product that are mentioned in user reviews. Aspect-level sentiment analysis dissects a review to determine the sentiment related to specific product features rather than analysing the sentiment of the review as a whole (Golait et al., 2025). Aspect-based sentiment analysis (ABSA) helps to identify the sentiment polarity of an aspect in a review sentence (Noh et al., 2019). This analysis helps consumers to know more about different aspects of the product and to make a better purchase decision. This process takes different key features of the product of customer choices and then finds sentiment polarity as positive, negative and neutral (Guha et al., 2015).

In this proposed study, product-based aspects are identified and listed. As each review contains multiple elements, it is segmented into short sentences using the sentence-transformers library. The segmented review is then given to BERT to analyze the sentiments of the aspect in each segment (Prabhudeva & Hariharan, 2024). A fallback mechanism is used with VADER to capture the sentiments if BERT fails. In sentiment identification, 0 represents negative sentiment, 1 represents neutral sentiment, and 2 represents positive sentiment (Liu, 2012). Two models developed in this research include one with Bi-LSTM and the other with enhanced Bi-LSTM with an attention mechanism for improved multi-aspect sentiment analysis (Zhang et al., 2022). To measure the effectiveness of the models, the results are compared. Reviews of laptops, mobile phones, and headsets collected from Kaggle are used for this study since it is difficult to generate reviews from e-commerce websites.

Literature Review

In recent years, the importance of Aspect-Based Sentiment Analysis (ABSA) sentiment analysis has increased as it analyzes different aspects of the products, which helps both customers and manufacturers in their decision making (Amer et al., 2025). Traditional sentiment analysis only finds out the overall sentiments of the product, but ABSA analyses the emotions behind different components of the product, like battery life, performance, or software, to overcome the constraint and to empower companies to implement more enhancements (Abubakar et al., 2021). Extracting useful information from consumer reviews is becoming more and more important as e-commerce and online shopping platforms expand (Xu et al., 2019).

The first methods of ABSA were lexicon-based, using dictionaries that were hand-picked to find sentiments and elements in evaluations. Despite their simplicity, these approaches were constrained by their lack of contextual awareness and domain reliance (Chehal et al., 2022). By learning from labeled datasets, supervised machine learning methods like SVM and Naïve Bayes enhanced performance; however, they necessitated a great deal of feature engineering (Brauwers & Frasincar, 2022). Significant advancements were later made by deep learning models, especially CNN and LSTM, which automatically learned hierarchical text features and the connections between sentiment expressions and attributes (Pateria & Choubey, 2016).

The most notable advancement was made by transformer-based models such as BERT, which provided deep contextual embeddings that greatly enhanced sentiment classification and aspect extraction (Saini et al., 2023). Recent adaptations, such as BERT-PT and DeBERTa-V3, have been fine-tuned for ABSA tasks, demonstrating state-of-the-art results in benchmark datasets like SemEval (Karimi et al., 2020). Moreover, hybrid models that combine transformer architectures with traditional attention mechanisms have shown improved performance in multi-aspect scenarios, where a single review contains sentiments about multiple product features.

The effectiveness of ABSA largely depends on the quality and diversity of the datasets used. SemEval-2014 remains one of the most widely used benchmark datasets, though many recent studies have created domain-specific corpora such as Amazon product reviews and hotel reviews (Abubakar et al., 2021; Iyer & Deshpande, 2024). A study by Chehal et al. introduced a structured dataset specifically annotated for aspect-level sentiment analysis, emphasising the importance of domain-specific annotation schemes for increasing classification accuracy (Chehal et al., 2022). Since sentiment analysis is done with real-world data, the models face challenges like sarcasm, implicit aspect references, and noisy data.

From different studies, it is clear that unsupervised and semi-supervised learning strategies must be implemented to handle issues related to domain-specific vocabulary, multilingual support, and aspect term ambiguity (Prabhudeva & Hariharan, 2024; Karimi et al., 2020). The performance of ABSA can be improved by considering relevant inputs which are in audio or images in addition to text data (Amer et al., 2025; Zhang et al., 2022).

2 Methodology

This section includes the detailed framework of the proposed model developed for an Aspect-Based Sentiment Analysis (ABSA) for various electronic products and particularly mobile phones, laptops and headsets. Figure 1 shows the methodology framework of the proposed ABSA with all the steps carried out to analyse the sentiment polarity of the reviews taken as input.

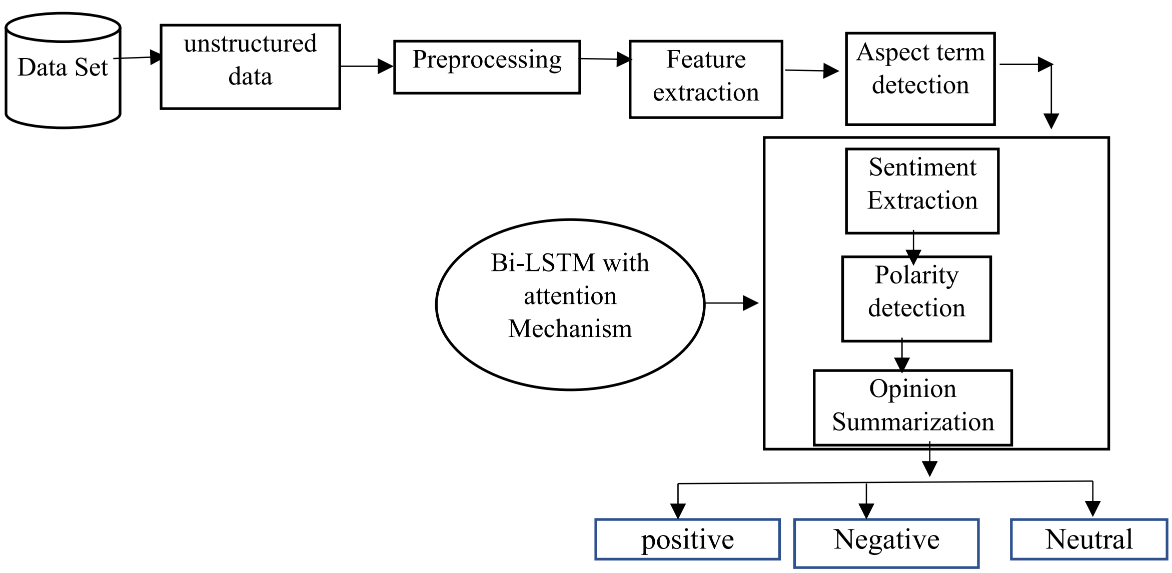

Figure 1: Methodology Framework for ABSA

1. Data Collection

As the dataset is not directly available from major e-commerce the data set for the study includes reviews of mobile phones, laptops, and headphones, which are collected from Kaggle.com. Reviews without any specifications or aspects are removed from the dataset, as they are not directly available from major e-commerce websites the datasets as it does not provide any relevance to this study. All the reviews where customers comment their opinion about multiple aspects, such as camera quality, performance, display, noise cancellation, design, are considered for selection. Since this study evaluates the performance of three electronic products, the model will be able to generalise to similar electronic products in ABSA. With 10,500 annotated reviews in 10 categories, the ABSA dataset shows the importance of domain variety (Sureshkumar et al., 2017; Saini et al., 2023). In addition, Chebolu et al., (2022); (Chebolu et al., 2022) examined 65 ABSA datasets from over 25 domains to specify the necessity of structured, annotated data. The data sets collected were assembled and labelled following these criteria as a guide.

2. Data Preprocessing

Prior to preparing the raw review texts for analysis, standard text preparation techniques were employed to ensure data homogeneity and quality. The initial step was to convert all textual data to lowercase so as to fix case sensitivity problems. To reduce textual noise, punctuation and numerical digits were then eliminated. Only the most semantically important phrases were kept after stop words—common words that have little relevance in sentiment analysis, such as "is," "the," and "was"—were eliminated. To ensure consistency across various inflections, lemmatization was used to reduce each word to its base form (for example, "running" and "ran" both become "run"). Consistent with recommended practices described in previous sentiment analysis studies, these preprocessing methods produced clean and normalized review texts that were prepared for sentence-level embedding and analysis (IŞIK & Dağ, 2020).

3. Sentence Segmentation

For more precise aspect detection and sentiment categorization, individual evaluations have to be divided into separate sentences because they frequently discuss several elements in a single text block. Sentence segmentation was conducted using the sentence-transformers/all-MiniLM-L6-v2 model, which not only identifies sentence boundaries but also creates high-quality semantic embeddings for each sentence. This step enables the model to perform fine-grained analysis at the sentence level, associating each sentence with its relevant aspect and sentiment, rather than attempting to interpret the entire review as a single opinion. With this level of detail, aspect-sentiment associations are far more accurate.

4. Aspect Detection

For detecting product aspects within the segmented sentences, a similarity-based approach was used. A pre-defined list of aspect keywords—including terms like "battery", "camera", "performance", "software", "display", and "audio" as mentioned in table 1was created based on domain relevance and frequency in reviews. Each sentence, already embedded using the same sentence transformer model, was compared against the embedding of each aspect keyword using cosine similarity. If the similarity between the sentence and a specific aspect exceeded a manually defined threshold value, the aspect was deemed to be discussed in that sentence. This unsupervised aspect detection method avoids reliance on manual tagging and scales well across domains while still being sensitive to contextual mentions of relevant features.

Table 1: Aspect Extracted

Product name	Aspects Selected
Mobile Phone	Display, performance, battery, camera, built_quality, connectivity, storage, price, software, design
Laptop	performance, battery_life, build_quality,display, keyboard, trackpad, connectivity, storage, ram, cooling_system, graphics, audio,operating_system, price, brand_reputation, design, user_experience, webcame, security, value_for_money
Head Phone	sound_quality, comfort, battery_life, build_quality, connectivity, noise_cancellation, microphone, controls, price, brand_reputation, design, user_experience, seller_trust, product_condition, value_for_money

5. Sentiment Analysis (Star-Based + Fallback)

Once aspects were identified, the corresponding sentiment expressed toward each aspect was classified using a hybrid sentiment analysis strategy. For sentiment identification, a three-point rating system is used where 0 represents negative sentiment, 1 represents neutral sentiment, and 2 represents positive sentiment, which are identified using a BERT-based model, nlptown/ bert-base-multilingual-uncased-sentiment, as it is optimized for predicting sentiment ratings in multi-language and domain-diverse situations. As a fallback strategy, the VADER sentiment analyser was also used when BERT fails to characterize the sentiment in short or unclear sentences. For product reviews and social media, VADER provides a rule-based solution offering a dependable fallback in the case of processing mistakes or low BERT confidence. This dual-method approach optimizes the robustness and scope of sentiment categorization across a variety of text styles and sentence forms.

6. Label Structuring

Once the sentiments are categorised, metadata was extracted. Each metadata includes a list of extracted aspects and associated sentiments, which are arranged as a table. The columns of the table are named as Extracted_ Aspects and Aspect_ Sentiment to organize extracted aspects and sentiments to facilitate multi-aspect sentiment modelling and allow for a methodical conversion into input that is suitable for machine learning. Özen and Katlav (2023) (Özen & Özgül Katlav, 2023) used a similar label structure approach to interpret customer evaluations by connecting particular product attributes with their related sentiment polarities to improve the evaluation method. Xue and Li (2019) (Xue & Li, 2018) enhanced interpretability and classification performance by incorporating aspect-sentiment mapping to organise opinion expressions.

7. Transformation into Multi-label Format

After the label structuring, the data was converted into a multi-label, multi-class format to train the proposed model in the form of a matrix with sentiments as columns for positive, negative and neutral and extracted aspects as rows. Binary representations of sentiment classes were created for each facet through one-hot encoding, and a matrix with the form (number_of_aspects × 3) was created from the review-level data. This format enables the neural network to learn and predict various aspect-sentiment pairs at the same time.

8. Model Architecture

Bidirectional Long Short-Term Memory (Bi-LSTM) is used as a foundation for deep learning in the proposed model, and additionally, an attention mechanism was added to enhance the Bi-LSTM model for capturing sentiment-rich tokens. The model's embedding layer maps each word in the review to a 128-dimensional vector. To identify the dependencies of sentiments, the Bi-LSTM layer evaluates the input text in both forward and backwards directions. To identify the most important sentiments of each aspect, a special attention layer is added, which helps the model to improve its performance. To minimize the overfitting problem, a dropout layer with a rate of 0.5 is used. Finally, a dense softmax layer generates sentiment probabilities across all dimensions. At an average rate of 0.002, the model is trained with an Adam optimizer to fit the structure (number_of_aspects, 3), and as a loss function, categorical cross-entropy is used.

9. Training and Evaluation

By using a supervised learning technique, the gathered dataset was divided into training and test sets to exercise the proposed model across ten epochs. Weighted average measures were adopted for assessment where unreliable sentiment classes are observed, such as the wide-ranging supremacy of positive comments. Performance metrics corresponding to accuracy, precision, recall, and F1-score, were obtained for assessing the model. The so stated measures were used against the test dataset to ensure that the model could be used for reviews that were unseen. Weighted measures were also employed in order to avoid underrepresented classes, like negative or neutral opinions, which might have been missed during evaluation.

10. Post-Evaluation and Visualization

Post training, the model's performance was observed, which showcased the behaviour and modified the component elements. The plots for training, validation accuracy and loss curves for each epoch aid in perceiving issues of underfitting or overfitting. A multi-domain sentiment evaluation helped to summarize the performance in multiple sentiment domains. Visualization tools, attention weight heat maps and confusion matrices were deployed to exhibit the specific tokens the model focused on while predicting. The model's strengths and weaknesses were observed post-evaluation for future improvement planning. The proposed method presents a scalable, interpretable, and robust framework for Aspect-Based Sentiment Analysis of product reviews across multiple domains. Semantic phrase segmentation, unsupervised aspect identification, and a hybrid sentiment analysis framework driven by BERT and VADER are all used by the system to collect rich, multi-aspect sentiments. Fine-grained sentiment prediction at the aspect level is made possible by structuring and transforming these outputs into a matrix form that can be used to train a Bi-LSTM model with attention. This pipeline shows promise in real-time sentiment tracking across a variety of product kinds, opinion summarization, and user feedback mining.

3 Results

The Laptop category's testing accuracy increased by 1.55%, from 96.5% to 98.0%, after an attention mechanism was added to the Bi-LSTM model, as shown in the Figure 2. The Headphone category also saw a notable improvement, with accuracy rising by 2.40 % (from 91.8% to 94.0%). In contrast, the Mobile category showed a negligible 0.10% decrease, indicating attention had minimal impact there. Overall, attention-enhanced Bi-LSTM models demonstrated clear benefits for categories with more complex data patterns than normal Bi-LSTM shown in Figure 1.

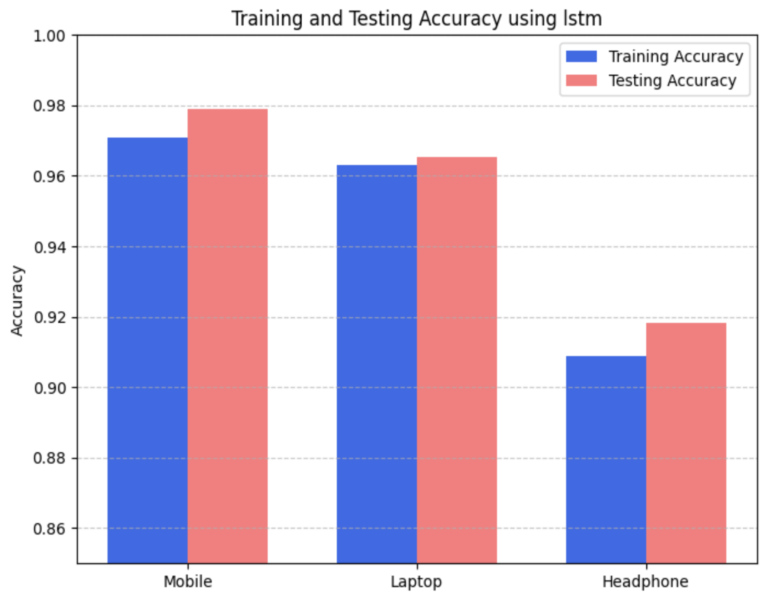

Figure 2: Accuracy Using Bi- LSTM

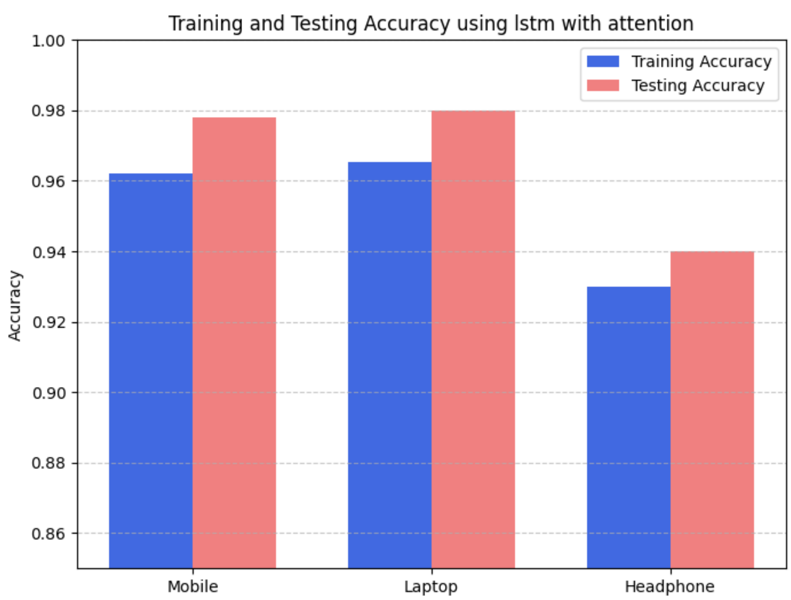

Figure 3: Accuracy Using Bi- LSTM with Attention

From Figures 4 and 5, it is clear that the laptop category saw a 2.04% increase in testing F1-score, rising from 95.1% with LSTM to 97.0% using LSTM with attention. Mobile improved by 1.04%, going from 96.1% to 97.1%. The Headphone category showed the most significant gain, with a 1.64% increase from 91.7% to 93.2%. Overall, the attention mechanism consistently enhanced F1-scores across all categories, especially in more complex cases.

Figure 4: F1-Score Using Bi- LSTM

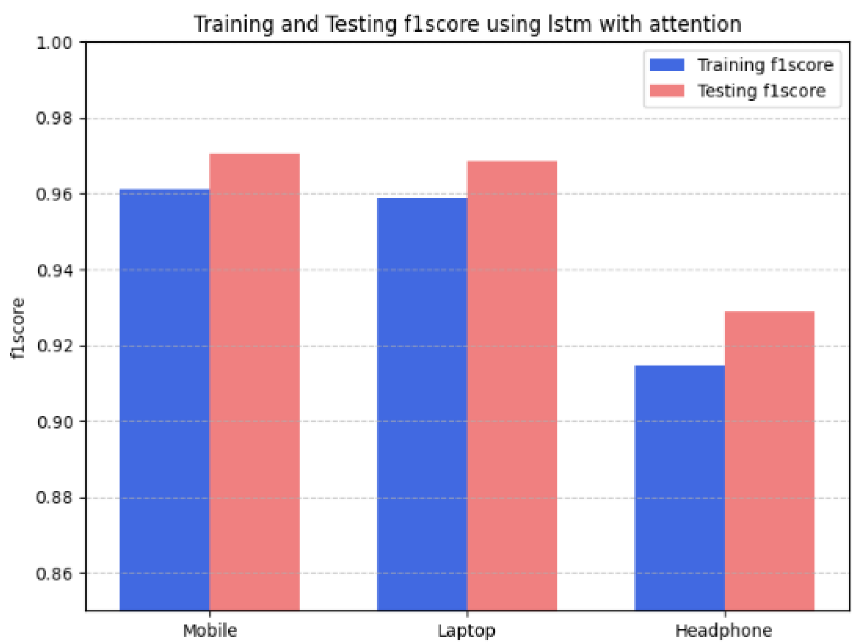

Figure 5: F1-Score Using Bi- LSTM with Attention

In terms of Precision, Figure 7 clearly states that the Bi-LSTM with attention model shows a 1.4% improvement in testing precision for the laptop category (from 95.2% to 96.6%) over standard Bi-LSTM in Figure 6. The mobile category also benefits with a 1.7% increase in testing precision (from 96.1% to 97.8%). The headphone category sees the largest improvement, with testing precision rising by 1.4% (from 91.4% to 92.8%). Overall, the attention mechanism consistently boosts testing precision across all categories, especially enhancing laptop performance significantly.

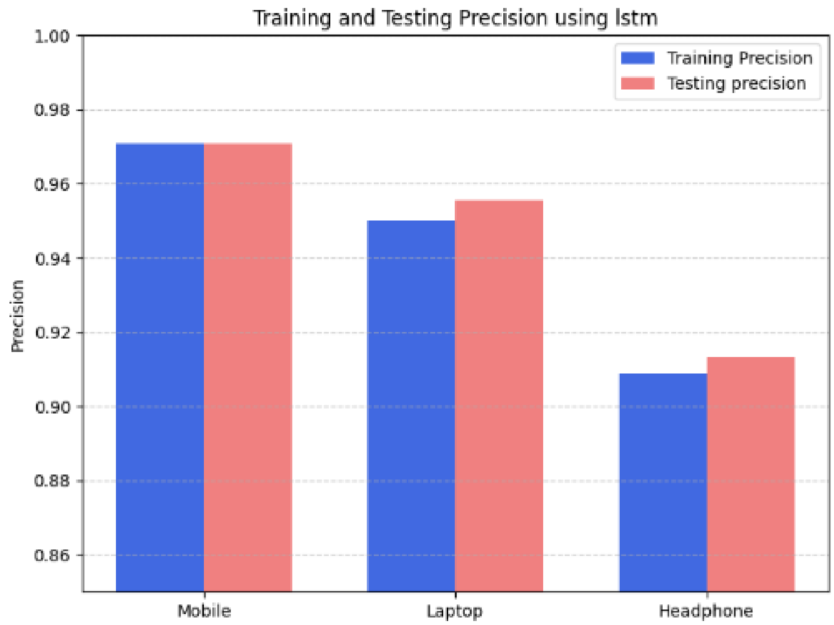

Figure 6: Precision using Bi- LSTM

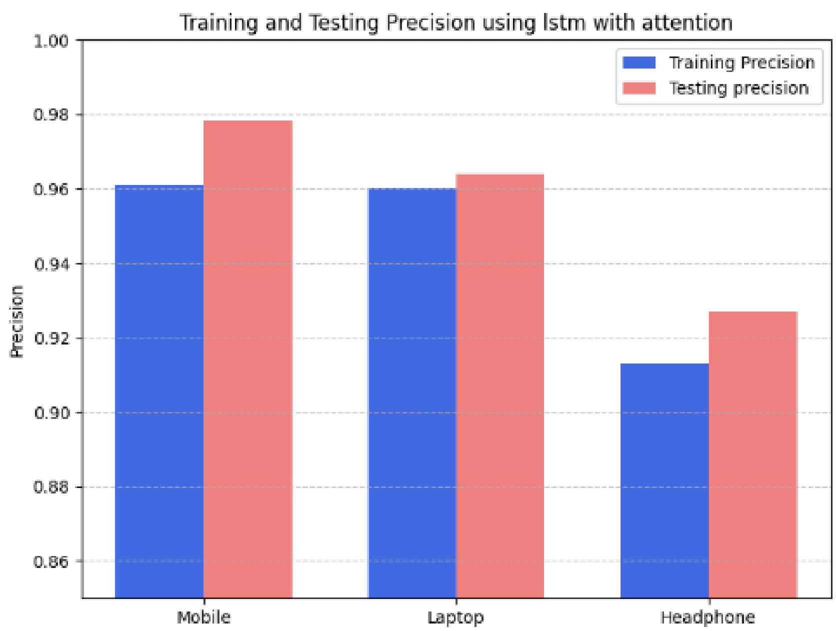

Figure 7: Precision using Bi- LSTM with attention

In all categories, from Figures 8 and 9, it is clear that the Bi-LSTM with attention model performs better than the normal Bi-LSTM when it comes to testing recall. About 1.2% more people could recall mobile devices, 0.9% more could recall laptops, and 1.7% more could recall headphones. These steady advances suggest that adding attention improves the model's capacity for better generalization in testing.

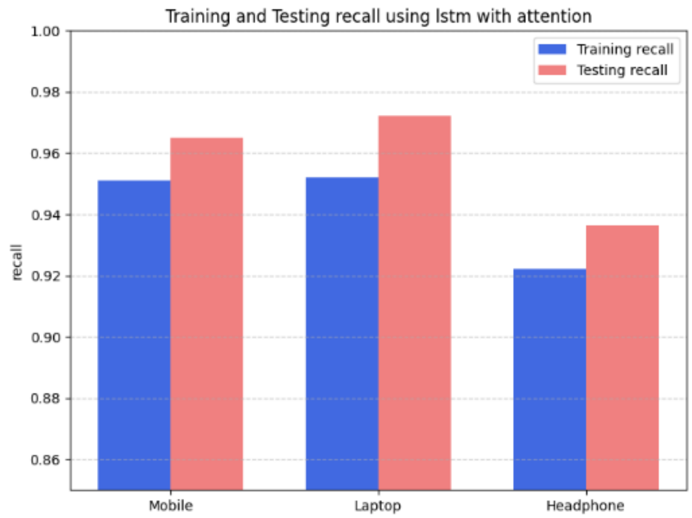

Figure 8: Recall Using Bi- LSTM

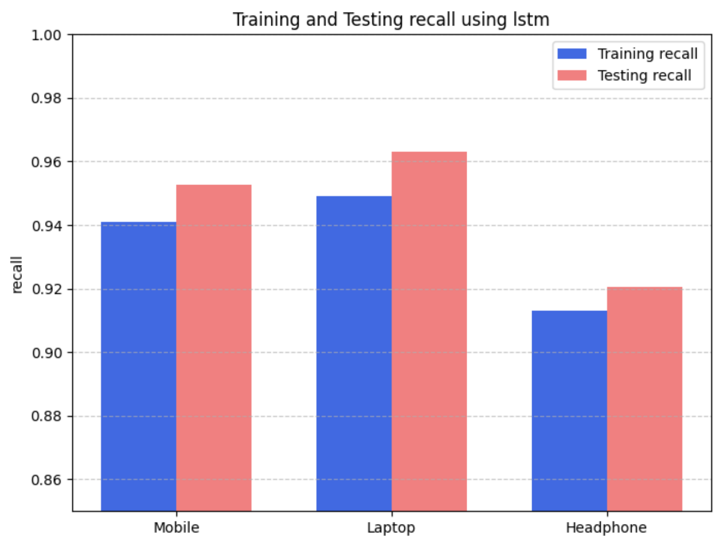

Figure 9: Recall Using Bi- LSTM with Attention

4 Conclusion

To sum up, this research offers a solid and expandable approach to fine-grained aspect-based sentiment analysis that makes use of both deep learning and sophisticated natural language processing methods. The methodology assurances precise identification of sentiment-bearing content by methodically processing user evaluations across several product categories, breaking them up into intelligible sentences, and identifying certain features using contextual embeddings. While the conversion of data into a structured multi-label format facilitates effective learning, the hybrid sentiment classification technique that combines BERT and VADER improves the system's dependability and adaptability to a variety of linguistic patterns. The amalgamation of an attention mechanism into a bidirectional LSTM network enhances sentiment prediction by concentrating on the most instructive phrase components. Evaluation findings support the model's higher performance in class-sensitive measures and accuracy, hence increasing its usefulness for practical applications. Overall, the suggested pipeline provides a thorough method for comprehending complex customer viewpoints, assisting users and producers in the e-commerce ecosystem in making well-informed decisions.

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Authors Biography

Seenia Joseph, is a research scholar at Karpagam Academy of Higher Education, Coimbatore, and an Assistant Professor at Bharata Mata College. She obtained her master's degree in Computer Applications from Calicut University in 2007. Her research focuses on data mining techniques applied across various domains. To date, she has authored 5 papers in national and international journals and contributed to 2 book chapters

Dr.S. Hemalatha, is presently an Associate Professor and Research Guide at Karpagam Academy of Higher Education in Coimbatore. Her research interests encompass data mining, image processing, and networking. With a prolific scholarly output, she has authored over 10 papers, which have been published in Scopus-indexed journals, along with an additional 5 papers in peer-reviewed journals.