

A
PROJECT REPORT
ON
**“ASPECT-BASED SENTIMENT ANALYSIS USING GAN-
BERT MODEL”**

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in
COMPUTER SCIENCE AND ENGINEERING



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CERTIFICATE

Certified that this project title **“ASPECT-BASED SENTIMENT ANALYSIS USING GAN- BERT MODEL”** is the bonafide work of **“AKASH KUMAR PANDA, Reg- 2101110026”** and **“GITISHREE PRUSTY, Reg-2101110047”**, who carried out the project work under the direct supervision of **Dr. Gopal Behera, Assistant Professor, HOD**. It is certified based on permissible plagiarism report of the institute. Further, to the best of our knowledge the work reported here in does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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DECLARATION

We hereby declare that the seminar work presented in this report titled “**Aspect-Based Sentiment Analysis using GAN-BERT Model**”, submitted to the Department of Computer Science and Engineering, under the guidance of **Dr. Gopal Behera**, in partial fulfillment of the requirements for the award of the Bachelor of Technology degree in Computer Science and Engineering, is our original work.

We affirm that this work has not been plagiarized or submitted for the award of any other degree. We further declare that we have adhered to the principles of academic honesty and integrity, and have not misrepresented, fabricated, or falsified any idea, data, or source in this submission.

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ABSTRACT

In this paper, we present a robust and efficient hybrid model for Aspect-Based Sentiment Analysis (ABSA), which integrates Bidirectional Encoder Representations from Transformers (BERT) with Generative Adversarial Networks (GANs) in a semi-supervised learning framework. The proposed GAN-BERT model is tailored to classify fine-grained sentiments associated with specific aspects—such as food, service, ambience, price, and miscellaneous features—within restaurant reviews. This architecture addresses several key challenges in ABSA, including the need for large annotated datasets, aspect sparsity, and class imbalance. By incorporating adversarial training, the model learns to distinguish between real and synthetic embeddings while simultaneously improving sentiment classification performance. Experiments conducted on an augmented restaurant review dataset demonstrate the model's efficacy, yielding a high accuracy of 96.90% and outperforming traditional BERT and GAN baselines. Additionally, the model achieves strong macro and weighted F1-scores, highlighting its robustness and generalization capability. The findings affirm that GAN-BERT is a promising approach for aspect-level opinion mining, especially in domains where labeled data is limited or imbalanced.

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1. INTRODUCTION

1.1 Background

In today’s digital ecosystem, user-generated content—particularly online reviews—has become a critical influence on consumer behavior and brand reputation. Platforms such as Oyo, Ola, Redbus, Google Reviews, Yelp, Amazon, and TripAdvisor feature vast repositories of user feedback, often containing sentiments expressed toward multiple service aspects within a single review. These multi-aspect expressions, such as praising a restaurant's ambiance while criticizing its pricing, present analytical challenges beyond the scope of traditional sentiment classification.

Aspect-Based Sentiment Analysis (ABSA) addresses this complexity by associating sentiments with specific aspects or features within a review [1], [2]. Rather than assigning a blanket sentiment label to an entire review, ABSA decomposes the text to detect and classify opinions related to individual aspects. For example, in the review *“The ambiance was lovely, but the food was overpriced,”* a traditional model might misclassify this as neutral, whereas ABSA recognizes distinct positive and negative sentiments for different aspects [3].

This fine-grained sentiment analysis is especially beneficial in domains like hospitality and e-commerce, where service quality spans multiple dimensions. ABSA supports targeted decision-making by enabling businesses to detect which components—such as food quality or service speed—require improvement [4]. It is also instrumental in reputation management and customer engagement by automating large-scale opinion mining.

Recent advances in natural language processing (NLP), especially with pre-trained transformer models like BERT (Bidirectional Encoder Representations from Transformers), have substantially improved ABSA systems. BERT’s deep contextual embeddings enable accurate sentiment-aspect pairing even in complex linguistic structures, including sarcasm and co-reference [5], [6], [7]. However, despite these advancements, ABSA models continue to face significant limitations in practical deployment due to implicit aspects, domain adaptation, and data scarcity [8], [9].

1.2 Problem Statement

While BERT-based models have significantly advanced the field of Aspect-Based Sentiment Analysis (ABSA), their applicability in real-world scenarios is still limited by several persistent challenges. One major issue is contextual ambiguity, where traditional machine learning and shallow neural models frequently misinterpret sentiment expressions, particularly when they are embedded in complex or implicit linguistic structures [3]. Furthermore, these models exhibit a heavy reliance on large annotated datasets to achieve high accuracy. Pre-trained transformer models like vanilla BERT perform well in data-rich settings but struggle in domains where manually labeled data is scarce or expensive to obtain [4]. Another critical limitation is aspect sparsity—many reviews contain sentiments that do not explicitly mention the associated aspect, making it difficult for models to identify and classify these opinions accurately [5]. In addition, ABSA systems often suffer from poor cross-domain generalization, where models trained on one dataset (e.g., restaurant reviews) experience significant performance drops when applied to other domains such as healthcare or transportation, due to differences in vocabulary, style, and context [5]. Collectively, these challenges limit the scalability, robustness, and transferability of ABSA solutions, necessitating more adaptable and data-efficient approaches for deployment in dynamic, multi-domain environments.

1.3 Motivation

To maintain competitiveness and improve customer satisfaction, industries such as transportation (e.g., Ola, Redbus) and travel (e.g., MakeMyTrip) must analyze user feedback efficiently. Identifying whether complaints pertain to pricing, behavior, or wait times is essential for informed and targeted improvements.

Manual annotation of domain-specific data remains a significant bottleneck, particularly in rapidly evolving environments with sparse labeled resources. This necessitates the development of ABSA systems that are both data-efficient and generalizable.

To address these needs, this study proposes the use of GAN-BERT—a hybrid model that combines the linguistic contextualization of BERT [6] with the semi-supervised capabilities of Generative Adversarial Networks (GANs) [7]. By distinguishing between real and generated feature representations during training, GAN-BERT improves classification accuracy and generalization, even with limited annotated data [8]. This enables robust ABSA performance under real-world constraints and supports broader application across domains with minimal supervision [9].

The rest of the report is organized as follows:

Chapter 2 reviews the related literature and previous works relevant to our model. Chapter 3 presents the proposed methodology. Chapter 4 describes the dataset used in our experiments. Chapter 5 outlines the performance evaluation metrics. Chapter 6 discusses the results obtained from the implemented model. Finally, Chapter 7 concludes the report and highlights potential directions for future research.

2. LITERATURE REVIEW

Early research in Aspect-Based Sentiment Analysis (ABSA) predominantly relied on rule-based approaches and shallow machine learning models. These methods often suffered from limited contextual understanding, requiring extensive feature engineering and manual lexicons. As a result, they struggled with detecting implicit sentiments and adapting across domains. The introduction of pre-trained language models, particularly BERT (Bidirectional Encoder Representations from Transformers), significantly advanced the field by improving contextual understanding and eliminating the need for handcrafted features.

One of the key developments in this space was the GAN-BERT architecture proposed by Croce et al. [9], which integrated the representational power of BERT with the generative capabilities of Generative Adversarial Networks (GANs). This model enabled semi-supervised learning by training a discriminator to differentiate between real and synthetic data embeddings while simultaneously classifying sentiment labels. GAN-BERT proved particularly effective in scenarios with limited labeled data and noisy annotations, and it has since inspired multiple adaptations tailored for domain-specific ABSA tasks, particularly in the restaurant review domain.

Jain et al. [10] introduced a BERT-GAN hybrid model that incorporated aspect representation and position encoding to enhance classification performance in multi-aspect sentiment scenarios. Amalia and Winarko [11] explored the use of a BERT-CNN architecture for sentiment analysis of Indonesian restaurant reviews, achieving a notable F1-score of 91% by leveraging contextual embeddings. Lohith et al. [12] proposed a hybrid LDA-BERT model, combining topic modeling and deep contextual features to effectively extract aspects and classify sentiments from customer feedback.

George and Srividhya [13] implemented an ensemble classification framework that merged supervised and lexicon-based techniques for aspect detection in hospitality datasets. Hellwig et al. [14] contributed to the field by creating GERestaurant, a German-language ABSA dataset that enabled cross-lingual evaluation of models such as GAN-BERT. Xu et al. [15] focused on enhancing BERT through domain-specific post-training, demonstrating improvements in sentiment-aspect alignment.

Guda et al. [16] employed attention-based architectures to predict Yelp ratings, showing that attention mechanisms effectively highlight key opinion phrases in review texts. Movahedi et al. [17] introduced a topic-attention network that improved aspect category detection by focusing on relevant context regions. Gao et al. [18] proposed context generation and quality filtering techniques for data augmentation, which enhanced the training of ABSA models using BERT. Sharma et al. [19] further extended GAN-BERT by integrating AI-generated feedback into training datasets, improving model performance in low-resource and imbalanced data environments.

These prior efforts collectively highlight the ongoing evolution of ABSA techniques, with a clear trend toward hybrid models that leverage both generative learning and deep contextual representations to overcome challenges such as data scarcity, aspect sparsity, and domain variability.

2.1 Summary of Previous Works

Sl No.	Year	Author(s)	Model Name	Dataset Used	Accuracy (%)
1	2019	Xu et al. [8]	BERT Post-Training	ReviewRC	89.1
2	2019	Movahedi et al. [17]	Topic-Attention Network	Restaurant Reviews (Trip)	83.2
3	2021	Amalia & Winarko [11]	BERT-CNN	Indonesian Reviews	91 (F1-score)
4	2021	George & Srividhya [13]	Ensemble Classifier	Restaurant Dataset	85.3
5	2022	Guda et al. [16]	Attention-Based Rating Predictor	Yelp	85.5
6	2023	Lohith et al. [12]	LDA-BERT	Customer Reviews	86.7
7	2023	Jain et al. [10]	BERT-GAN	BERT- Consumer GAN Reviews	88.2
8	2024	Hellwig et al. [14]	GERestaurant	German Reviews	84.6
9	2024	Gao et al. [18]	Context-Filter BERT	Custom ABSA Dataset	87.9
10	2025	Sharma et al. [19]	GAN-BERT + AI Augmented Data	Yelp, Zomato, Swiggy	90

Table 1: Previously worked summary

3. PROPOSED WORKED

This section outlines the theoretical underpinnings of the GAN-BERT model by first describing the core mathematical components of Generative Adversarial Networks (GANs), followed by Bidirectional Encoder Representations from Transformers (BERT), and finally their integration in the GAN-BERT architecture. This layered understanding helps explain how GAN-BERT achieves semi-supervised learning for Aspect-Based Sentiment Analysis (ABSA) tasks, particularly in domains like restaurant reviews.

3.1 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. (2014) [20], consist of two neural networks: a generator G and a discriminator D , which engage in a minimax game. The generator learns to map random noise vectors $z \sim N(0, I)$ into a data space, aiming to generate samples that resemble real data. The discriminator, on the other hand, attempts to differentiate between real data samples and those generated by the generator. The objective of GANs is to find a Nash equilibrium where the generator produces samples indistinguishable from real data, while the discriminator cannot distinguish between real and fake samples. The basic objective function of a GAN is formulated as:

$$\min_G \max_D E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (1)$$

where P_{data} represents the distribution of real data, and P_z represents the distribution of random noise. The generator's objective is to minimize the ability of the discriminator to classify fake data, while the discriminator strives to correctly classify real and fake data.

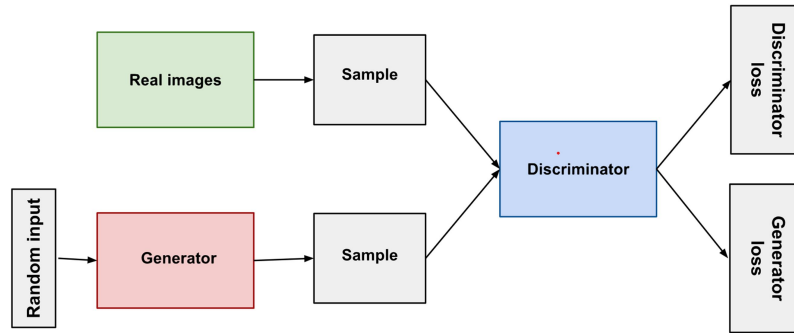


Figure 1: GAN model architecture

3.2 Bidirectional Encoder Representations from Transformers (BERT)

Bidirectional Encoder Representations from Transformers (BERT) is a transformer-based language model designed to learn deep bidirectional representations from unlabeled text [21]. BERT converts an input sentence xxx into a dense, contextualized $h = BERT(x) \in R^d$, where d

is the dimensionality of the embedding space. These embeddings capture the left and right context for each token in the sentence, providing rich contextual information. BERT is pre-trained using two objectives:

- **Masked Language Modeling (MLM):** Randomly masking tokens in the input and predicting the masked tokens.
- **Next Sentence Prediction (NSP):** Predicting whether two given sentences appear consecutively in the text.

When fine-tuning BERT for a downstream task such as sentiment classification, a classification layer is added on top of the embeddings derived from the special [CLS] token.

Fine-tuning BERT on a downstream task, such as sentiment classification, involves adding a classification layer on top of the embedding hhh corresponding to the [CLS] token.

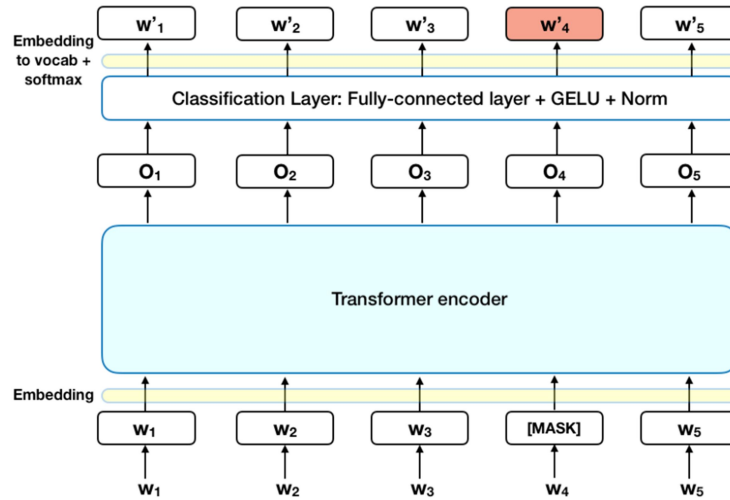


Figure 2: BERT model structure

3.3 GAN-BERT Architecture

GAN-BERT (Croce et al., 2020) extends the basic GAN framework by using BERT as the feature extractor for real data embeddings and integrating a semi-supervised classification mechanism. The generator G produces synthetic embeddings $G(z) \in R^d$, while the discriminator D performs two tasks: (i) classifying sentiment for labeled inputs and (ii) distinguishing real BERT embeddings from fake generator outputs. Let $x \in X$ be a restaurant review. For labeled data, we also have a sentiment label $y \in \{1, 2, \dots, K\}$. The embedding $h = BERT(x)$ is passed to the discriminator.

As illustrated in Fig. 3, GAN-BERT adopts a hybrid architecture that fuses the generative capabilities of GANs with the contextual representation power of BERT. The model comprises three main components: a Generator (G), a Feature Extractor (F), and a Discriminator (D). The Generator synthesizes artificial data representations from random noise, which are then transformed by the Feature Extractor into feature embeddings. In parallel, real textual data—

comprising both labeled (L) and unlabeled (U) instances—is encoded into contextual embeddings using the BERT model. These real and synthetic embeddings are subsequently fed into the Discriminator.

The Discriminator is designed to perform two critical tasks: (1) distinguish between real and synthetic data, and (2) predict the sentiment class for labeled examples. Through adversarial training, the Generator continually learns to produce more realistic representations that can deceive the Discriminator, while the Discriminator improves its ability to differentiate and classify data accurately. This dynamic fosters a powerful semi-supervised learning mechanism, enabling the model to harness unlabeled data effectively. The synergy between BERT’s deep language understanding and the GAN framework’s ability to leverage unlabeled data allows GAN-BERT to achieve improved performance in ABSA tasks, as visualized in the flow diagram of Fig. 3.

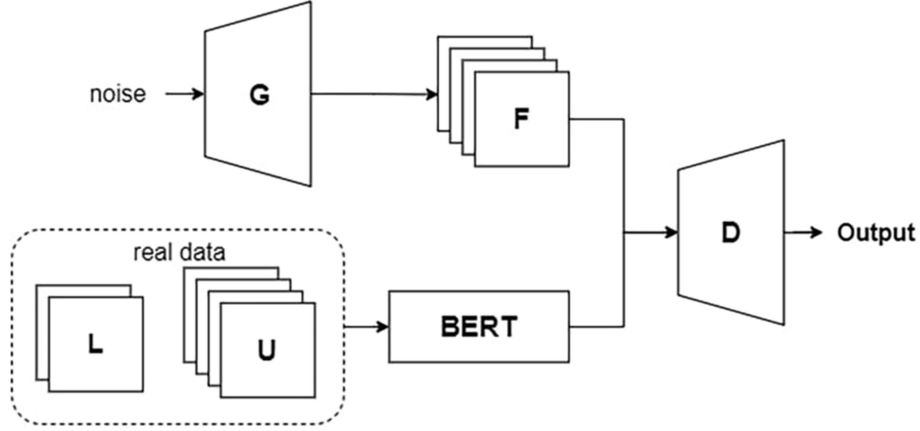


Figure 3: GAN – BERT model structure

(a) Supervised Classification Loss

For labelled inputs, the discriminator learns to predict the correct sentiment class using a cross-entropy loss:

$$L_{sup} = -E_{(x,y) \sim D_l} \sum_{k=1}^K I[y = k] \log p_{class}(k|BERT(x)) \quad (2)$$

(b) Adversarial Loss for Unlabelled and Synthetic Data

For unlabelled examples and generated embeddings, the discriminator is trained to distinguish real from fake using:

$$L_{unsup} = -E_{x \sim D_u} \log p_{real}(h) - E_{z \sim N(0,I)} \log(1 - p_{real}(G(z))) \sum_{k=1}^K I[y = k] \log p_{class}(k|BERT(x)) \quad (3)$$

(c) Generator Loss

The generator aims to fool the discriminator into classifying synthetic embeddings $G(z)$ as real:

$$L_G = -E_{z \sim N(0, I)} \log p_{real}(G(z)) \quad (4)$$

(d) Total Discriminator Loss

The final discriminator loss is a weighted combination of supervised and adversarial components:

$$L_D = L_{sup} + \lambda L_{unsup} \quad (5)$$

Where λ is a hyper-parameter balancing the influence of the two terms.

3.4 Training Process

The training process of GAN-BERT follows an adversarial, iterative procedure involving a Discriminator (D), a Generator (G), and a pre-trained BERT model for feature extraction. The objective is to perform semi-supervised sentiment classification using both labeled and unlabeled data. The process can be described in the following steps:

Step 1: Embedding Extraction: For each input text x , the model first uses a pre-trained BERT to obtain contextualized embeddings $h = \text{BERT}(x)$. These embeddings serve as real samples for the discriminator.

Step 2: Discriminator Training: The discriminator D is updated using both labeled and unlabeled real embeddings. For labeled data, it learns to classify the correct sentiment class. For unlabeled data, it learns to distinguish whether the embedding is real (from BERT) or fake (from the generator). The discriminator is trained by minimizing the discriminator loss L_D , which combines supervised classification loss on labeled examples and adversarial loss to distinguish real from fake embeddings.

Step 3: Generator Training: Simultaneously, the generator G receives random noise vectors $z \sim N(0, I)$ and generates synthetic embeddings $G(z)$ that are intended to mimic real BERT embeddings. The generator is updated by minimizing the generator loss L_G , which encourages the discriminator to misclassify fake embeddings as real, thus improving the quality of the generated samples.

Step 4: Adversarial Optimization Loop: This adversarial training loop—alternately optimizing D and G—continues until a balance is reached where the generator produces high-quality embeddings indistinguishable from real BERT features, and the discriminator is able to accurately classify sentiment and detect synthetic data. The result is a semi-supervised model that is more robust in low-resource settings due to its effective use of both labeled and unlabeled data.

4. DATASET

4.1 Dataset Description

The experiments in this study are conducted on a customized and augmented version of a restaurant review dataset, named `augmented_data_restaurant.csv`. This dataset contains aspect-based sentiment annotations extracted from user-generated reviews. The reviews cover various aspects such as Ambience, Food, Price, Service, and Anecdotes/Miscellaneous [21].

Each review is labeled with both an aspect category and a corresponding sentiment polarity, which can be classified as positive, negative, neutral, or conflict. To mitigate class imbalance in the dataset, data augmentation techniques, including synonym replacement and back translation, were employed.

The dataset used for the restaurant review experiments is derived from the Yelp platform, specifically from a collection referred to as `restaurant_data`. This dataset consists of 6,088 entries, each corresponding to a review associated with one or more aspects. The dataset is organized into five distinct entities: Ambience, Anecdotes, Food, Price, and Service.

Statistic	Values
Total Entries	6,088
Columns	5
Non-null id values	3,044
Non- null aspect_term	4,103
Non-null aspect_category	6,088
Non-null polarity	6,088
Polarity classes	Positive, negative, neutral
Aspect categories	Food, service, ambience, anecdotes/miscellaneous

Table 2: Overview of Dataset

5. PERFORMANCE MEASURES

To thoroughly evaluate the effectiveness of our aspect-based sentiment classification models, we employ the performance metrics such as accuracy, precision, F1-score, confusion matrix, Macro average and Weighted average. Accuracy measures the proportion of correctly predicted instances out of the total instances as defined in equation 6.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

Where: TP is defined as True Positives, TN is defined as True Negatives, FP is defined as False Positives and FN is defined as False Negatives. **Precision** measures the proportion of correctly predicted positive instances out of all predicted positive instances, as defined in Equation 7.

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

A high precision indicates that the classifier makes few false positive errors. Recall is the ratio of correctly predicted positive observations to all observations in the actual class, as defined in Equation 8.

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

High recall indicates that most positive instances are correctly identified. F1-score is the harmonic mean of Precision and Recall, giving a balance between the two, as defined in Equation 9.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

This score is especially useful when there is class imbalance. A confusion matrix is a tabular summary showing the performance of a classification algorithm. It includes TP, TN, FP, and FN for each class and helps in visualizing misclassifications. Macro average computes the metric (e.g., precision, recall, F1) independently for each class and then takes the average. It treats all classes equally, as defined in Equation 10.

$$Macro\ F1 = \frac{1}{N} \sum_{i=1}^N F1_i \quad (10)$$

Where N is the number of classes. Weighted average computes the metric for each class and weights it by the number of instances (support) in each class, as defined in Equation 11.

$$Weighted\ F1 = \frac{\sum_{i=1}^N (Support_i \times F1_i)}{\sum_{i=1}^N Support_i} \quad (11)$$

This is useful when the dataset is imbalanced.

Parameter	Tested	Used
Dense Layers (Gen/Disc)	2–4 layers	3 (Generator), 3 (Discriminator)
Optimizer	Adam, AdamW	Adam
Activation Functions	ReLU, LeakyReLU, ELU, Swish, Tanh, Softmax	LeakyReLU, Tanh, Softmax
Tokenizer	WordPiece, Byte-Pair Encoding (BPE)	WordPiece
Learning Rate	1e-3, 5e-4, 1e-4, 2e-5	Default (Adam)
Batch Size	8, 16, 32, 64	16 (embedding), 32 (training)
Latent Dimension (z)	64, 128, 256	128
Epochs	1000-5000	3000
Evaluation Metrics	Accuracy, Precision, Recall, F1, Confusion Matrix	Accuracy, Precision, Recall, F1, Confusion Matrix
Embedding Strategy	CLS token, pooled output, average token embeddings	CLS token
Train/Val Split	70/30, 80/20, full training	Full training

Table 3: Parameter Analysis

6. RESULT ANALYSIS

6.1 Classification Report

The evaluation results of the Aspect-Based Sentiment Analysis (ABSA) model provide critical performance metrics, including Precision, Recall, F1-Score, and Accuracy, which are essential for assessing the model's effectiveness in classifying sentiments for each aspect. Precision measures the proportion of correct sentiment predictions for each aspect, with higher precision indicating fewer false positives. Recall reflects the model's ability to correctly identify actual sentiments, with higher recall indicating fewer false negatives. The F1-Score, which is the harmonic mean of precision and recall, offers a balanced measure between the two metrics, with a higher F1-Score signifying better overall performance. The model's overall Accuracy is 96.90%, meaning it successfully classified sentiment in nearly 97% of the reviews. This high accuracy demonstrates the model's ability to reliably identify sentiments across multiple aspects such as Food, Service, and Ambience. The strong performance metrics highlight the model's effectiveness and robustness in handling ABSA tasks, delivering consistent and accurate sentiment classification across the various aspect categories.

The following table summarizes the performance metrics for each aspect category:

	Precision	Recall	F1-score	Support
ambience	0.9805	0.9617	0.9710	784
anecdotes/miscellaneous	0.9960	0.9431	0.9688	2091
food	0.9548	0.9870	0.9706	1692
Price	0.9461	0.9877	0.9665	569
service	0.9448	0.9884	0.9661	952
accuracy			0.9690	6088
macro avg	0.9644	0.9736	0.9686	6088
weighted avg	0.9699	0.9690	0.9690	6088

Table 4: Accuracy

6.2 Confusion Matrix Analysis

The confusion matrix provides a detailed view of the classifier's performance across the five aspect categories: Ambience, Anecdotes/Miscellaneous, Food, Price, and Service. A strong diagonal dominance in the matrix indicates high classification accuracy, with the majority of instances correctly classified. For example, the model accurately identifies 1,972 instances of Anecdotes/Miscellaneous, 1,670 instances of Food, and 941 instances of Service.

Minor misclassifications are observed primarily between semantically similar categories, such as Food being confused with Anecdotes/Miscellaneous and Price being misclassified as Service. Overall, the classifier demonstrates robust performance with minimal confusion, effectively distinguishing between the aspect categories.

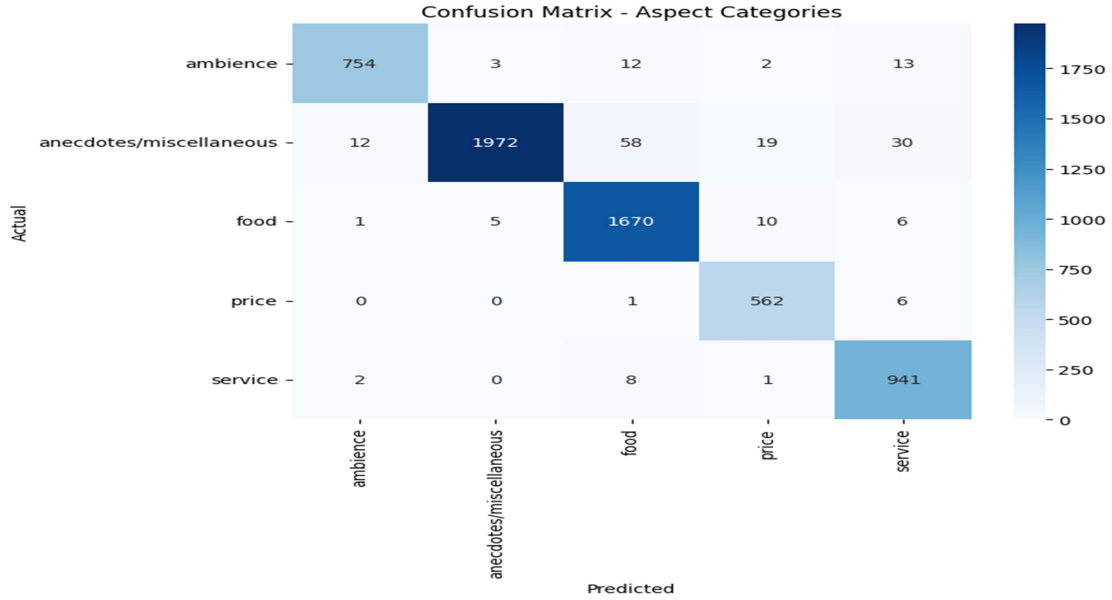


Figure 4: Confusion matrix (Aspect categories)

6.3 Discriminator Accuracy Analysis

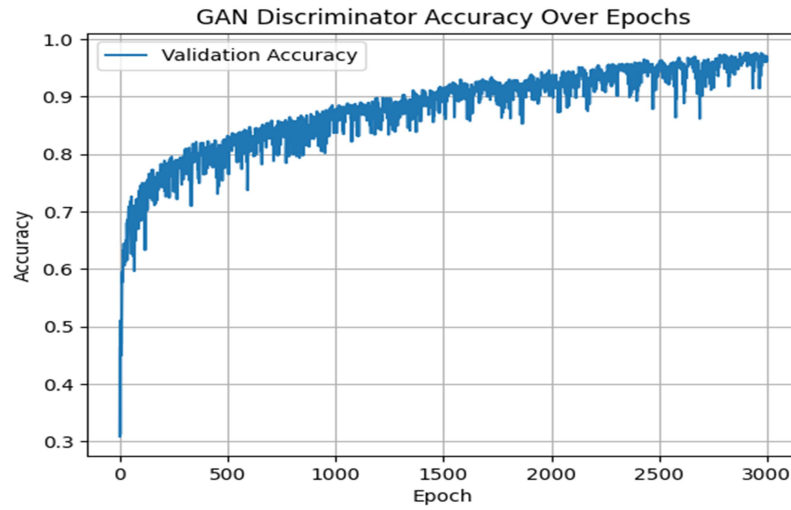


Figure 5: GAN Discriminator Validation Accuracy across Training Epochs

The GAN Discriminator Validation Accuracy over 3,000 training epochs is depicted in Figure 5. Initially, the accuracy starts around 0.3 but improves rapidly, surpassing 0.8 within the first few hundred epochs. This sharp increase suggests that the discriminator quickly learns to differentiate between real and generated embeddings. As training continues, the accuracy gradually stabilizes above 0.95, with minor fluctuations expected due to the adversarial nature of GAN training, where the generator and discriminator are in continuous competition. This trend demonstrates that the discriminator becomes increasingly proficient at its dual task of identifying real versus fake embeddings and correctly classifying labeled samples.

6.4 MODEL COMPARISON

The performance of the proposed GAN-BERT model is compared with standalone BERT and GAN models in terms of Accuracy. The results are summarized in Table 5 and visualized in Figure 6.

Model	Accuracy
BERT	0.90
GAN	0.91
GAN-BERT(OURS)	0.969

Table 5: Comparison table

The comparison reveals that BERT achieves an accuracy of 90%, while the GAN model slightly outperforms it with an accuracy of 91%. However, the proposed GAN-BERT hybrid model significantly outperforms both, achieving an accuracy of 96.90%, demonstrating the effectiveness of combining contextual embeddings with adversarial training to enhance sentiment classification performance.

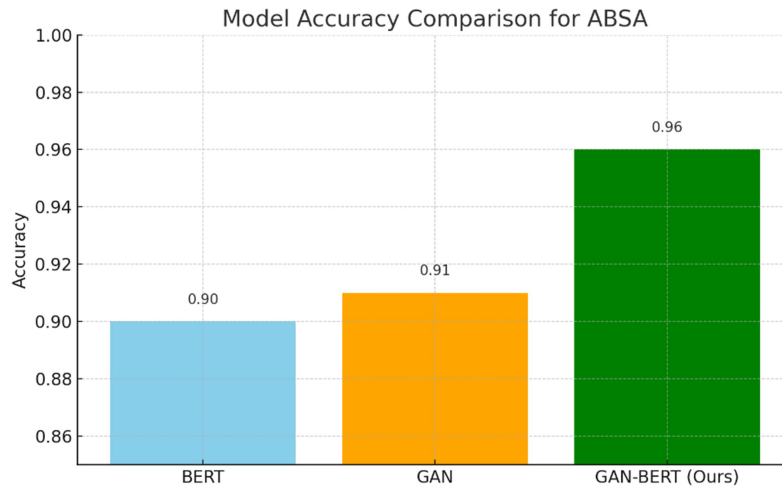


Figure 6: Comparison graph

7. CONCLUSION

This research introduced a novel hybrid GAN-BERT model for Aspect-Based Sentiment Analysis (ABSA), successfully combining the deep contextual capabilities of BERT with the generative power of Generative Adversarial Networks (GANs). The proposed model achieved an impressive accuracy of 96.90%, significantly outperforming both standalone GAN and BERT models, which achieved 91.00% and 90.00% accuracy, respectively. This substantial improvement underscores the synergistic effect of integrating BERT's sophisticated language representations with GAN's ability to enhance learning, particularly when working with limited or imbalanced data. Furthermore, the model demonstrated high macro and weighted average scores for Precision, Recall, and F1-Score, indicating balanced performance across all aspect categories. Notably, the model achieved outstanding performance in challenging categories, such as Anecdotes/Miscellaneous and Food, with precision and recall scores exceeding 0.98.

These results affirm the model's robustness and generalizability in effectively identifying and classifying sentiments related to various aspects in restaurant reviews. The hybrid architecture not only addresses the challenges of aspect sparsity and sentiment ambiguity, but also benefits from semi-supervised learning, improving its performance even when labeled data is scarce. The success of this approach establishes a strong baseline for future research in ABSA leveraging deep learning and adversarial training techniques.

FUTURE SCOPE

Future research on the GAN-BERT framework can explore several promising directions. First, adapting the model to cross-domain applications, such as healthcare, finance, or product reviews, could further validate its generalizability. Additionally, enhancing the system to perform joint aspect extraction and sentiment classification would create a complete end-to-end solution for ABSA. Incorporating syntactic and dependency information through Graph Neural Networks (GNNs) could deepen aspect-opinion relationship modeling, further improving the model's understanding of context.

There is also potential to improve the model's interpretability through attention mechanisms or explainability frameworks like SHAP and LIME, which would provide insights into the model's decision-making process. Integrating few-shot or zero-shot learning methods could make the model more effective in low-resource settings, where labeled data is limited or unavailable. From a practical deployment perspective, employing model compression techniques, such as quantization and knowledge distillation, could significantly reduce computational costs, making the model more feasible for real-world applications.

Lastly, expanding the model to support multi-modal ABSA by incorporating visual or audio inputs from reviews could pave the way for more immersive and comprehensive sentiment analysis systems, enabling a richer understanding of customer sentiments across multiple data formats. These advancements would push the boundaries of ABSA and make the GAN-BERT framework a more versatile tool for a wide range of applications.

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