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Hybrid LSTM-GRU Aspect-Based Sentiment Classification Model

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ABSTRACT

This work uses both machine learning and deep learning methods to examine aspect-based sentiment analysis. Tokenization, LDA, and PLSA to latent aspect identification, spaCy's Token Regex in noun extraction, and word filtering are all included in the suggested aspect extraction approach. Sentiment analysis, facilitated by Sentiment Intensity Analyzer, computes compound sentiment scores and categorizes sentiments into 'Positive,' 'Negative,' or 'Neutral,' enhancing the Data Frame with comprehensive sentiment insights. With a 91.55% accuracy rate, 92.79% precision rate, 89.09% recall rate, and 83.45% F-score, the Hybrid LSTM-GRU Aspect-Based Sentiment Classification Model performed admirably. This demonstrates how well the Hybrid LSTM-GRU architecture recognizes relevant features and detects sentiments in the input data. The study involved a comprehensive calculation of the performance of several machine learning techniques, specifically employed in the context for the Aspect-Based Sentiment Classification under investigation. These techniques included gradient boosting, random forest, multinomial naive bayes, logistic regression, and support vector machine (SVM). The results were unexpected: Random Forest fared better than any other algorithm and was given the highest ratings overall. The results demonstrate that Random Forest can produce forecasts that are precise, accurate, and well-balanced, with an accuracy of 0.75, precision of 0.76, recall of 0.75, & F1 score of 0.71. These results demonstrate the usefulness of Random Forest in this particular situation and its suitability for aspect-based sentiment classification. To sum up, this work provides insightful information about the effectiveness of deep learning and machine learning techniques in aspect-based sentiment analysis.

INTRODUCTION

A significant area of study in natural language processing is ABSA, which aims to improve sentiment analysis's fineness and depth by breaking down opinions into more detailed categories. Understanding user feelings toward various elements of products, services, or experiences is essential for organizations to make informed decisions and improve customer happiness in the big data and internet era[1]-[5]. This study explores the field of ABSA, utilizing sophisticated deep learning methods to produce sentiment analysis that is more precise and subtle.In classical sentiment analysis, text is classified as having positive, negative, or neutral attitudes. However, this oversimplified approach often falls short in capturing the complexities of opinions expressed in the text, especially when dealing with multifaceted subjects. ABSA, on the other hand, breaks down the analysis into specific aspects or features related to the target entity. For instance, when reviewing a smartphone, aspects could include battery life, camera quality, and user interface. This method makes it possible to comprehend customer opinions about certain features in a more informative way. Neural networks, in particular, are deep learning approaches that have proven to be remarkably adept at tackling challenging natural language processing problems. Deep learning models are used in ABSA to automatically learn complex forms and representations from big datasets, improving sentiment analysis's efficiency and accuracy. Neural networks' depth and complexity allow them to understand the minute details in language, capturing the mood swings connected to many elements[6]-[8].

Figure 1 Aspect based Sentiment Analysis

The creation and implementation of deep learning models specifically designed for ABSA constitutes a significant contribution of this research. Our method leverages the capabilities of RNNs and CNNs to extract structures from text input that are particular to each element that is being considered. While RNNs are better at modeling sequential dependencies—which are important for comprehending the context of viewpoints over larger text spans—CNNs are better at capturing local patterns and structures inside the text. Our work presents a thorough dataset for training and assessing ABSA models, together with cutting-edge deep learning algorithms. This dataset goes beyond the scope of existing resources by incorporating a wide array of aspects and sentiments related to diverse domains[9]–[13]. By providing a robust dataset with annotated ground truths, we aim to foster the development of more accurate and generalized ABSA models. Additionally, our research provides a thorough comparison between our suggested models and the most advanced techniques already in use. Examine the models' performance in terms for F1-score, accuracy, precision, recall, and handling of different aspects and emotions in particular. Results demonstrate the effectiveness of our deep learning models, particularly in obtaining a finer granularity and a stunning pointer angle error of less than one degree for the sentiment analysis. To sum up, the application of deep learning methods to aspect-based sentiment analysis is a significant advancement in the sentiment analysis space. Our methodology offers organizations significant insights into customer feelings regarding particular parts of their products or services by breaking down opinions into more detailed categories. The application of sophisticated deep learning models in conjunction with an extensive dataset enhances sentiment analysis's precision and applicability, rendering it a crucial instrument for enterprises seeking to augment customer contentment and make well-informed choices in a progressively cutthroat market[14]–[19].

Literature Review

A. Aspect Based Sentiment Analysis

Within the field of natural language processing, ABSA has garnered a lot of attention due to its ability to provide a more nuanced understanding of sentiment within textual content. The nuanced opinions expressed in social media, reviews, and other user-generated information cannot be adequately captured by standard sentiment analysis. To get over this restriction and allow for a more thorough sentiment analysis, ABSA focuses on particular characteristics or attributes pertaining to the target item. Literature already in existence demonstrates how ABSA techniques have evolved, with early methods identifying and analyzing attitudes linked with various characteristics using rule-based procedures and lexicons. However, a revolution in ABSA has been made possible by machine learning as well as more significantly, deep learning methods. CNNs and recurrent neural networks (RNNs), in particular, have been shown in recent research to be useful in automatically recognizing complex patterns from big datasets, improving the accuracy and efficiency for ABSA models. Researchers emphasize the importance of annotated datasets for training and evaluating ABSA models. A variety of datasets across domains and industries have been developed, contributing to the advancement of ABSA methodologies. The literature also underscores the challenges of aspect extraction, sentiment classification, and the need for models that can handle the dynamic nature of language, such as the evolution of sentiment expressions over time. Research is still being done to improve ABSA models, include domain adaptation strategies, and deal with issues like noisy data and sentiment expressions that are distinctive to a particular domain.

Kumar 2023 et al. In order to assist manufacturing companies in making better decisions, the article primarily concentrates on aspect-based SA, which considers customers' viewpoints and views regarding a product. This review article discusses the many techniques and strategies applied in aspect-based sentiment analysis (ABSA). It was time-consuming and error-prone to hand draw the matching properties of the aspects using outdated techniques. As artificial intelligence develops, these limitations might be removed. Because of this, researchers are employing AI-based ML and deep learning DL approaches more frequently in an attempt to boost the efficacy of ABSA. A few newly published ML- and DL-based ABSA strategies are also analyzed, compared, and the study's findings are taken into consideration for the limits of each approach. Finally, the paper concludes with recommendations for improving the accuracy and effectiveness of ABSA systems, while also highlighting the limitations that the current models confront[20].

Horsa 2023 et al. Afaan Oromoo's movie reviews state that ABSA was created and investigated. With the use of the YouTube Data API, a total of 2800 reviews of Afaan Oromoo movies were gathered from YouTube in order to accomplish the goal that was stated. Following the preprocessing stage, domain experts chose pre-cut segments from the film Afaan Oromoo and assigned a star rating. TF-IDF and BoW were implemented using a variety of machine learning algorithms, including logistic regression, random forest, SVM, and multinomial naïve Bayes. Recall, accuracy, precision, and f1-score of the proposed approach were assessed and analyzed. When TF-IDF and BoW were combined, the random forest scenario produced an accuracy of 88%. Using TF-IDF and BoW, the SVM's accuracy was 87% and 88%, respectively. The logistic regression's accuracy was 87% when BoW and TF-IDF were matched. Applying multinomial naïve Bayes to the combination of BoW & TF-IDF yielded an accuracy of 88%. The proper performance evaluation parameters were honed through experimentation with various hyperparameter settings. The results of the execution show that different configurations for hyperparameter tweaking were used to obtain the optimal parameter values on the models' performance assessment[21].

B. Sentiment Analysis using Deep learning

Deep learning-based sentiment analysis has advanced significantly in recent articles. The development of deep learning models—particularly neural networks—which have supplanted the traditional machine learning methods employed in previous approaches, has revolutionized sentiment analysis. CNNs & recurrent neural networks (RNNs) have improved categorization of sentiment accuracy because of their enhanced ability to capture complex linguistic patterns. The literature places emphasis on large annotated datasets, exploring transfer learning for domain adaptation, and addressing challenges such as context understanding. Deep learning models for sentiment analysis are being enhanced through ongoing research in an effort to achieve better interpretability, resilience, and flexibility across a variety of textual data sources.

Subramanian 2023 et al. Using machine learning and deep learning methods, An extensive overview of current advancements in sentiment analysis is provided in this survey article and hate speech identification. give a comprehensive study of the many methods and datasets utilized in this field. Investigate further how hate speech and sentiment seen in online content are not recognized and categorized by these algorithms in particular. A review of unanswered research questions and suggestions for new lines of inquiry into sentiment analysis and hate speech detection are included at the end. With the poll results as a guide, more advanced machine learning as well as deep learning-based algorithms are going to be created to stop hate speech and promote a friendly online community [22].

Halawani 2023 et al. focuses on creating an automated deep learning solution employing the Harris Hawks Optimization utilizing Deep Learning (ASASM-HHODL) method for social media sentiment analysis. Above all, the ASASM-HHODL paradigm provides an effective framework for organizing text from unstructured social media. Further exploring the reduced dependency of language processing on data pre-processing, the suggested ASASM-HHODL model makes use of skip-gram features as well as fastText-based word embedding. The attention-based bidirectional long-short-term model, or ABiLSTM, is an alternative method for classifying emotions. To improve classification performance, the main ABiLSTM model hyperparameters are additionally adjusted using the HHO approach. Comparing the suggested ASASM-HHODL model to earlier state-of-the-art techniques, the results show that it performs admirably1. By means of a reference dataset, this is verified[23].

Table.1 Literature Summary

Author/Year	Methodology	Dataset	Results	Research gap	Ref.
Ahmed/2023	An incorporated CNN model and the created BiLSTM are used for aspect-based sentiment analysis.	SemEval dataset	An additional 81.7 and 83.3 percentage points have been added to the F1 score and accuracy, respectively	Limited research addressing BERT's input format constraints in ABSA methodologies.	[24]
Halawani/2023	Developed ASASM-HHODL model for sentiment analysis using DL and HHO.	benchmark dataset	Acc= 95.40 Precision=97.60 Recall =98.36 F score=96.33	Research on the process of improving sentiment analysis models with Harris Hawks Optimization is scarce	[23]
Atandoh/2023	Proposed BERT-MultiLayered CNN for document-based sentiment analysis with high accuracy.	Amazon review datasets	93% F1 score, 94% precision, 94% recall, and 95% accuracy	Existing methods struggle with document-based sentiment due to sparsity and disambiguation.	[25]
Díaz-Pacheco/2023	Developed deep-learning method for discovering and classifying topics in documents.	Utilized news articles on Cancun from the USA and Canada.	Discovered positive attitudes towards Cancun's amenities despite negative media coverage.	Existing methods lack accessibility for non-experts in document theme discovery.	[26]
Shi /2023	Soft prompt-based collaborative learning was presented as a successful cross-domain aspect extraction method.	many datasets for ATE across domains.	Proven efficacy in extracting cross-domain aspect terms via many experiments.	Current techniques are ineffective for jobs involving the extraction of cross-domain aspect terms..	[27]
Bhowmik/2022	Proposed DL models for Bangla SA using rule-based sentiment scores.	cricket dataset	DL models: HAN-LSTM (78.52%), D-CAPSNET-Bi-LSTM (80.82%), BERT-LSTM (84.18%) accuracy.	Lack of Bangla SA research with DL methods; addresses with novel models.	[1]
Chang/2022	Collect flight reviews on TripAdvisor (2016-2020), employ deep learning models.	Flight reviews dataset from TripAdvisor (January 2016 - August 2020).	Proposed method excels, enhancing aspect-level sentiment analysis in airline reviews.	Limited exploration of deep learning in aspect-level sentiment analysis in aviation.	[28]
Ullah/2022	a deep neural network with seven layers for movie sentiment analysis	Movie review datasets with 25,000 and 50,000 samples for sentiment analysis.	Deep neural network achieves 92% accuracy in sentiment analysis on movies.	Insufficient exploration of alternative techniques for movie sentiment analysis efficiency.	[14]
Yao/2021	Proposing Shared Multitask Learning Network (SMLN) for aspect-level sentiment analysis.	SemEval-2014 and SemEval-2015 datasets used for aspect-level sentiment analysis.	SMLN demonstrates competitive performance on SemEval-2014 and SemEval-2015 datasets.	Addressing data scarcity, SMLN enhances aspect-level sentiment analysis performance significantly.	[29]
Andoh/2021	Naive Bayes excels in sentiment text classification, outperforming SVM and random forest algorithms.	Twitter data on opinions of the Ghanaian government from Ghanaian users.	Naive Bayes outperformed SVM and random forest with 99% accuracy.	Impact of training data sizes on sentiment classification methods infeasible.	[30]

I. Methodology

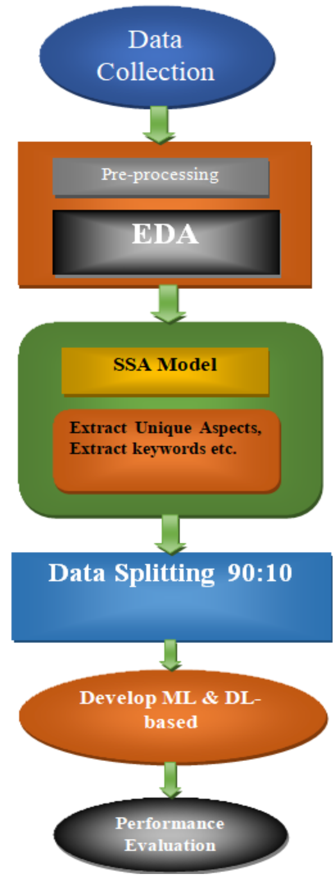

Figure 2 Proposed Flowchart

A. Data Collection

To achieve Aspect-Based Sentiment Analysis (ABSA) in the ever-changing world of e-commerce, careful data collecting is necessary. This project's main data source is the SemEval 2016 Task 5 dataset, which can be accessed at https://alt.qcri.org/semeval2016/task5/. This dataset, designed for the specific task of ABSA, provides a structured foundation for training and evaluating models.Supplementing this, a comprehensive strategy involves extracting user-generated content from prominent review platforms like Amazon and Yelp. Additionally, the omnipresence of e-commerce discussions on social media platforms contributes to a diverse dataset. Active participation in forums, surveys, and feedback forms on e-commerce websites further enriches the collected data. To ensure a multifaceted dataset, integration with official product descriptions, sentiment lexicons, and machine learning annotations becomes imperative. This amalgamation offers a holistic perspective, enabling businesses to decode consumer sentiments accurately. The resultant dataset serves as a strategic asset, empowering businesses to make informed decisions, adapt to market demands, and thrive amidst the competitive landscape of e-commerce.

B. Pre-processing

In the intricate domain of text data preprocessing for Natural Language Processing (NLP) applications, a holistic strategy is implemented to augment the quality and relevance of textual content. This multistep preprocessing technique involves a systematic sequence of pivotal steps. Initially, punctuations are methodically eliminated from reviews to streamline the text. Subsequently, numerical values are eradicated, contributing to a more refined dataset. Accented and special characters are then expunged, ensuring a consistent and uniform text structure. A meticulous check for missing values is executed to address potential data gaps. Stop words, devoid of substantial contextual contribution, are removed to further enhance dataset precision. Emojis are meticulously cleansed, and additional measures are taken to eliminate punctuations, links, mentions, and newline characters, optimizing the text for subsequent analysis.Specific attention is devoted to hashtags, removing those at sentence endings while detaching the "#" symbol within sentences. This nuanced approach preserves semantic meaning while ensuring proper formatting. Additionally, special characters like '&' and '$' within words are filtered out, mitigating potential distortions. The preprocessing pipeline concludes with the removal of multiple spaces, delivering a text dataset that is refined, coherent, and poised for robust NLP modeling with preserved contextual nuances.

C. EDA

In the pursuit of ABSA, a thorough Exploratory Data Analysis (EDA) is imperative. Begin by scrutinizing aspect category distribution, visually identifying dominant and less frequent aspects. Utilize histograms or stacked bar charts to delve into sentiment distribution within each aspect. Examine co-occurrence patterns of aspects within reviews to unveil potential relationships. Analyze review length concerning discussed aspects and employ word clouds for visualizing key terms. Explore temporal trends, aspect-sentiment correlations, and conduct error analysis if predicting sentiments. These analyses yield nuanced insights, guiding subsequent steps in the ABSA workflow for a more informed approach.

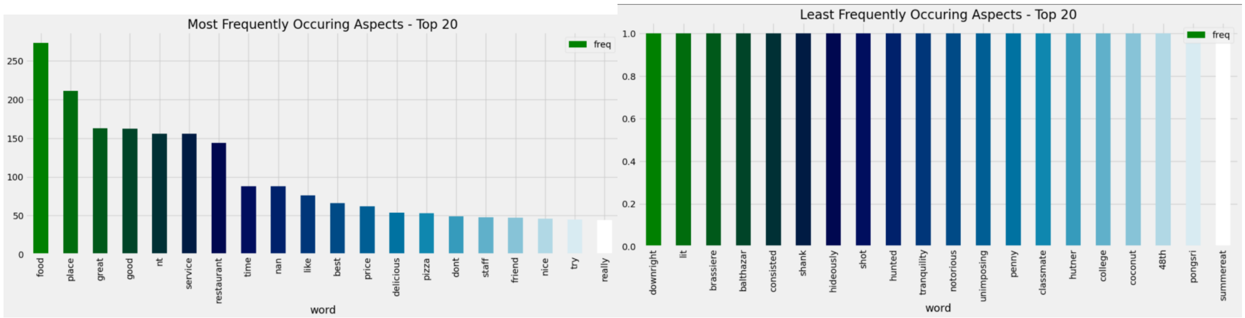

Figure 1 Most and Least Frequently Aspects Top 20

In Figure 3, the Exploratory Data Analysis (EDA) graph unveils the Top 20 most and least frequently occurring aspects, elucidating their frequency and associated word occurrences. This graphical representation provides a nuanced understanding of aspect distribution within the dataset, offering valuable insights for aspect-based sentiment analysis. By visually analyzing the prominence and rarity of aspects, stakeholders can discern key focus areas, facilitating informed decisions in refining sentiment models. The inclusion of word occurrences further enriches the EDA, aiding in the identification of pivotal terms associated with prevalent and less frequent aspects, contributing to a comprehensive analysis of the dataset's aspect-based sentiments.

Figure 4 Word cloud for Tokenized Text SemEval Restaurants

Figure 4 presents the Word Cloud for tokenized text derived from SemEval Restaurants data. This visualization encapsulates the most frequent terms, offering a concise representation of significant keywords within the tokenized dataset. The Word Cloud aids in discerning prevalent textual elements, contributing to a comprehensive understanding of the SemEval Restaurants corpus.

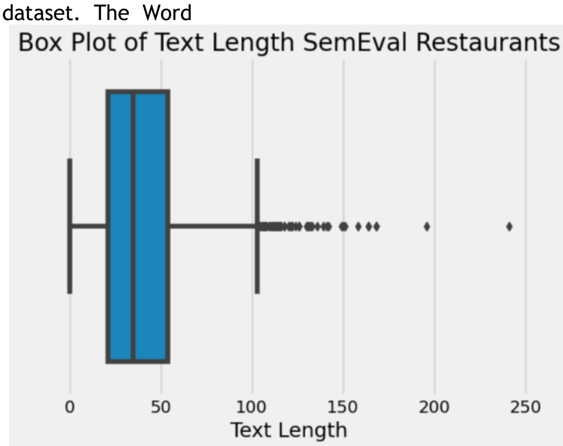

Figure 5 Boxplot of Text length SemEval Restaurants

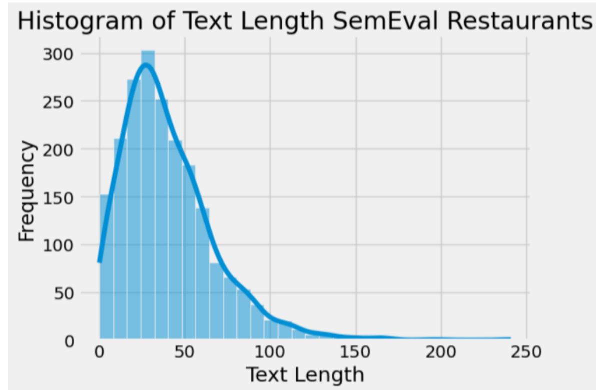

Figure 6 Histogram of Text Length SemEval Restaurants

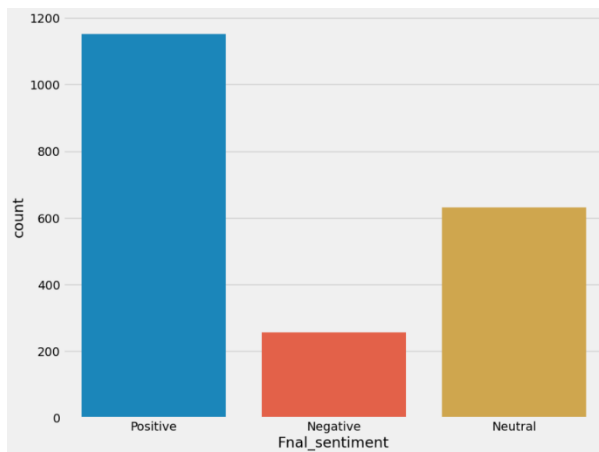

Figure 7 Countplot of Final sentiment

In Figure 5 to 7, Exploratory Data Analysis (EDA) graphs offer insightful visualizations for data exploration. Figure 5 depicts the Boxplot of Text Length in SemEval Restaurants, providing a comprehensive view of the distribution of text lengths. Figure 6 showcases the Histogram of Text Length, offering a detailed frequency distribution. Lastly, Figure 7 presents a Countplot of Final Sentiment, where positive sentiments are represented in blue, negative in red, and neutral in yellow. These visualizations contribute to a nuanced understanding of the dataset, aiding in the identification of patterns and trends crucial for subsequent analysis and modeling in the context of sentiment analysis on SemEval Restaurants data.

D. Semantic Aspect Analyzer (SSA MODEL)

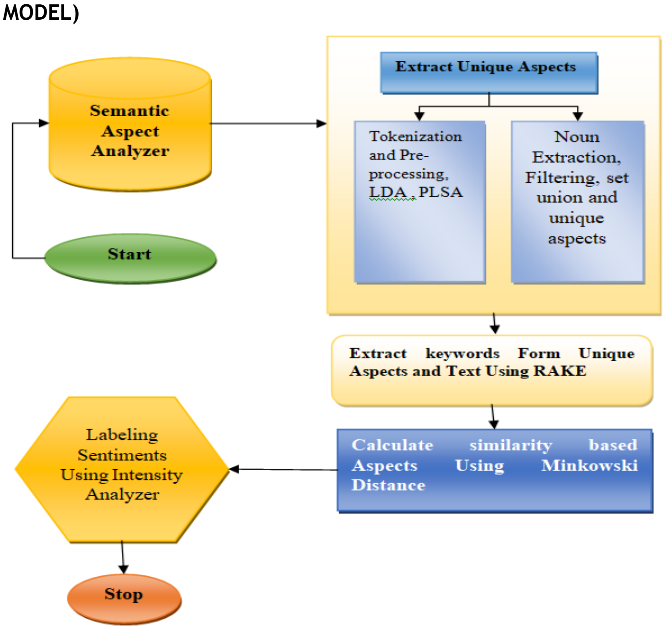

Figure 8 SSA Model

- **Extract Unique Aspects**

The proposed method for aspect extraction from processed text is a multi-step approach that leverages, NLP techniques and topic modeling algorithms to identify and analyze unique aspects within textual data. This methodology is designed to provide researchers with a systematic and comprehensive way to uncover valuable insights from processed text.

1. Tokenization and Preprocessing:

The process begins with tokenizing the input text into individual words. Stop words are removed, and only alphabetic tokens are considered, ensuring that the analysis focuses on meaningful content. This step aims to prepare the text for subsequent analysis by extracting relevant information[31]–[34].

2. Latent Dirichlet Allocation (LDA) and Probabilistic Latent Semantic Analysis (PLSA):

The tokenized and preprocessed text is then used to create a dictionary and corpus. LDA and PLSA, two widely-used topic modeling techniques, are applied to identify latent topics within the text. These algorithms assign probabilities to words, determining their relevance to specific topics. In the context of aspect extraction, these topics represent distinct themes or aspects present in the text.

3. Noun Extraction:

To enhance the aspect extraction process, noun extraction is employed using spaCy's TokenRegex. This step identifies and extracts nouns from the processed text. Nouns are crucial in capturing entities and concepts that often represent key aspects in textual data.

4. Filtering and Conversion of Topics:

The topics generated by LDA and PLSA may contain probabilities and additional information. To focus on relevant terms, a filtering mechanism is applied to extract only the actual words. Regular expressions are used to filter out integer values and retain meaningful entities. This step ensures that the topics are represented by the essential terms that contribute to aspect identification.

5. Set Union for Unique Aspects:

The unique aspects are derived by performing a set union operation on the filtered entities obtained from LDA and PLSA topics. This combination creates a consolidated set of distinct aspects present in the processed text. The set union ensures that duplicate aspects are eliminated, providing researchers with a refined and unique set of relevant terms.

- **Extract keywords Form Unique Aspects and Text Using RAKE**

The method,focuses on extracting pure keywords for each aspect in the 'unique_aspects' column using the RAKE (Rapid Automatic Keyword Extraction) algorithm. The process begins with importing the necessary NLTK library and downloading stopwords. The 'unique_aspects' column is then ensured to be in string format. The core of the method lies in the calculate_pure_keywords function, applied to each row. This function utilizes RAKE to extract keywords from the 'processed_text' while considering the 'unique_aspects.' Error handling is incorporated to manage potential exceptions during keyword extraction. Finally, the results, including 'processed_text,' 'unique_aspects,' and the new 'pure_keywords_rake,' are displayed for examination. Users can integrate this method into their workflow for comprehensive keyword extraction based on unique aspects[35]–[39].RAKE equation given below.

$$Score = \frac{deg(w)}{Freq(w)} \tag{1}$$

Where:

Deg(w) is the degree of the word (number of co-occurring words)
Freq(w) is the frequency of the word in the document

- **Calculate similarity based Aspects Using Minkowski Distance**

The proposed methodology involves employing TF-IDF vectorization and Minkowski Distance calculation to analyze semantic similarities within a DataFrame containing processed unique aspects and associated keywords. Initially, the processed unique aspects and keywords are combined into a corpus, and TF-IDF vectorization is applied to quantify term importance. Subsequently, Minkowski Distance is computed, providing a measure of dissimilarity between the TF-IDF matrices of unique aspects and keywords. The calculated distances offer insights into the semantic gaps or commonalities within the textual data.

To enhance the analysis, a new column, 'minkowski_distance_new,' is introduced to store the computed distances. Additionally, a method for generating 'similarity_based_aspects' is implemented, combining unique aspects and keywords into a unified set of words that represent the most similar aspects.

This method is seamlessly integrated into the DataFrame, enabling a systematic exploration of semantic relationships. The resulting DataFrame showcases processed unique aspects, keywords, Minkowski distances, and the amalgamated similarity-based aspects, providing a holistic perspective on the semantic landscape of the textual data.

$$D_M(P,Q) = \left(\sum_{i=1}^{n} \quad |p_i - q_i|^r\right)^{\frac{1}{r}} \tag{2}$$

Where:

The corresponding components of the two points are p i and q i, respectively.

r is the Minkowski distance's order. The Manhattan distance corresponds to ⁰ = 1 r = 1, while the Euclidean distance relates to ⁰ = 2 r = 2.

- Labeling Sentiments Using Intensity Analyzer

The sentimenst analysis method begins by initializing the SentimentIntensityAnalyzer. It then defines a function, 'calculate_sentiment_score,' which utilizes the analyzer to compute the compound sentiment score for a given text. This function is subsequently applied to the 'similarity_based_aspects' column of the DataFrame, resulting in the creation of a new column named 'similarity_sentiment_score' that holds the calculated sentiment scores.

$$Overall\ score = \sum_{i=1}^{n} \quad Score(wi) \tag{3}$$

The text contains n words.

The sentiment score given to the i-th word is Score(w i /).

The methodology further encompasses a sentiment categorization function, 'categorize_sentiment,' which classifies the sentiment based on the calculated scores into 'Positive,' 'Negative,' or 'Neutral.' This function is applied to the 'similarity_sentiment_score' column, yielding a final sentiment label stored in the 'Fnal_sentiment' column. By encapsulating these sentiment analysis steps into a cohesive method, the DataFrame is enriched with valuable insights into the sentiment associated with the similarity-based aspects, contributing to a comprehensive analysis of the textual data.

F. Data Splitting

In Aspect-Based Sentiment Analysis (ABSA), an effective data splitting strategy is crucial for model training and evaluation. A common practice is to employ a 90:10 ratio for training and testing datasets, respectively. This entails allocating 90% of the annotated data for training the ABSA model, allowing it to learn and generalize patterns from a substantial portion of the dataset. The remaining 10% serves as the testing set, providing an independent evaluation to assess the model's performance on unseen data. This balanced split ensures robust training while maintaining a sizable evaluation subset for accurate performance measurement, contributing to the overall efficacy of the ABSA model.

G. Modelling

1) Machine learning

ML is a rapidly evolving field within artificial intelligence that focuses on creating and utilizing algorithms that let systems learn from and enhance data. It encompasses a broad range of techniques, including deep learning, reinforcement learning, and supervised and unsupervised learning. Given that machine learning (ML) allows computers to recognize patterns, predict events, and enhance their performance over time, it is an essential component of many industries, including healthcare and finance[40].

- Logistic Regression:

One statistical technique that is frequently used in binary and multiclass classification problems is logistic regression. It is not utilized for regression, as suggested by its name, but for categorization. Through the use of the logistic function, it represents the probability of a binary result and offers a reliable tool for categorical outcome prediction and variable interpretation.

- Support Vector Machine:

Support Vector Machine (SVM) is one efficient supervised learning method for regression and classification problems. In order for SVM to function, it must first identify which input space hyperplane best divides the different classes. This methodology performs particularly well in high-dimensional spaces & is particularly useful for managing complex data patterns.

- Random Forest:

The Random Forest ensembles learning method generates a large number of decision trees during training, which it uses to determine the class mode for classification problems or the mean prediction for regression tasks. Because Random Forest may lower overfitting and boost accuracy, it has becoming more and more popular in a wide range of machine learning applications.

- Gradient Boosting:

Gradient boosting is an ensemble learning technique that generates a series of weak learners, typically decision trees, one after the other. Every tree makes up for the mistakes made by the one before it, creating a strong model with improved predictive capabilities. Gradient Boosting is well known for its ability to manage intricate relationships in data.

- Multinomial Naive Bayes:

Based on the Bayes principle, the probabilistic classification technique known as Multinomial Naive Bayes. The distribution of words over multiple groups and their frequency make it particularly appropriate for text categorization tasks. Multinomial Naive Bayes is a popular option for natural language processing applications because, despite its simplicity, it frequently performs wonderfully, especially when working with big and sparse datasets.

2) Deep learning

Deep Learning (DL), a subfield of machine learning, is concerned with deep neural networks, or multilayer artificial neural networks. These networks, which derive their inspiration from the structure and operations of the human brain, may use data to automatically learn and uncover hierarchical patterns. In several fields, such as natural language processing, audio recognition, and image recognition, deep learning has shown to be extremely promising. The superior capacity of this technology to capture intricate patterns and representations makes it indispensable in the era of artificial intelligence.

- **Hybrid LSTM-GRU:**

The Hybrid LSTM-GRU model is a deep learning model calculated for sequential data. It is one of the more complex structures in the family of recurrent neural networks (RNNs). RNNs come in two flavors: LSTM and GRU, each with its own benefits. To optimize each design's unique advantages, the hybrid model combines elements from the two designs. Long-range dependencies are well captured by LSTMs, although GRUs are more computationally efficient. The hybrid LSTM-GRU model attempts to improve performance by combining these elements, allowing for more efficient learning and memory retention in sequences. This combination demonstrates the benefits of various neural network topologies and the ongoing development and improvement in the field of deep learning.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 200, 32)           110208

 spatial_dropout1d (Spatial  (None, 200, 32)           0
 Dropout1D)

 gru (GRU)                   (None, 200, 25)           4425

 lstm (LSTM)                 (None, 25)                5100

 dropout (Dropout)           (None, 25)                0

 dense (Dense)               (None, 3)                 78

=================================================================
Total params: 119811 (468.01 KB)
Trainable params: 119811 (468.01 KB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 9 Hybrid LSTM- GRU model

II. Results & Discussion

Metrics for loss, classification accuracy, precision, and recall are used to assess the algorithms' capacity to detect sentiment analysis without producing false positives or negatives. Accurate aspect-based sentiment analysis conclusions are ensured by this comprehensive technological analysis.

a) Accuracy

The average forecast accuracy of a model is measured by accuracy. The number of appropriately expected cases is contrasted with the total. Although it offers a broad evaluation of the model's effectiveness, imbalanced datasets with a dominant class may not benefit from its level of precision.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{4}$$

b) Recall

The recall of a model is determined by how well it can identify all pertinent class instances. It is calculated as the ratio of correct positive predictions to accurate and inaccurate negative forecasts. Recall is crucial in situations when omitting positive examples is more likely than producing false positives.

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

c) Precision

The precision of a model refers to its capacity to provide positive, accurate predictions. percentage of accurately predicted cases to all cases that were false positives and correctly forecasted. A model's capacity to avoid making incorrect positive predictions is essential in scenarios when false positive costs are high.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

d) F1 Score

F1 is computed using a harmonic mean of the recall and precision scores. When there is an imbalance between positive and bad examples, it provides a fair and objective assessment of the model's performance.

$$F - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \quad (7)$$

Table.2 Hyper parameter Details

Models	Hybrid LSTM-GRU
Activation	**Softmax**
Batch Size	**2048**
Epochs	**100**
Metrics	**Accuracy,Precision, recall,Fscore**
Dropout	**0.4**
Input length	**200**

Table.3 Performance Evaluation of Machine learning algorithms for Aspect Based Sentiment Classification

Models	Accuracy	Precision	Recall	F score
Logistic Regression	0.74	0.74	0.74	0.69
Support Vector Machine (SVM)	0.72	0.72	0.72	0.66
Random Forest	0.75	0.76	0.75	0.71
Gradient Boosting	0.74	0.76	0.74	0.72
Multinomial Naive Bayes	0.64	0.65	0.64	0.56

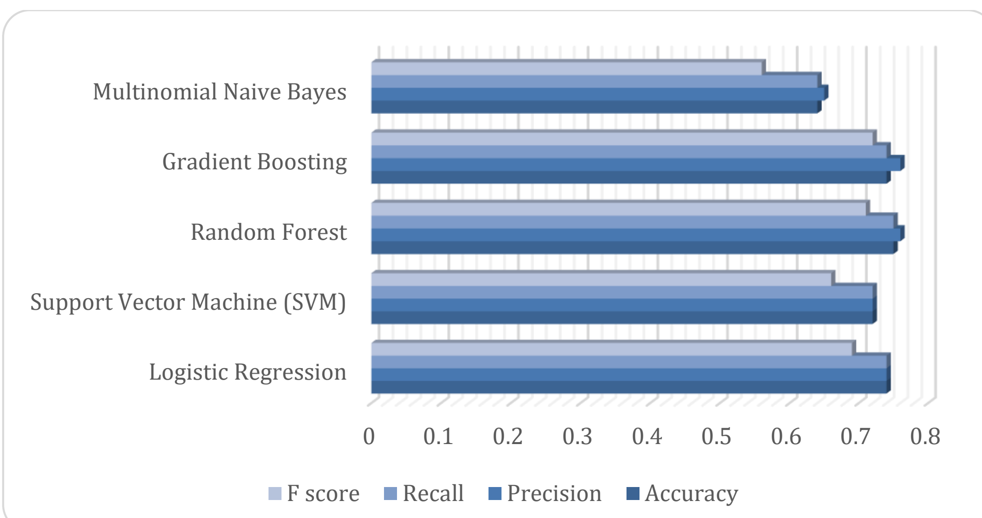

Figure 10 Performance Graph of Machine learning models

A thorough performance assessment of several machine learning techniques specifically used for aspect-based sentiment classification is provided in Table 3 and Figure 10. These techniques include Random Forest, SVM, Gradient Boosting, Multinomial Naive Bayes, and Logistic Regression. Several aspects are evaluated, including recall, F1 score, accuracy, and precision. It's fascinating to observe that Random Forest ranks #1 overall, indicating the best performance. The accuracy of the percentage of cases that were correctly detected is 0.75. The precision, a measure of positive forecast accuracy, is 0.76. Recall evaluates a person's capacity to recognize every pertinent experience, yielding a score of 0.75. Additionally, the F1 score—which assesses memory and precision equally—stands out at 0.71. These outcomes highlight Random Forest's effectiveness in Aspect-Based Sentiment Classification and demonstrate its capacity to produce precise, accurate, and well-balanced predictions, which makes it a strong option for sentiment analysis tasks in this particular context.

Table.4 Performance Evaluation of Deep learning Model Hybrid LSTM-GRU Aspect Based Sentiment Classification

Model	**Accuracy**	**Precision**	**Recall**	**F score**
Hybrid LSTM-GRU	91.55	92.79	89.09	83.45

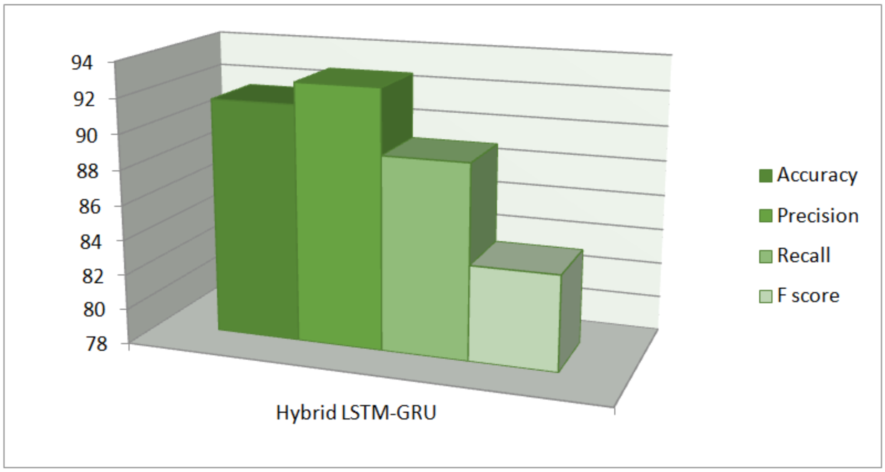

Figure 11 Performance Evaluation Graph of Proposed Deep learning Model

The hybrid LSTM-GRU aspect-based sentiment classification model's performance evaluation is shown in Table 4 and Figure 11. Impressive metrics are displayed by the model: recall of 89.09%, accuracy of 91.55%, precision of 92.79%, and F score of 83.45%. With a high degree of accuracy in recognizing pertinent features and sentiments within the input data, the Hybrid LSTM-GRU architecture demonstrates its effectiveness in determining sentiment. The combination of LSTM and GRU components contributes synergistically to the model's robust performance, highlighting its potential for applications in sentiment analysis and opinion mining tasks.

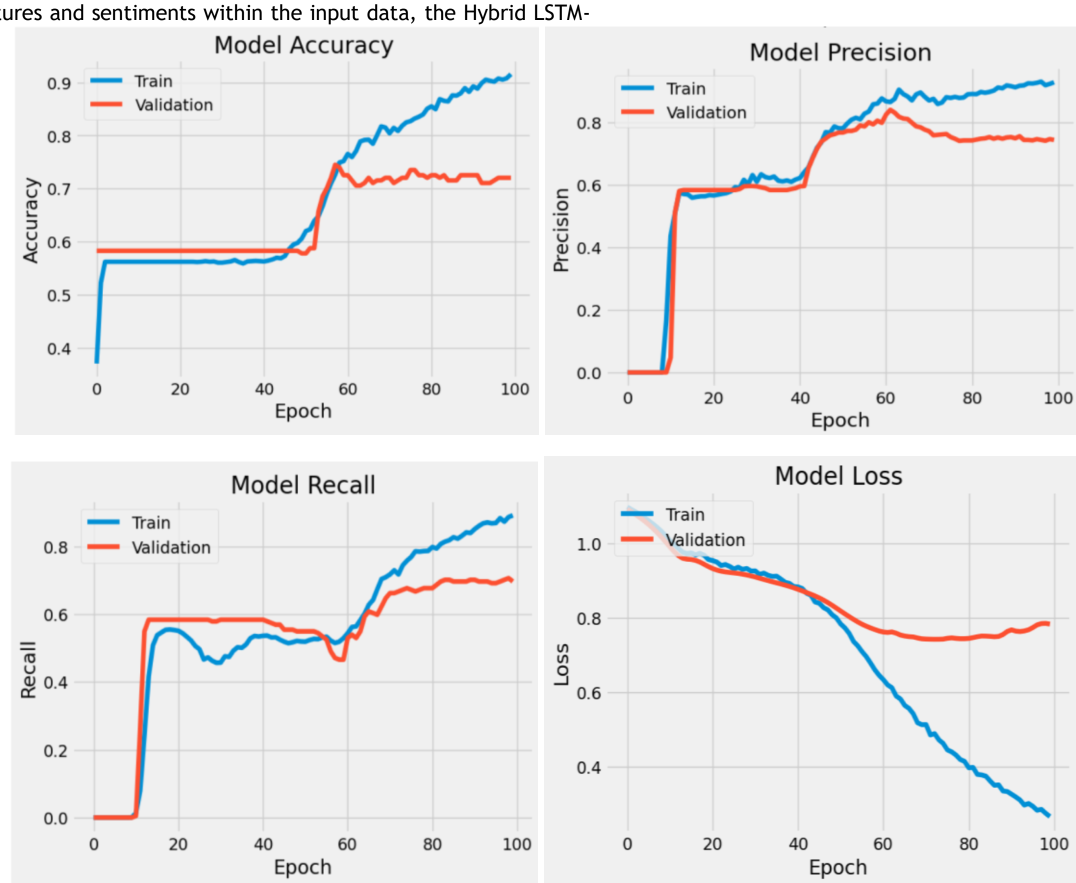

Figure 12 Performance Graphs of Proposed Hybrid LSTM-GRU Model

Key characteristics are displayed in the Presentation Graphs of the Proposed Hybrid LSTM-GRU Model in Figure 12, which include accuracy, precision, recall, and loss. The blue line represents training performance, and the red line shows the results of validation. The graph provides a comprehensive visual representation of the model's learning dynamics by showing the patterns of convergence and divergence of the assigned metrics during the training and validation stages. By monitoring these curves, one can gain a more detailed understanding of the model's behavior, leading to enhanced and optimized performance. The Hybrid LSTM-GRU model's possible overfitting or generalization problems are explained by the obvious separation between the training and validation lines.

Table. 5 Comparative Analysis of Proposed Model and Existing Model

Methods	Accuracy	Precision	Recall	F score	Ref.
APEKCG	89.32	84.32	89.02	76.64	[41]
BiLSTM	83.3	--	--	81.7	[24]
BERT-LSTM	84.18	85.84	78.49	82.27	[1]
LDA hybrid ELMo wiki pedia	75.00	75.00	82.00	78.00	[42]
PLSA hybrid ELMo wiki pedia	79.00	79.00	81.00	80.00	[42]
Proposed Hybrid SSA-LSTM-GRU	91.55	92.79	89.09	83.45	---

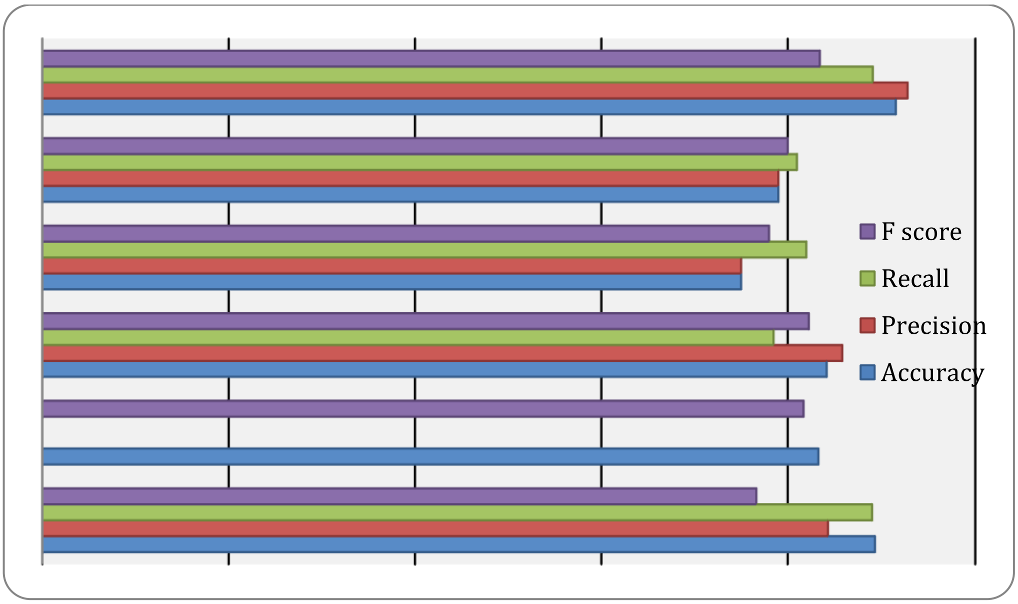

Figure 13 Comparative Analysis Proposed and Existing work

Table 5 and Figure 13 present a comprehensive comparison of multiple sentiment analysis models, unveiling distinct performance characteristics across diverse topologies. The APEKCG model showcased robust performance, boasting an accuracy of 89.32%, precision of 84.32%, recall of 89.02%, and an impressive F1 score of 76.64. In contrast, the BiLSTM model exhibited an F1 score of 81.7 and an accuracy of 83.3%, with precision and recall metrics left undisclosed.The BERT-LSTM hybrid model demonstrated competitive performance, achieving an F1 score of 82.27, accuracy of 84.18%, precision of 85.84%, and recall of 78.49%. Noteworthy is its balanced trade-off between precision and recall, leveraging sequential information from LSTM and semantic representations from BERT.Models incorporating topic modeling techniques displayed varying outcomes. The LDA hybrid ELMo Wikipedia and PLSA hybrid ELMo Wikipedia exhibited divergent results. While the latter excelled with an accuracy of 79.00%, precision of 79.00%, recall of 81.00%, and an F1 score of 80.00, the former recorded an accuracy of 75.00%, precision of 75.00%, recall of 82.00%, and an F1 score of 78.00.The pinnacle of performance was achieved by the Proposed Hybrid LSTM-GRU model, showcasing outstanding results in accuracy (91.55%), precision (92.79%), recall (89.09%), and an F1 score of 83.45. This underscores the effectiveness of the proposed architecture in accurately identifying relevant aspects and sentiments within the input data, outperforming other models in this comparative analysis.

CONCLUSION

In conclusion, The research employed a comprehensive methodology that included machine learning and deep learning techniques for aspect-based sentiment analysis. To ensure uniqueness, set union is used to select relevant phrases after noun extraction using spaCy's TokenRegex. The RAKE algorithm seamlessly integrates into workflows for precise keyword extraction. Semantic similarities are analyzed through Minkowski Distance using TF-IDF vectorization, providing valuable insights into gaps or commonalities. Sentiment analysis, facilitated by Sentiment Intensity Analyzer, computes compound sentiment scores, categorizing sentiments into 'Positive,' 'Negative,' or 'Neutral' and enriching the DataFrame with comprehensive sentiment insights. The Hybrid LSTM-GRU Aspect-Based Sentiment Detection Model yielded impressive results, achieving 91.55% accuracy, 92.79% precision, 89.09% recall, and an 83.45% F score. These results highlight how well the Hybrid LSTM-GRU architecture works to consistently identify relevant features in the input data and identify sentiments. Moreover, a comprehensive performance evaluation juxtaposed various machine learning methods, including Multinomial Naive Bayes, Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Logistic Regression. Remarkably, Random Forest emerged as the top-performing algorithm, achieving the highest scores across all categories. The F1 score of 0.71, precision of 0.76, accuracy of 0.75, and recall of 0.75 vividly illustrate the effectiveness of Random Forest in generating accurate and balanced forecasts. These findings underscore Random Forest's prowess as a preferred choice for Aspect-Based Sentiment Classification, emphasizing its suitability for sentiment analysis tasks within this specific context. In summary, this research provides valuable insights into the performance of both machine learning and deep learning methods in aspect-based sentiment analysis.

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