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A Lightweight Approach for Sentiment Analysis Using Data Augmentation, Aspect-Based, and Priority-Based Strategies

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Abstract

This Sentiment analysis, which is a vital task in NLP, strives to identify the emotional tone contained in text-based data. Despite the fact that deep learning architectures such as BERT have set high performance, they tend to be computationally expensive and complicated by class imbalance issues in data. In this study, we introduce a light yet powerful method for improving sentiment analysis performance by a hybrid strategy combining data augmentation, aspect-based, and priority-based methods. Data augmentation techniques such as synonym replacement and back-translation are utilized to counteract class imbalance and increase dataset diversity. In addition, aspect-based sentiment analysis (ABSA) is added specially for the restaurant review dataset to achieve more fine-grained and context-sensitive sentiment classification. In contrast to previous BERT-based hybrid models, we rely on a Decision-Based Recurrent Neural Network (D-RNN) only, which retains high accuracy at the cost of less computational overhead. Experimental verification on a combined dataset that includes Twitter tweets, Amazon product reviews, and restaurant reviews proves the efficacy of the introduced technique. Comparative analysis with techniques like LSTM, Bi-LSTM, CNN, and GRU further establishes the superiority and generalization ability of the introduced method. This work opens the door to effective sentiment analysis in low-resource settings without sacrificing model performance.

Keywords: Sentiment Analysis, Data Augmentation, Synonym Replacement, Back-Translation, Aspect-Based Sentiment Analysis (ABSA), Priority-Based Sentiment Analysis (PBSA), Decision-Based Recurrent Neural Network (D-RNN), Class Imbalance Handling, Natural Language Processing (NLP), Deep Learning, Text Classification

1. Introduction

Sentiment analysis, also known as opinion mining, is a central discipline in natural language processing (NLP) dedicated to the task of extracting subjective information from text data. It seeks to label text as having positive, negative, or neutral sentiment. Sentiment analysis is applied across industries like e-commerce, healthcare, political polling, and social media monitoring, allowing businesses and organizations to gain valuable insights from enormous volumes of unstructured text[1].

Traditional sentiment analysis methods often relied on rule-based approaches and machine learning models using manually engineered features. However, these approaches struggle with the complex linguistic characteristics of human language, such as sarcasm, figurative speech, and context-dependent word meanings[2]. The advent of deep learning models, including Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and more recently, transformer-based models like BERT, has significantly advanced the field by improving the contextual understanding of text.

Even with these progressions, tremendous challenges remain. Two of the most important concerns are the underrepresentation of particular sentiment classes for the class imbalance problem and the computationally costly nature of the transformer-based models, which compromises their use for low-resource conditions or real-time settings. Last but not least, most present models are purely for overall sentiment identification, where they tend to neglect more precise, aspect-specified opinions with different weights among the text.

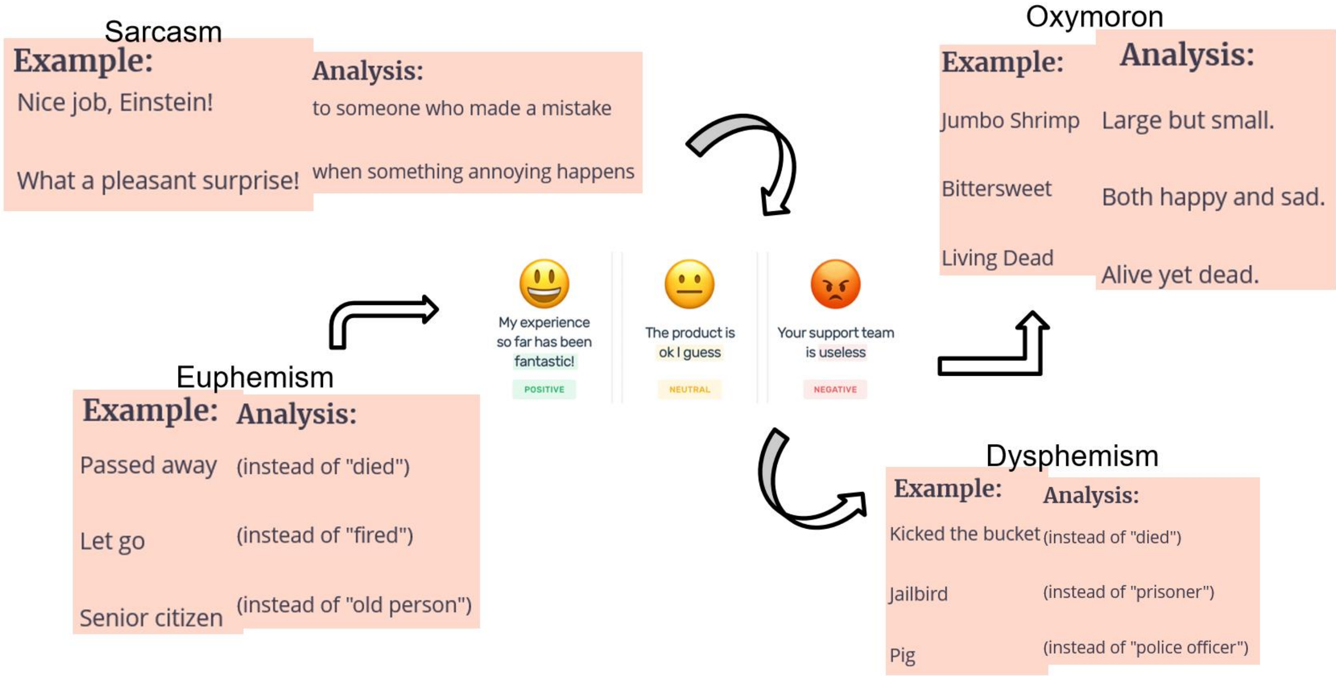


Fig 1.1 Introduction of Sentiments

In this paper, we introduce a more refined approach to sentiment analysis through combining data augmentation methods (namely synonym substitution and back-translation) to mitigate class imbalance, and aspect-based and priority-based sentiment analysis to obtain finer-grained and informative sentiment extraction. Unlike earlier works depending on computationally costly models such as BERT, in this paper we apply a lightweight yet effective Decision-Based Recurrent Neural Network (D-RNN) for sentiment classification.

The new method attempts to:

- Augment training data in a compact way with improved diversity and richness to the original training set.

- Improve the model robustness and ability to generalize to multiple styles of languages.
- Perform fine-grained sentiment analysis by selecting focused aspects and prioritizing meaningful sentiment-carrying constituents.
- Meet high accuracy and efficiency using transformer-architecture-agnostic methodologies and being capable for use with low-resource as well as real-time settings.

Our experiments are done on a set of mixed datasets, which cover Twitter tweets, Amazon product reviews, and restaurant reviews, in order to justify the efficacy and flexibility of the approach. The results prove that high-quality and context-sensitive sentiment classification is feasible with substantially less computational effort but overcoming some serious limitations encountered by current models.

2. Related Study

Sentiment analysis has seen dramatic improvements with the advent of deep learning models, data augmentation techniques, and context-sensitive methods. Several studies have suggested techniques for improving sentiment classification by mitigating the intrinsic challenges in text data like ambiguity, class imbalance, and domain-related variations.

Khan et al. (2023) proposed a Sentiment and Context-Aware Hybrid Deep Neural Network (SCA-HDNN) that leverages BERT embeddings, BiLSTM networks, CNNs, and an attention mechanism. Their method focuses on incorporating wide-coverage sentiment lexicons and linguistic semantic rules to enhance the model's capacity for capturing context-dependent sentiment features[1].

Kukkar et al. (2023) centered on managing stretched words in social media messages, suggesting a new lexicon-based approach that maintains the emotional strength of elongated words (e.g., "happpyyyy"). By computing summed sentiment scores for these words, their method improved over standard approaches that did not consider such variations[2].

Durga and Godavarthi et al. (2023) proposed Deep-Sentiment model, integrating BERT-large-cased pretraining with Decision-Based Recurrent Neural Network (D-RNN). Their paper used aspect-based and priority-based sentiment analysis and improved performance through targeting sentiment aspects that are significant in multi-domain datasets such as Twitter, restaurant, and laptop reviews[3].

Alsayat et al. (2022) investigated an ensemble deep learning framework that integrates LSTM networks with leading-edge classifiers. Their ensemble solution outperformed by learning context relationships between words and performing well with rare or out-of-vocabulary words in novel scenarios like pandemic-related sentiment on social media[4].

Tami et al. (2023) discuss the importance of crime prediction in law enforcement and the application of social media, specifically Twitter, to improve prediction accuracy. They introduce a ConvBiLSTM model that incorporates a data fusion method to combine semantic information from tweets and past crime data. Their research shows that the multimodal strategy, wherein tweet sentiment is used along with crime data, yields a superior performance compared to conventional deep learning and BERT-based models, attaining an excellent accuracy of 97.75% in identifying crime incidents[5].

Pathak et al. (2021) suggested a model that determines topics at the sentence level by employing online latent semantic indexing with regularization constraint and later uses topic-level attention mechanism in long short-term memory network to carry out sentiment analysis. The proposed model is tested on in-domain and out-of-domain datasets and proves effective in dealing with large-scale sentiment analysis and topic modeling of streaming social media data[6].

Chen et al. (2019) examine sentiment analysis of social media posts, with an emphasis on data from Taiwan's Militarylife PTT online forum. The research builds a sentiment analysis framework and procedures for social media to suggest a self-built military sentiment dictionary for enhancing sentiment classification and compare the performance of various deep learning models with diverse parameter calibration combinations[7].

Omuya et al. (2022) investigate social media tweet sentiment analysis using dimensionality reduction and natural language processing methods. The research solves the issues of noise, the curse of dimensionality, the data domains and the size of data used for training and testing by integrating part-of-speech tagging and dimensionality reduction in a sentiment analysis model. The model is experimented with Naïve Bayes, support vector machine, and K-nearest neighbor algorithms and its performance is compared with the performances of two other sentiment analysis models[8].

Amangeldi et al. (2024) analyze public perception of climate change and the environment over a decade from 2014 to 2023. Using the Pointwise Mutual Information (PMI) algorithm, they identify sentiment and explore prevailing emotions expressed within environmental tweets across various social media platforms, namely Twitter, Reddit, and YouTube. Their results indicate that negative environmental tweets are much more prevalent than positive or neutral ones, the most widely tweeted about including climate change, air quality, emissions, plastic, and recycling. The most prevalent emotions in environmental tweets include fear, trust, and anticipation, showing the extensive and multifaceted nature of public response[9].

Subbaiah et al. (2024) also suggest a multimodal sentiment analysis hybrid approach on social media addressing the shortcomings of single-modality analysis and dealing with inter-related social images. The work presents an AOA-HGS-optimized Ensemble Multi-scale Residual Attention Network (EMRA-Net) to investigate modal correlations such as texts, audio, social relationships, and video data. The outcomes show that this approach performs much better compared to the current multimodel sentimental analysis methods of HALCB, HDF, and MMLatch when tested against the Multimodal Emotion Lines Dataset (MELD) and EmoryNLP datasets. Furthermore, despite the difference in the size of the training set, the presented approach performed better than other methods based on recall, accuracy, F score, and precision and is faster to calculate in both datasets[10].

These works emphasize the current trend towards hybrid approaches that blend semantic knowledge, context awareness, and ensemble techniques to obtain strong sentiment analysis. Based on these findings, our work seeks to further improve sentiment analysis by combining data augmentation (synonym substitution and back-translation), aspect- and priority-based annotation, and effective D-RNN-based modeling to overcome class imbalance and contextual sentiment extraction issues.

3. Problem Statement

In spite of the increasing popularity of deep learning models for sentiment analysis, a few major challenges are still unresolved.

Class imbalance remains a challenge to model performance, particularly when datasets possess imbalanced distributions between sentiment classes (positive, negative, neutral). Underrepresented classes tend to result in biased predictions and reduced generalization ability. Contextual comprehension is restricted in most models, especially where sentiments are based on particular aspects (e.g., restaurant food quality in a restaurant review) or entail prioritizing some aspects over others according to their contribution towards overall sentiment. Current methods tend to overlook aspect-specific as well as priority-specific sentiment subtleties and result in shallow analysis.

Additionally, efficiency in the use of resources is a concern. Models such as BERT that are transformer-based are computationally costly and inappropriate for low-resource or real-time usage.

Lastly, the ineffectiveness of data augmentation methods further worsens the shortage of high-quality, diverse training samples, particularly for minority sentiment classes. Without remedy to this, models fail to generalize to real-world inputs of varying types.

Therefore, there is an urgent need for a sentiment analysis methodology that:

- Is efficient in class handling.
- Includes aspect-based and priority-based sentiment extraction.
- Is computationally light and efficient.
- Increases diversity in datasets by intelligent data augmentation.

This paper seeks to address these shortcomings through the introduction of a strong, efficient, and context-sensitive model of sentiment analysis using data augmentation, aspect-priority modeling, and Decision-Based Recurrent Neural Networks (D-RNN).

4. Dataset

To ensure a comprehensive and diverse evaluation of the proposed sentiment analysis approach, three publicly available datasets from different domains were combined:

4.1 Twitter Tweets: Twitter data provides concise, casual, and frequently unstructured texts full of slang, abbreviations, emojis, and other social media-based usage patterns. This makes it a great data source for training models to recognize real-world, conversational expressions of sentiment.

4.2 Amazon Product Reviews : Amazon reviews are rich and well-structured user opinions, frequently including direct references to product features, levels of satisfaction, and user experiences. These reviews have more grammatically coherent sentences and complete sentences than tweets, which enables the model to learn formal sentiment expressions.

4.3 Restaurant Reviews: Restaurant reviews contain user comments regarding different aspects like food, quality of service, atmosphere, and price. Restaurant reviews tend to be semi-structured and contain sentiment indicators closely related to specific service attributes, enabling the model to learn aspect-based sentiment classification.

Review	Sentiment
The food was delicious, and the ambience was cozy.	1
The service was slow, but the food was decent.	0
The restaurant was noisy, and the food was bland.	-1
Loved the atmosphere, but the service was terrible.	0
Great food and friendly staff!	1
The ambiance was nice, but the food was overpriced.	0
The waiter was rude, and the food was undercooked.	-1
The place was clean, and the food was excellent.	1
The service was okay, but the ambiance was dull.	0
The food was too spicy, and the seating was uncomfortable.	-1

⟹

Overall = IF(AND(Food=1, OR(Ambience=1, Service=1)),1,0)

Review	Food	Ambience	Service	Overall
The food was delicious, and the ambience was cozy.	1	1	0	1
The service was slow, but the food was decent.	1	0	-1	0
The restaurant was noisy, and the food was bland.	-1	-1	0	0
Loved the atmosphere, but the service was terrible.	0	1	-1	0
Great food and friendly staff!	1	0	1	1
The ambiance was nice, but the food was overpriced.	0	1	0	0
The waiter was rude, and the food was undercooked.	-1	0	-1	0
The place was clean, and the food was excellent.	1	1	0	1
The service was okay, but the ambiance was dull.	0	-1	0	0
The food was too spicy, and the seating was uncomfortable.	-1	-1	0	0

Fig 4.1 Manually added Aspects and Priority for Restaurant Dataset

Preprocessing of the dataset: Before training models, all datasets went through:

- Deletion of special characters, hyperlinks, and emojis.
- Conversion of text to lower case.
- Tokenization and stop-word filtering.
- Balancing data through synonym replacement and back-translation augmentation to tackle class imbalance.

The datasets were then combined into a single corpus, with metadata retained regarding their origin to enable dataset-specific evaluation should it be necessary.

5. Proposed Methodology

The suggested method raises sentiment analysis to the next level by integrating data augmentation, feature enrichment, light deep learning models, and performance optimization methods. The full methodology is organized as follows:

5.1 Data Collection

The research leverages a combination of three publicly accessible datasets to provide varied sentiment coverage:

- **Twitter Tweets** : brief casual texts representing social media utterances.
- **Amazon Product Reviews** : customer reviews expressing product satisfaction.
- **Restaurant Reviews** : formalized feedback on service and food quality.

The cleaned and standardized datasets were then merged to obtain a combined dataset ready for robust sentiment classification. The data were initially processed using cleaning operations like stopwords removal, special character removal, and removal of useless metadata. Thereafter, standardization processes like text lowercasing and token normalization were executed. The data were then combined after these operations in order to form an aggregated corpus that integrates the diversity and richness of the three sources into one, producing a stronger basis for training a generalizable sentiment model.

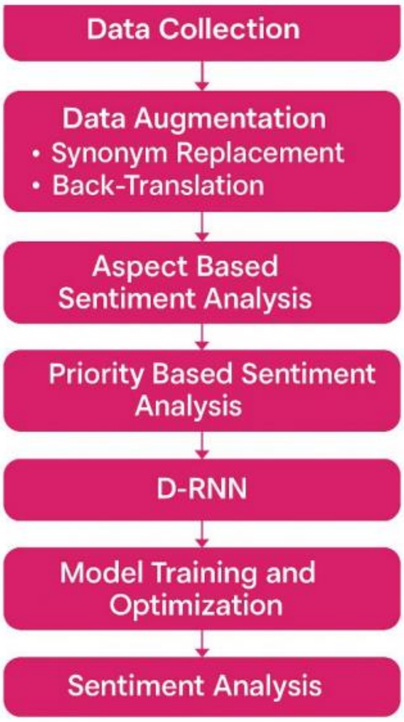


Fig 5.1. Flowchart of Proposed Methodology

5.2 Data Augmentation

Data augmentation was vitally necessary to address problems like class imbalance (when one sentiment class can be prevalent over the rest) and enhance the generalization capability of the model across unseen data. Two particular augmentation strategies were employed:

- **Synonym Replacement**: For this method, certain words in a sentence were substituted with their synonyms from a hand-curated thesaurus. This preserved the sentence's semantic meaning while adding variability at the lexical level. By generating several versions of the same sentence with minute differences in wording, the model learned to attend to underlying sentiment instead of memorizing phrases.
- **Back-Translation**: This method entailed translating a sentence into another language (e.g., French or German) and back into English. The process yielded paraphrased sentences of the original sentences that preserved their essence. Back-translation adds natural variability to sentence forms and phrases, increasing the diversity of the training set without human intervention.

Combined, these augmentation techniques greatly enhanced the size and variety of the training set, enabled the model to learn more informative representations of minority classes, and minimized overfitting.

5.3 Feature Extraction and Word Embedding

High-quality feature extraction is critical to developing an effective sentiment classifier. In order to obtain rich semantic and contextual subtleties in text, two advanced word embedding approaches were employed:

- **Word2Vec**: Word2Vec creates dense word vector representations from the context in which a word is found. By learning neighboring words or being learned by neighbors (within Skip-Gram or CBOW models), Word2Vec embeddings capture semantic similarity so that the model can identify that "happy" and "joyful" words are semantically similar.
- **GloVe (Global Vectors for Word Representation)**: GloVe embeddings were learned by using word co-occurrence statistics over a large corpus. In contrast to Word2Vec, GloVe is designed to capture global word relationships, leading to embeddings that capture more general language structure.

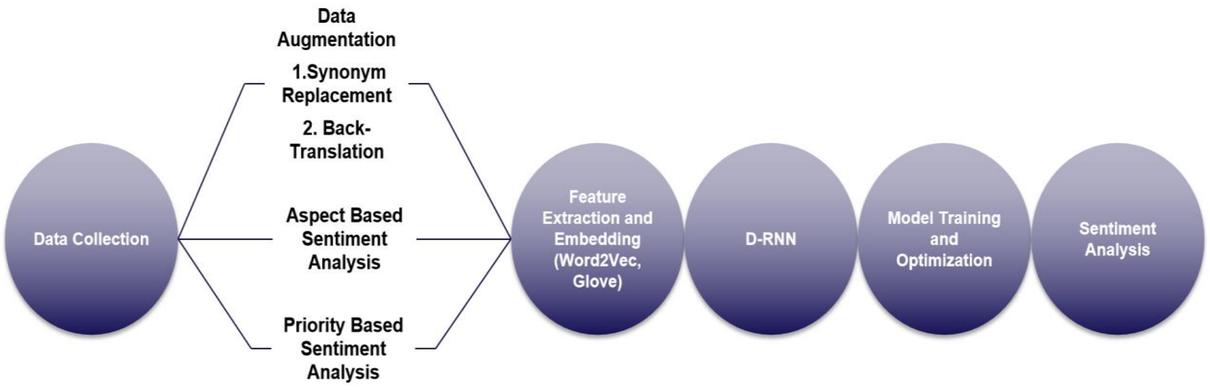


Fig 5.2 Flow Diagram of Proposed Methodology

Both pre-trained embeddings were also fine-tuned during model training to fit the domain-specific language features of social media updates, product reviews, and restaurant comments. Their combination enabled the model to learn local context and global semantic relations concurrently.

5.4 Decision-Based Recurrent Neural Network (D-RNN)

The core of the proposed model is the Decision-Based Recurrent Neural Network (D-RNN) that is a tailored light-weight architecture for efficient sentiment prediction. Some of the features are: Key features of the D-RNN include:

- **Sequential Modeling**: Similar to standard RNNs, D-RNN reads input text word by word sequentially, carrying over memory from one step to another to preserve the order and interdependence of words, important for grasping the progression of sentiment in a sentence.

- **Decision-based Branching**: One of the distinguishing aspects of D-RNN is its branching mechanism, where the model can branch into various computational paths depending on intermediate decisions. For example, if an early detection of a certain threshold of positive sentiment is made, the network can change its path accordingly. This enhances the capability of the model to process multi-aspect sentiment analysis where various sections of a review may convey different sentiments.
- **Managing Long-Term Dependencies**: D-RNN applies techniques to combat vanishing gradient issues common to standard RNNs, thereby being more proficient at remembering longer sequences than plain RNNs but less than LSTMs or GRUs.

D-RNN was utilized instead of transformer-based models like BERT because it provides high accuracy at the cost of lower computational intensity, which is feasible for real-time use and on resource-limited environments.

5.5 Model Training

A well-organized and disciplined training process was adopted to guarantee the effectiveness of the model:

- **Loss Function**: The categorical cross-entropy loss function was utilized as the task was multiclass classification (positive, negative, neutral).
- **Optimizer**: The Adam optimizer was chosen due to its adaptive learning rate property, which improves convergence speed and sparse gradients management, particularly in NLP tasks.
- **Batch Size and Epochs**: Extensive experimentation was conducted to select appropriate batch sizes and number of epochs. This tuning helped in finding a balance between efficient training and prevention of issues like overfitting (memorizing the training set) or underfitting (failing to learn enough from the data).
- **Early Stopping**: Early stopping was utilized, tracking validation loss throughout training. When the model's performance over the validation set didn't get better for some number of epochs, training was automatically stopped to conserve resources and avoid overfitting.

Data was divided into independent training and validation splits so that model evaluation was done based on unseen data and hence gave a better approximation of actual-world performance.

5.6 Performance Optimization

In addition to model structure and training, a number of performance improvement techniques were included::

- **Learning Rate Scheduling**: The learning rate was dynamically scheduled during training. It started off high to learn quickly and then decreased gradually to make fine tuning possible during the last training epochs, leading to smoother convergence towards the best solution.
- **Dropout Regularization**: Dropout layers were added in between D-RNN layers to randomly "drop" a set of neurons during training. This avoids over-dependence on certain features and aids in regularizing the model, enhancing its ability to generalize to unseen data.
- **Data Balancing Techniques**: In spite of augmentation, small oversampling of sparse classes was done after augmentation to maintain a balanced class distribution. This avoids the model learning a bias towards majority classes during training.

- **Hyperparameter Tuning**: Grid search (comprehensive parameter search over a given set) and random search (randomized search over the parameter space) were combined to determine the best configuration for learning rate, batch size, number of layers, and dropout rate.

These techniques together ensured that the model attained state-of-the-art performance without being inefficient and deployable.

5.7 Output Generation

The last trained model was able to generate multiple informative outputs:

- **Sentiment Class Labels**: Given an input text, the model predicts one out of three sentiment classes Positive, Negative, or Neutral. This straightforward output makes it easy to integrate into downstream applications such as customer feedback monitoring, product review analysis, or social media trend analysis.
- **Aspect and Priority Scores** (for Restaurant Reviews):
  - **Aspect-Based Tagging**: The model classifies certain aspects of a review, e.g., food, service, ambiance, etc., enabling more fine-grained sentiment analysis rather than one overall tag.
  - **Priority-Based Tagging**: In addition to aspect detection, the model gives each aspect a priority score reflecting its significance to the overall sentiment conveyed in the review. For example, bad service could be given more weight than minor issues with food presentation.
- **The Evaluation Metrics**: The model's performance was critically tested with traditional classification metrics accuracy (overall accuracy), precision (correct positive predictions among all positive predictions), recall (correct positive predictions among all actual positives), and F1-score (harmonic mean of precision and recall). These metrics gave a complete idea about the strengths and weaknesses of the model.

6. Results and Comparative Analysis

This section describes the empirical assessment of the suggested sentiment analysis model grounded on data augmentation, aspect-priority enhancement, and Decision-Based Recurrent Neural Network (D-RNN). The experiments are carried out by utilizing a mixed dataset consisting of Twitter tweets, Amazon product reviews, and restaurant reviews, and the proposed approach is compared to common deep learning models like Bi-LSTM, CNN, GRU, and LSTM.

6.1 Model Accuracy and Loss Performance

Table 6.1 compares the accuracy, test loss, and true positivity rate of each model. D-RNN attained a comparable accuracy of 94.99% with a test loss of 0.1085, and a true positivity rate of 23218 / 24442, reflecting efficient generalization. Although models such as Bi-LSTM and GRU attained superior accuracy (98.73% and 98.70%, respectively), they necessitated drastically greater computational complexity because of their deeper architectures.

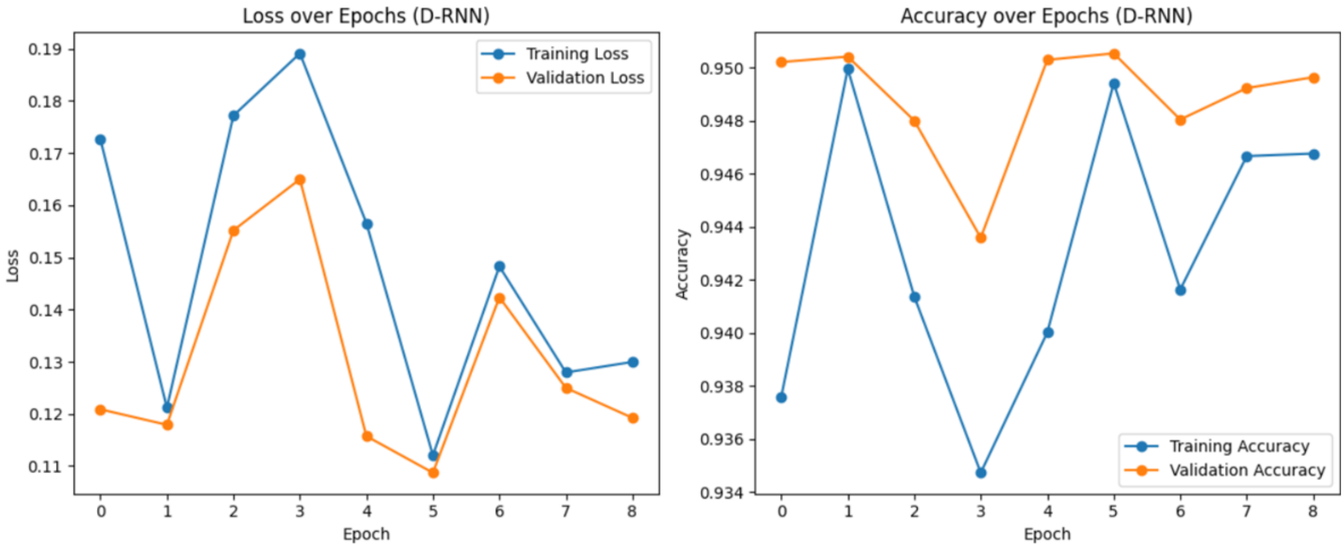


Fig 6.1 Loss over Epochs vs Accuracy over Epochs Graph for D-RNN

Model	Accuracy	Test Loss	TP + TN
D-RNN	94.99%	0.1085	23218
Bi-LSTM	98.73%	0.0356	24132
CNN	97.61%	0.0482	23902
GRU	98.70%	0.0375	24125
LSTM	98.45%	0.0454	24135

Table 6.1 Accuracy vs Test Loss

6.2 Training and Validation Trends

Training and validation accuracy and loss comparisons between models. Deep models such as Bi-LSTM, GRU, and LSTM achieved high training accuracy with fast learning, whereas the D-RNN demonstrated consistent, controlled learning. The D-RNN's stable, slightly fluctuating validation accuracy and moderate loss indicate improved generalization, rendering it appropriate for practical applications where overfitting is undesirable. Figure 6.3 illustrates that while D-RNN did not perform better against other models in peak accuracy, it did keep a minimal gap between training and validation accuracy, supporting the stability of the model.

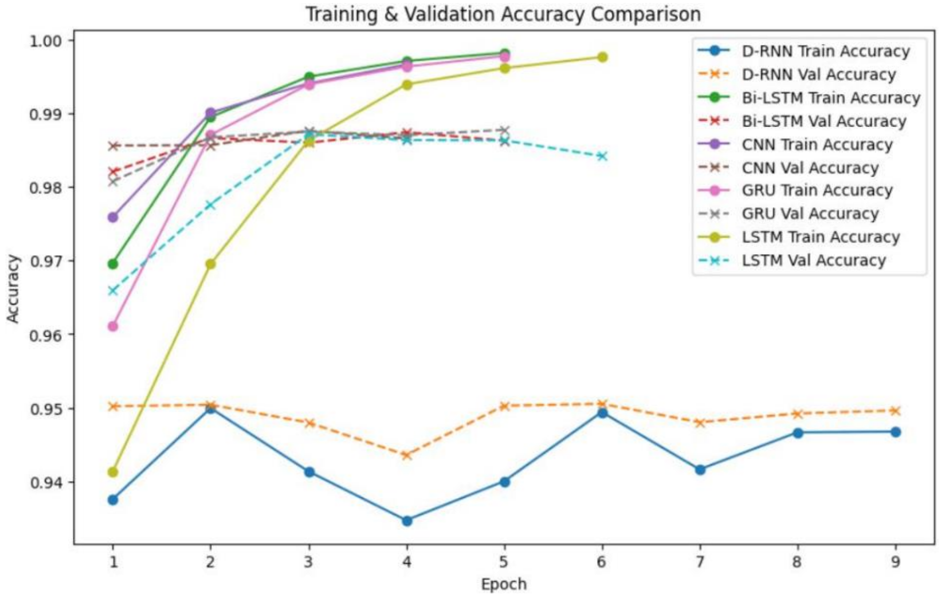


Figure 6.4 shows that the loss of D-RNN is a bit higher than other models but has a smooth and regular pattern across epochs.

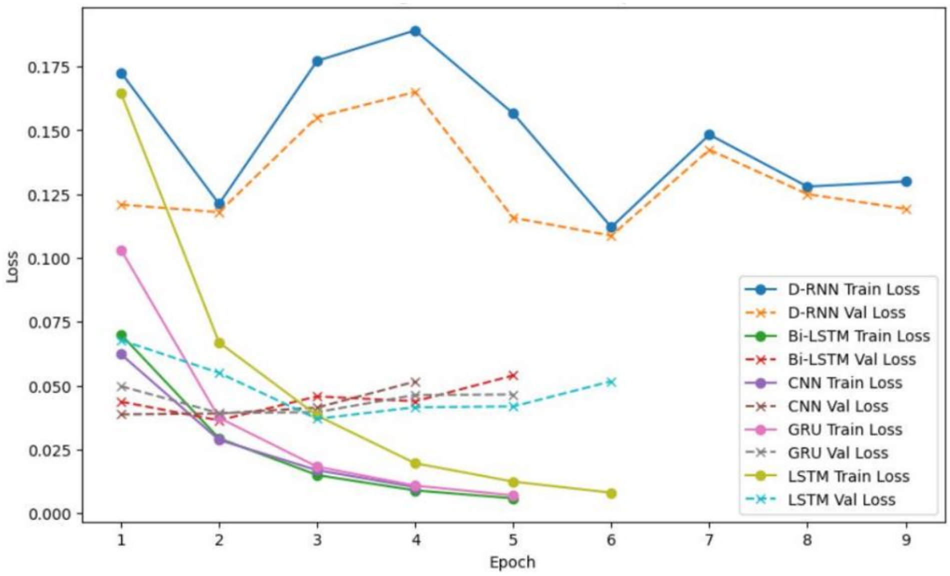


Fig 6.3 Training and Validation Loss Graph Comparison

6.3 Confusion Matrix Metrics: Precision, Recall, and F1-Score

A more precise assessment was made through confusion matrix measures (Table 2), including precision, recall, and F1-score. The D-RNN model recorded 95% on all three measures, while Bi-LSTM and GRU recorded up to 98.7%, indicating marginal gains for increased model complexity.

Model	TP	TN	FP	FN	Accuracy	Precision	Recall	F1 Score
D-RNN	11609	11609	611	611	94.99%	95.0%	95.0%	95.0%
LSTM	12037	12037	183	183	98.50%	98.5%	98.5%	98.5%
Bi-LSTM	12066	12066	155	155	98.73%	98.7%	98.7%	98.7%
CNN	11951	11951	245	245	97.61%	97.9%	97.9%	97.9%
GRU	12062	12062	160	160	98.70%	98.7%	98.7%	98.7%
LSTM	12067	12067	154	154	98.45%	98.7%	98.7%	98.7%

Table 6.1 Comparative Analysis of different Models

6.4 Comparative Visualization

Figure 10.3 illustrates the balance between test accuracy and test loss for all models. Although the models such as Bi-LSTM and GRU perform better than D-RNN in both metrics, the D-RNN still achieves comparable accuracy and loss performance with a much less complex architecture. This renders D-RNN the best option for lightweight and scalable sentiment analysis applications, particularly where computational resources are scarce.

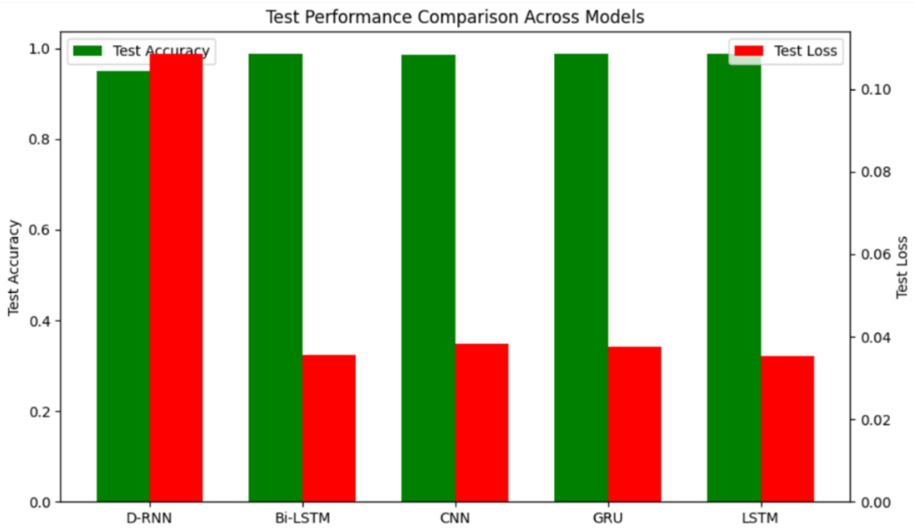
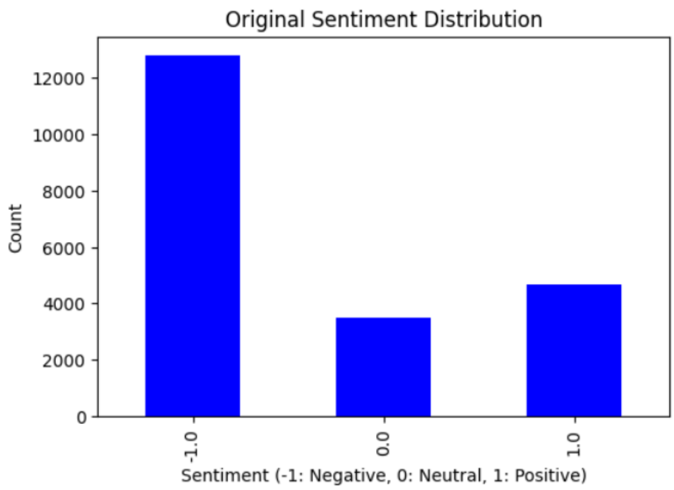


Fig 6.4 Test Accuracy vs Test Loss Comparison of Different Models

6.5 Addressing Class Imbalance Using Data Augmentation

One of the main difficulties faced in the raw dataset was class imbalance, where negative sentiment overwhelmingly dominated neutral and positive ones. Figure 10.4 demonstrates the original sentiment distribution, showing a lopsided dataset with more than 12,000 negative samples and much fewer neutral and positive ones.



To counteract this imbalance, targeted data augmentation was carried out using synonym replacement and back-translation methods. These were applied selectively to the minority classes (positive and neutral), creating semantically similar but syntactically diverse instances. This not only augmented dataset size but also maintained label diversity and improved model generalization.

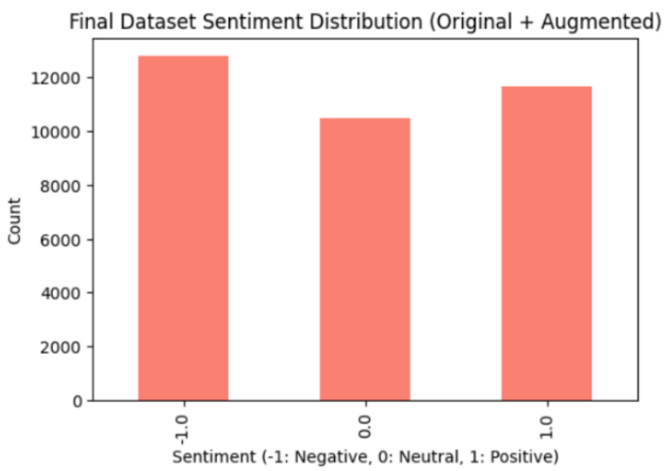


Fig 6.6 Augmented Dataset for handling Class Imbalance

Figure 6.6 reveals the distribution after augmentation. The data was made more balanced, with the three classes of sentiment having almost equal proportions. This greatly enhanced the model to learn patterns specific to each class, resulting in better classification performance and more accurate F1-scores for all classes.

7. Conclusion and Future Work

This work introduced an extensive and lightweight method for improving sentiment analysis through the use of data augmentation methods and the combination of aspect-based and priority-based sentiment approaches. Through the use of synonym substitution and back-translation, the issue of class imbalance in the source dataset was successfully addressed, resulting in better generalization and model performance. Utilizing a Decision-Based Recurrent Neural Network (D-RNN) showed that substantial accuracy (94.99%) can be attained even without burdensome transformer-based models such as BERT, particularly when aided by richly balanced and enriched training data. Comparative testing with models such as Bi-LSTM, CNN, GRU, and LSTM validated the competitive performance of the developed method, especially in regard to computational efficiency and deployability readiness.

In the future, the model may be expanded using more sophisticated augmentation methods like contextual embeddings or generative techniques like GPT-based paraphrasing. Additionally, multimodal sentiment analysis with images or audio in combination with text might also make the system more relevant across a broader range of applications. Finetuning on domain-specific datasets and implementing the model in real-time applications like customer feedback systems or social media monitoring platforms will also be investigated. On top of that, interpretability and explainability methods can be incorporated to make the insights from the model transparent about the decision-making process.

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