AMAZON PRODUCT REVIEWS: SENTIMENT SYNTHESIS USING BOOSTED ENSEMBLE AGGREGATION TECHNIQUE SENTIMENT ANALYSIS: SENSE-BEAT

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Abstract

This study focuses on sentiment analysis of Amazon product reviews, which are important in the e-commerce industry since they influence consumers' decisions. The paper discusses the shortcomings of the methods used in sentiment analysis today, including their exclusive reliance on techniques like aspect-based approaches, bigram, trigram, polarity score, and unigram. The wide range of emotions conveyed in reviews is difficult for these conventional approaches to adequately represent, especially when working with unbalanced datasets. The Sentiment Synthesis with Boosted Ensemble Aggregation Technique (SENSE-BEAT) is presented as a solution to these issues and a more thorough method. A variety of sentiment classification techniques, such as aspect-based methods, polarity score, trigram, bigram, and unigram, are combined in SENSE-BEAT. For fine-grained sentiment categorization, the model first builds a Bag-of-Words representation before using a majority voting approach. Based on the total number of votes, this technique classifies reviews as Strongly Positive, Mildly Positive, Strongly Negative, Mildly Negative, or Neutral. The boosted ensemble aggregation technique is used with classifiers like Random Tree, Decision Stump, and SMO, and it is further enhanced with the AdaBoostM1 algorithm to improve the SENSE-BEAT technique even more. The SENSE-BEAT method improves the model's ability to identify different patterns and apply them to new data, which in turn strengthens the model's prediction accuracy. Using a preprocessed Amazon Product Reviews dataset, SENSE-BEAT outperforms other methods in terms of F1-score, accuracy, precision, and recall. Outstanding predictive performance is demonstrated by the suggested boosted ensemble aggregation method, establishing SENSE-BEAT as a cutting-edge approach to fine-grained sentiment analysis for online product reviews.

Keywords: Fine-grained Sentiment Analysis, Imbalanced Datasets, Amazon Product Reviews, Boosted Ensemble Aggregation Technique, Sentiment Synthesis

1 INTRODUCTION

Within the ever-changing world of online commerce, Amazon product reviews play a vital role in shaping consumer opinions and influencing purchasing decisions [1]. These reviews provide a wealth of valuable information, offering a diverse range of insights that reflect the experiences and feelings of customers. However, navigating through this vast sea of feedback has become a complex task for businesses, requiring the use of advanced sentiment analysis techniques [2]. In this dynamic environment, the ability to understand and interpret the subtle emotions expressed in Amazon product reviews is essential for companies aiming to succeed in a competitive market. Our study focuses on exploring the complexities of sentiment analysis, specifically within the context of Amazon product reviews. Recognizing the importance of understanding customer sentiments for achieving and maintaining business success, our research aims to uncover the underlying patterns and trends in these reviews, providing businesses with actionable insights for informed decision-making and strategic planning.

To conduct this analysis, we rely on a meticulously preprocessed dataset of Amazon Product Reviews. Preprocessing is a crucial step in the sentiment classification process, ensuring that the dataset is clean, standardized, and ready for analysis [3]. This meticulous process is necessary to handle the inherent noise and variability present in reviews. Cleanliness involves the elimination of irrelevant information, while standardization promotes consistency in data representation. Readiness involves converting raw data to meet the requirements of machine learning algorithms. In sentiment analysis, where language intricacies are abundant, preprocessing techniques such as removing stopwords and replacing slang words become essential. These efforts prepare the dataset, allowing the sentiment classification model to effectively navigate varied reviews and provide accurate classifications. Previous studies in sentiment analysis have made significant contributions using strategies like unigram, bigram, trigram, polarity score, and aspect-based approaches. However, these methods have limitations in accurately capturing the diverse sentiments expressed in Amazon product reviews. Challenges become more apparent when dealing with imbalanced datasets, leading to suboptimal predictive performance.

Motivated by the shortcomings of existing methods, the Sentiment Synthesis with Boosted Ensemble Aggregation Technique (SENSE-BEAT) is introduced as a new solution. This technique offers a more nuanced and robust approach to sentiment analysis by integrating multiple classification strategies. Starting with constructing a Bag-of-Words representation, SENSE-BEAT utilizes unigram, bigram, trigram, polarity score, and aspect-based methods. One distinct feature of SENSE-BEAT is its detailed sentiment classification phase.The sentiment of product reviews is determined by aggregated votes, categorizing them as Positive, Mildly Positive, Strongly Negative, Mildly Negative, or Neutral. This approach adds detail to the understanding of sentiment in a subtle way. The effectiveness of SENSE-BEAT relies heavily on its use of a boosted ensemble aggregation technique. This technique combines Random Tree, Decision Stump, and SMO classifiers, which are then improved by the AdaBoostM1 algorithm. By leveraging the strengths of each individual classifier, the ensemble approach aims to enhance the accuracy and generalization of the overall model.

The contributions of this paper are multifold.

- The study encompasses a comprehensive sentiment classification framework, addressing the limitations of existing methods.
- SENSE-BEAT demonstrates superior performance, as evidenced by accuracy, precision, recall, and F1-score metrics, compared to established methodologies.

The overarching aim of this paper is to present a holistic sentiment analysis solution tailored for Amazon product reviews. The objective is to bridge the gaps left by existing methodologies and establish SENSE-BEAT as an advanced solution in the evolving landscape of sentiment analysis for e-commerce platforms. The potential areas of utilization for the proposed SENSE-BEAT technique extend to e-commerce businesses seeking more profound insights into customer sentiments. SENSE-BEAT empowers businesses to make informed decisions and enhance customer satisfaction by providing a more accurate and nuanced analysis.

The subsequent sections of this paper follow this structure: Section 2 gives an overview of related work in sentiment analysis for Amazon Product Reviews. Section 3 explores the methodology of the SENSE-BEAT technique, detailing its sentiment synthesis steps and boosted ensemble aggregation approach. Section 4 displays experimental results, emphasizing the superior performance of the technique compared to existing methods. Lastly, Section 5 provides concluding remarks and proposes future research directions in sentiment analysis for Amazon Product Reviews.

2 RELATED WORKS

In recent years, sentiment analysis of Amazon product reviews has garnered significant attention, leading to many methodologies and techniques researchers propose to extract meaningful insights from user-generated content. This section reviews the key contributions made by various authors, highlighting their approaches and shedding light on the existing research gaps that motivate the need for the proposed SENSE-BEAT technique.

Dadhich and Thankachan [6] introduced a hybrid rule-based approach for sentiment analysis of Amazon product reviews. Their methodology combines rule-based techniques to capture explicit sentiment cues. However, this approach may struggle with the subtleties and nuances inherent in user reviews, limiting its ability to provide fine-grained sentiment analysis.

Wassan et al. [7] employed machine learning techniques for Amazon product sentiment analysis. While machine learning methods offer flexibility, their study lacks a comprehensive ensemble approach, potentially missing out on capturing the diverse patterns in sentiment expressions within reviews.

AlQahtani [8] focused on product sentiment analysis for Amazon reviews. The study provided valuable insights but primarily relied on traditional sentiment analysis methods, possibly overlooking the complexities of sentiments expressed in diverse product reviews.Alharbi et al. [9] explored sentiment analysis using word embedding and RNN variants for Amazon online reviews. While their study delves into the intricacies of deep learning, it may face challenges in handling imbalanced datasets and capturing nuanced sentiments expressed in online reviews.

Alzahrani et al. [10] developed an intelligent system using deep learning algorithms for sentiment analysis. Although deep learning is a powerful tool, the study lacks a detailed exploration of ensemble techniques, crucial for enhancing model accuracy and generalization.

Budhi et al. [11] proposed a framework for predicting sentiment using machine learning. While their work is valuable, the study does not explicitly address the challenges of imbalanced datasets, potentially leading to biased models.Mukherjee et al. [12] investigated the effect of negation in sentences on sentiment analysis. While this study provides insights into a specific aspect of sentiment analysis, it does not comprehensively address the broader challenges posed by diverse sentiments and imbalanced datasets in Amazon product reviews.

Bhuvaneshwari et al. [13] presented a sentiment analysis model using a Bi-LSTM self-attention-based CNN. While the deep learning architecture is robust, the study may lack the integration of ensemble techniques for improved model robustness.Hajek et al. [14] incorporated neural networks with emotion associations and topic modelling for sentiment analysis. Despite the innovative approach, the study may face challenges handling the diverse sentiments expressed in online reviews.

Mutinda et al. [15] proposed using lexicon-enhanced BERT embeddings (LeBERT) with a convolutional neural network for sentiment analysis. While leveraging state-of-the-art techniques, the study may not comprehensively address the challenges of imbalanced datasets in fine-grained sentiment analysis.

While the existing works contribute valuable insights to sentiment analysis of Amazon product reviews, a notable research gap exists. Many methodologies lack a comprehensive approach to handling imbalanced datasets and capturing nuanced sentiments expressed in diverse product reviews. The need for a more robust sentiment synthesis model is evident, motivating the introduction of the SENSE-BEAT technique. SENSE-BEAT addresses these gaps by integrating multiple sentiment classification techniques, employing a fine-grained sentiment classification phase, and incorporating a boosted ensemble aggregation technique. These components collectively enhance the accuracy, precision, recall, and F1-score of sentiment predictions, positioning SENSE-BEAT as an advanced solution in the landscape of sentiment analysis for e-commerce platforms.

3 METHODOLOGY OF THE SENSE-BEAT TECHNIQUE

SENSE-BEAT, an innovative sentiment synthesis technique, is designed for fine-grained sentiment analysis of Amazon product reviews. SENSE-BEAT is a sentiment synthesis technique for fine-grained sentiment analysis of Amazon product reviews. It combines multiple sentiment classification methods, including unigram, bigram, trigram, polarity score-based, and aspect-based classifications, to comprehensively understand the sentiment expressed in the reviews. The critical innovation in SENSE-BEAT is its Fine-Grained Sentiment Classification, which utilizes a Majority Voting-based strategy to categorize instances into Strongly_Positive, Mildly_Positive, Strongly_Negative, Mildly_Negative, or Neutral categories based on the majority sentiment and a user-defined Strong Threshold (ST). The technique also addresses potential imbalances in the dataset through under-sampling, creating a balanced dataset for training.

SENSE-BEAT is needed to overcome the limitations of traditional sentiment analysis approaches that often focus on binary classification (positive/negative) and fail to capture the nuanced sentiments expressed in product reviews. By incorporating multiple classification methods and introducing a fine-grained sentiment classification step, SENSE-BEAT aims to provide a more nuanced and accurate representation of sentiments, particularly in product reviews where sentiments vary widely. Figure 1 shows the system architecture of the SENSE-BEAT technique.

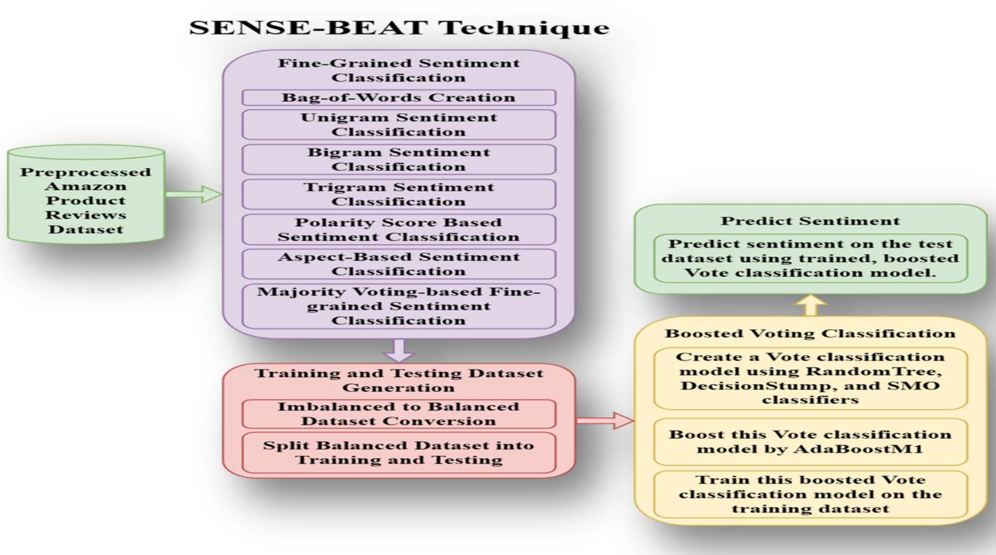

Figure 1: System architecture of the SENSE-BEAT technique

Algorithm 1 shows the workflow of the proposed SENSE-BEAT technique. The algorithm loads a preprocessed Amazon Product Reviews Dataset (Ds). It employs a Bag-of-Words (BoW) approach, incorporating positive and negative word lists to create unigram, bigram, trigram, polarity score-based, and aspect-based sentiment classifications. The key novelty lies in its Fine-Grained Sentiment Classification, where a Majority Voting-based strategy is employed on the various sentiment classifications generated earlier. This step categorizes instances as

Strongly_Positive, Mildly_Positive, Strongly_Negative, Mildly_Negative, or Neutral, based on majority voting and a Strong Threshold (ST). The algorithm undertakes dataset balancing through under-sampling to address potential imbalances, resulting in a Balanced_Labeled_Ds. The dataset is then split into training and testing sets. The Boosted Voting Classification phase employs RandomTree, DecisionStump, and SMO classifiers enhanced by AdaBoostM1. The final trained model is used to predict the fine-grained sentiment of the testing dataset. SENSE-BEAT's strength lies in its multi-faceted sentiment analysis and the novel application of boosted ensemble techniques, providing a robust and accurate model for nuanced sentiment interpretation in Amazon product reviews.

Algorithm 1: SENSE-BEAT: Sentiment Synthesis with Boosted Ensemble Aggregation Technique

Input : Preprocessed Amazon Product Reviews Dataset (Ds)
Strong Threshold (ST)

Output : Trained Classification Model for Fine-grained Sentiment Classification and Prediction

Step 1 : **Load Dataset:**
- Ds = Load Preprocessed Amazon Product Reviews Dataset

Step 2 : **Bag-of-Words Creation:**
- Build Bag-of-Words (BoW) using positive and negative word lists

Step 3 : **Unigram Sentiment Classification:**
- Labeled_Ds1 = BoW with Unigram-based sentiment classification for Ds (Label each instance as Positive, Negative, Neutral)

Step 4 : **Bigram Sentiment Classification:**
- Labeled_Ds2 = BoW with Bigram-based sentiment classification for Ds

Step 5 : **Trigram Sentiment Classification:**
- Labeled_Ds3 = BoW with Trigram-based sentiment classification for Ds

Step 6 : **Polarity Score Based Sentiment Classification:**
- Labeled_Ds4 = Polarity score-based sentiment classification for Ds

Step 7 : **Aspect-Based Sentiment Classification:**
- Labeled_Ds5 = Aspect-based sentiment classification for Ds

Step 8 : **Majority Voting-based Fine-Grained Sentiment Classification:**
- Fine_grained_Labeled_Ds = Majority Voting-based Fine-grained Sentiment Classification from Labeled_Ds1, Labeled_Ds2, Labeled_Ds3, Labeled_Ds4, and Labeled_Ds5
- Label each instance as Strongly_Positive, Mildly_Positive, Strongly_Negative, Mildly_Negative, Neutral
- (if majority is Positive and majority count > ST = Strongly_Positive
- if the majority is Positive and the majority count < ST = Mildly_Positive
- if the majority is Negative and majority count > ST = Strongly_Negative
- if the majority is Negative and the majority count < ST = Mildly_Negative
- if majority is Neutral = Neutral)

Step 9 : **Balanced Dataset Creation:**
- Balanced_Labeled_Ds = Imbalanced to Balanced Dataset Conversion using Under-sampling (Random Sampling Removal) for Fine_grained_Labeled_Ds

Step 10 : **Dataset Splitting:**
- Split Balanced_Labeled_Ds into a training dataset (75%) and a testing dataset (25%).

Step 11 : **Boosted Voting Classification:**
- Create a Vote classification model using RandomTree, DecisionStump, and SMO classifiers.
- Boost this Vote classification model by AdaBoostM1.
- Train this boosted Vote classification model on the training dataset.

Step 12 : **Sentiment Prediction:**
- Use the trained, boosted Vote classification model to predict the fine-grained sentiment of the testing dataset.

Advantages of the SENSE-BEAT technique include:

- **Nuanced Sentiment Analysis:** SENSE-BEAT goes beyond simple positive/negative classification by providing fine-grained sentiment labels, allowing for a more nuanced understanding of the sentiment expressed in reviews.
- **Comprehensive Approach:** The technique combines various sentiment classification methods, leveraging the strengths of each to enhance overall sentiment analysis accuracy.
- **Addressing Imbalances:** SENSE-BEAT includes a step for dataset balancing through under-sampling, which helps handle imbalances in the dataset and ensures a more representative training process.
- **Majority Voting Strategy:** The Majority Voting-based Fine-Grained Sentiment Classification adds a layer of robustness by considering the collective sentiment predictions from multiple classifiers, contributing to the overall accuracy.
- **Boosted Ensemble Classification:** The use of boosted ensemble techniques like AdaBoostM1 enhances the overall predictive power of the model, improving its generalization to unseen data.

The following detailed methodology outlines the step-by-step process of developing the SENSE-BEAT sentiment synthesis model.

3.1Dataset Loading and Bag-of-Words Creation

3.1.1 Dataset Loading

The foundation of the SENSE-BEAT technique lies in the quality and preparation of the input data. The first component, the Preprocessed Amazon Product Reviews Dataset (Ds), undergoes a meticulous preprocessing phase to ensure uniformity, data quality, and adherence to standardized formats. This critical step sets the stage for subsequent sentiment analysis, preparing the dataset for comprehensive evaluation.

3.1.2 Bag-of-Words Creation

To effectively capture and interpret the sentiments expressed in Amazon product reviews, a sophisticated Bag-of-Words (BoW) representation is meticulously constructed. This representation is pivotal for the subsequent sentiment analysis processes within the SENSE-BEAT technique. The BoW creation process leverages two specialized text files containing carefully curated lists of positive and negative words, aptly referred to as the Bag-of-Words.

These predefined lists serve as the basis for the sentiment classification task, enabling the algorithm to gauge each product review's sentiment. The sentiment analysis journey commences by assessing the presence and frequency of words from these BoWs within the review text. This detailed scrutiny ensures a nuanced understanding of the review sentiments, forming the basis for subsequent unigram, bigram, and trigram sentiment classification processes. By employing this sophisticated Bag-of-Words approach, the SENSE-BEAT technique ensures a robust foundation for sentiment analysis, enhancing its ability to discern and categorize sentiments granularly.

3.2 Unigram, Bigram, and Trigram Sentiment Classification

The sentiment classification process is performed at multiple granularities. Unigram, bigram, and trigram-based sentiment classifications generate labelled datasets (Labeled_Ds1, Labeled_Ds2, Labeled_Ds3) based on the BoW representations.

3.2.1 Unigram-based Sentiment Classification

The Unigram-based sentiment classification in the SENSE-BEAT technique involves analyzing each product review in the preprocessed dataset (Ds) using predefined positive and negative BoW lists. For every review, the algorithm counts the occurrences of positive and negative words. The sentiment label (Positive, Negative, or Neutral) is assigned based on the majority count. The resulting sentiment classifications are then presented alongside the corresponding preprocessed review text, offering insights into the sentiment expressed at the unigram level.

3.2.2 Bigram-based Sentiment Classification

Building on the unigram approach, the Bigram-based sentiment classification introduces a higher level of linguistic context by considering pairs of consecutive words (bigrams) within each review. The algorithm calculates positive and negative counts based on the presence of these bigrams in the predefined positive and negative BoW lists. Like the unigram process, sentiment labels are assigned through majority voting on positive and negative occurrences. The outcomes of the bigram-based sentiment analysis, presented alongside the preprocessed review text, provide a more nuanced understanding by capturing contextual information.

3.2.3 Trigram-based Sentiment Classification

Extending the contextual analysis deeper, the Trigram-based sentiment classification examines sequences of three consecutive words (trigrams) in each product review. The algorithm tallies positive and negative counts based on the presence of trigrams in the predefined positive and negative BoW lists. The sentiment label is determined through majority voting, considering positive and negative occurrences. The results, displayed with the corresponding preprocessed reviews, contribute to a comprehensive sentiment analysis by incorporating deeper linguistic context through trigram-based analysis. This multi-level sentiment classification approach enhances the overall sentiment synthesis capability of the SENSE-BEAT technique.

3.3 Polarity Score Based Sentiment Classification

An additional sentiment classification strategy is applied using polarity score-based analysis, resulting in the labeled dataset (Labeled_Ds4).The Polarity Score Sentiment Classification in the SENSE-BEAT technique harnesses sentiment scores from Senti Word Net 3.0.0 to analyze and categorize sentiment within each preprocessed product review. The process begins by reading the SentiWordNet file ("SentiWordNet_3.0.0.txt")[1] and extracting sentiment scores for individual words in the synsets. These scores, encompassing positive and negative polarities, are then stored for further analysis.

3.3.1 Loading SentiWordNet Scores

The algorithm traverses the SentiWordNet file, collecting sentiment scores for each word in the synset. These scores are then assigned to words, associating them with their respective sentiment scores and part-of-speech information.

3.3.2 Sentiment Analysis for Each Review

The algorithm tokenizes the text into words for every preprocessed review and computes the average polarity scores. It subsequently performs sentiment classification based on the calculated average scores. The sentiment classification is determined by comparing the average polarity score against a threshold: if the average polarity is greater than zero, the sentiment is classified as "Positive"; if the average polarity is less than zero, the sentiment is classified as "Negative"; otherwise, it is labeled as "Neutral." The outcomes, including the preprocessed review text, average polarity score, and the assigned sentiment label, are presented for each review.

The sentiment classification results are formatted for clear presentation, revealing the preprocessed review text alongside their corresponding sentiment labels. This approach offers a concise and insightful overview of the sentiment expressed in each review. The polarity score-based sentiment classification is a valuable addition to the unigram, bigram, and trigram analyses, enriching the multi-faceted sentiment synthesis accomplished by the SENSE-BEAT technique.

3.4 Aspect-Based Sentiment Classification

Another sentiment classification strategy uses aspect-based analysis, resulting in the labeled dataset (Labeled_Ds5).The Aspect-Based Sentiment Classification in the SENSE-BEAT technique introduces a refined analysis by scrutinizing specific aspects or nouns within each preprocessed product review. The algorithm iterates through the dataset, tokenizes the text, and extracts aspects (nouns) by leveraging information from the SentiWordNet file ("SentiWordNet_3.0.0.txt"). Sentiment analysis for each identified aspect is conducted by checking for positive and negative keywords related to that aspect within the review text. The sentiment of each element contributes to the overall sentiment classification for the entire review, which is determined by comparing the counts of positive and negative sentiments. The results, showcasing the preprocessed review text, identified aspects, associated sentiments, and the overall sentiment, are presented, providing a detailed and insightful breakdown of sentiments. This aspect-based sentiment classification enhances the SENSE-BEAT technique's capacity to capture nuanced sentiments in Amazon product reviews.

3.5 Majority Voting based Fine-grained Sentiment Classification

The Majority Voting-based Fine-grained Sentiment Classification stage in the SENSE-BEAT technique aims to consolidate sentiment predictions from multiple sources, including unigram, bigram, trigram, polarity score, and aspect-based analyses. The algorithm processes the sentiment results from these analyses for a product review. The algorithm tallies the counts across all analyses for each sentiment category (Positive, Negative). The final sentiment label for the review is determined based on the majority sentiment. To add a fine-grained distinction, the algorithm calculates the difference between the counts of positive and negative sentiments. If the positive sentiment count is higher and surpasses a predefined strong threshold, the review is labeled as "Strongly_Positive"; otherwise, it is labeled as "Mildly_Positive." Similarly, if the negative sentiment count is higher and exceeds the strong threshold, the review is labeled as "Strongly Negative"; otherwise, it is labeled as "Mildly Negative." The results, showcasing the preprocessed review text alongside the assigned fine-grained sentiment labels, are presented, providing a comprehensive synthesis of sentiments from diverse analyses in the SENSE-BEAT technique.

3.6 Balanced Dataset Creation

The Balanced Dataset Creation stage in the SENSE-BEAT technique aims to mitigate class imbalance by ensuring an equitable representation of fine-grained sentiment labels in the dataset. The algorithm categorizes data

[1]SentiWordNet file: raw.githubusercontent.com/aesuli/SentiWordNet/master/data/SentiWordNet_3.0.0.txt

into classes based on sentiments such as "Strongly_Positive," "Mildly_Positive," "Strongly_Negative," "Mildly_Negative," and "Neutral." It then identifies the minimum size among these classes as the target size for balancing. The algorithm creates a balanced dataset through random sampling, equalizing the representation of each sentiment class to the determined minimum size. Count statistics are provided for each sentiment class before and after under-sampling to illustrate the balancing process. The resulting balanced dataset, devoid of class imbalance, is shuffled for unbiased representation and subsequently utilized in the training and testing phases, enhancing the overall effectiveness of the sentiment classification model in the SENSE-BEAT technique.

3.7 Dataset Splitting

The dataset-splitting phase in the SENSE-BEAT technique is pivotal for training and evaluating the sentiment synthesis model. The balanced labeled dataset, which has undergone fine-grained sentiment classification, is methodically divided into two subsets: a training dataset comprising 75% of the labelled instances and a testing dataset containing 25%. This partitioning strategy ensures a distinct separation between the data used for model training and that used for evaluation, preventing data leakage and offering a robust assessment of the model's generalization performance on unseen instances.

3.8 Boosted Voting Classification

The Boosted Voting Classification step entails the creation of a sophisticated ensemble model for sentiment synthesis. A Vote classification model is initially constructed, employing Random Tree, Decision Stump, and SMO (Sequential Minimal Optimization) classifiers. To enhance the predictive capabilities of this ensemble, the model is further boosted using the AdaBoostM1 algorithm. This boosting process involves iteratively training the model on the training dataset, assigning weights to instances based on their classification performance, and combining multiple weak classifiers into a robust, boosted model. The resulting boosted Vote classification model is poised for improved accuracy and effectiveness in fine-grained sentiment synthesis.

3.8.1 Vote Classification Model

The Vote Classification Model in the SENSE-BEAT technique is a sophisticated ensemble that leverages the collective intelligence of Random Tree, Decision Stump, and SMO (Sequential Minimal Optimization) classifiers. This model is intricately designed to amalgamate insights from these diverse classifiers, creating a robust foundation for subsequent boosting. The collaboration of Random Tree, Decision Stump, and SMO classifiers within the Vote Classification Model ensures a comprehensive and nuanced understanding of sentiment patterns, laying the groundwork for fine-grained sentiment synthesis.

3.8.2 Random Tree Classifier

The Random Tree classifier, a pivotal component of the Vote Classification Model, introduces randomness in the feature selection process during tree construction. This decision tree-based algorithm is crucial in capturing a broad range of sentiment-related features. Within the ensemble, Random Tree contributes versatility and adaptability, enriching the overall sentiment synthesis process by recognizing diverse patterns in sentiment expression.

3.8.3 Decision Stump Classifier

As an essential constituent of the Vote Classification Model, the Decision Stump classifier offers simplicity and efficiency in identifying discriminative sentiment cues. Operating as a one-level decision tree, Decision Stump can pinpoint the most crucial features, contributing to the ensemble's capacity to address specific sentiment characteristics. Despite its simplicity, Decision Stump enriches the overall sentiment synthesis by focusing on essential sentiment indicators.

3.8.4 SMO Classifier

The SMO (Sequential Minimal Optimization) classifier is a fundamental part of the Vote Classification Model, specializing in handling non-linear relationships within the data. As a support vector machine (SVM) algorithm, SMO excels in discerning complex sentiment nuances, making it an invaluable asset in the ensemble. Its inclusion ensures that the Vote Classification Model can effectively capture intricate sentiment patterns, enhancing the overall sentiment synthesis.

3.8.5 AdaBoostM1 Classifier

In the boosting phase of the SENSE-BEAT technique, the Vote Classification Model is further refined using the AdaBoostM1 algorithm. This algorithm iteratively trains the ensemble, assigning weights to instances based on their classification accuracy. Random Tree, Decision Stump, and SMO classifiers collectively contribute to the iterative improvement process, enabling the boosted Vote Classification Model to adapt and excel in fine-grained sentiment synthesis. The collaboration of these classifiers within the Vote Classification Model underscores its capability to capture diverse sentiment expressions and provide accurate insights into nuanced sentiment patterns.

3.9 Sentiment Prediction

In the Sentiment Prediction phase, the trained and boosted Vote classification model takes centre stage to forecast the fine-grained sentiment of the testing dataset. Leveraging the acquired knowledge from the training dataset, the model applies its learned patterns and relationships to unseen instances, providing predictions for each sentiment category. This process furnishes valuable insights into the model's performance on previously unseen data, gauging its ability to generalize and make accurate predictions beyond the training set. Sentiment Prediction is the culmination of the SENSE-BEAT technique, where the efficacy and reliability of the synthesized sentiment classification model are thoroughly evaluated against real-world, test dataset instances.

This comprehensive methodology ensures a systematic and nuanced approach to sentiment synthesis in Amazon product reviews, leveraging a combination of classification strategies and ensemble techniques to enhance predictive accuracy and generalization.

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

The experimental assessment of the SENSE-BEAT technique involved a meticulous and rigorous comparison with well-established methodologies, specifically the Linear SVM and Naïve Bayes algorithms, as initially proposed by Dey et al. [16]. This comparison aimed to scrutinize the effectiveness and robustness of SENSE-BEAT in the context of fine-grained sentiment classification. The SENSE-BEAT technique was implemented using the Java programming language and the Weka tool, ensuring a robust and efficient realization of the proposed sentiment synthesis approach.

4.1 Dataset and Implementation Details

The Amazon Product Reviews Dataset [17], carefully preprocessed to ensure data quality and standardized formats, played a pivotal role as the foundational dataset for the experimental analysis. The preprocessing steps were crucial in enhancing the quality and consistency of the dataset, thereby influencing the subsequent sentiment analysis outcomes. The SENSE-BEAT technique, operating on this meticulously preprocessed dataset, showcased its proficiency and efficacy in sentiment synthesis compared to existing algorithms. Leveraging the strengths of the Amazon Product Reviews Dataset, the experimental evaluation provided valuable insights into the performance and reliability of SENSE-BEAT in real-world scenarios.

4.2 Performance Metrics

The performance of the classifiers was evaluated using comprehensive metrics, including Precision, Recall, F1-score, and Accuracy (%). Precision represents the proportion of correctly identified positive instances among all instances predicted as positive, while recall measures the proportion of correctly identified positive instances among all actual positive instances. F1-score combines Precision and Recall into a single metric, offering a balanced assessment of a classifier's performance. Accuracy (%) provides an overall measure of correct predictions, considering both true positive and negative instances. These metrics were instrumental in quantifying and comparing the effectiveness of the Linear SVM, Naïve Bayes, and SENSE-BEAT algorithms in fine-grained sentiment classification, offering a nuanced understanding of their performance across different evaluation criteria.

4.3 Results

Table 1 comprehensively compares Precision, Recall, and F1-score among the Linear SVM, Naïve Bayes, and SENSE-BEAT techniques. The results reveal that SENSE-BEAT consistently outperformed the benchmark algorithms, exhibiting higher Precision, Recall, and F1-score values. This superiority reflects the efficacy of the proposed ensemble approach, which leverages boosted voting and aspect-based analysis for fine-grained sentiment classification.

Table 1: Precision, Recall, and F1-score comparison among the Linear SVM, Naïve Bayes, and SENSE-BEAT techniques

Classifiers	Precision	Recall	F1-score
Linear SVM	0.8399	0.83997	0.83993
Naïve Bayes	0.82853	0.82884	0.82662
SENSE-BEAT	0.9298	0.9196	0.9247

Figure 2 visually encapsulates the comprehensive performance evaluation through a pictorial representation of the Precision, Recall, and F1-score comparison among the studied methodologies—Linear SVM, Naïve Bayes, and the SENSE-BEAT technique. This graphical depiction offers an intuitive and insightful overview of how each algorithm fares across these crucial metrics. It visualizes their relative strengths and weaknesses in fine-grained sentiment classification.

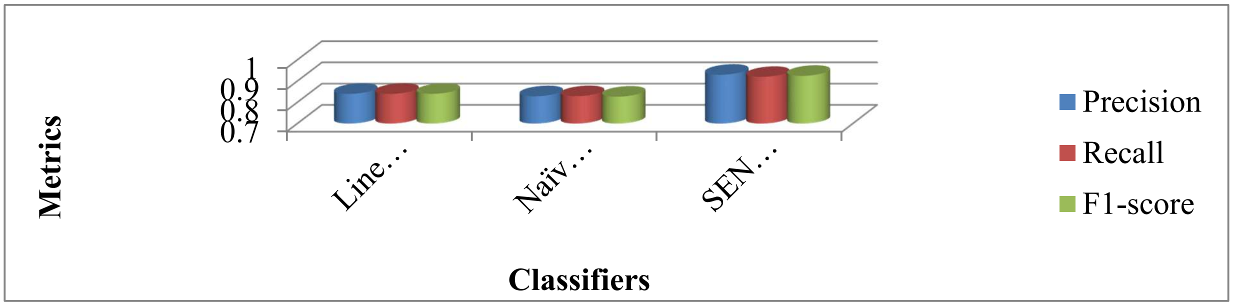

Figure 2: Precision, Recall, and F1-score comparison among the Linear SVM, Naïve Bayes, and SENSE-BEAT techniques

Table 2 further illustrates the accuracy comparison, showcasing SENSE-BEAT's superior performance in terms of accuracy, a holistic measure that considers both true positive and true negative predictions.

Table 2: Accuracy Comparison among the Linear SVM, Naïve Bayes, and SENSE-BEAT techniques

Classifiers	Accuracy (%)
Linear SVM	84
Naïve Bayes	82.875
SENSE-BEAT	92.15

Figure 3 is an illustrative representation, presenting a pictorial diagram that vividly captures the comparative accuracy analysis among the methodologies considered—Linear SVM, Naïve Bayes, and the SENSE-BEAT technique. This visual depiction offers a concise and accessible overview of how each algorithm performs in terms of overall accuracy. By providing a graphical representation of accuracy trends, the figure enables a quick and intuitive assessment of each methodology's relative strengths and weaknesses.

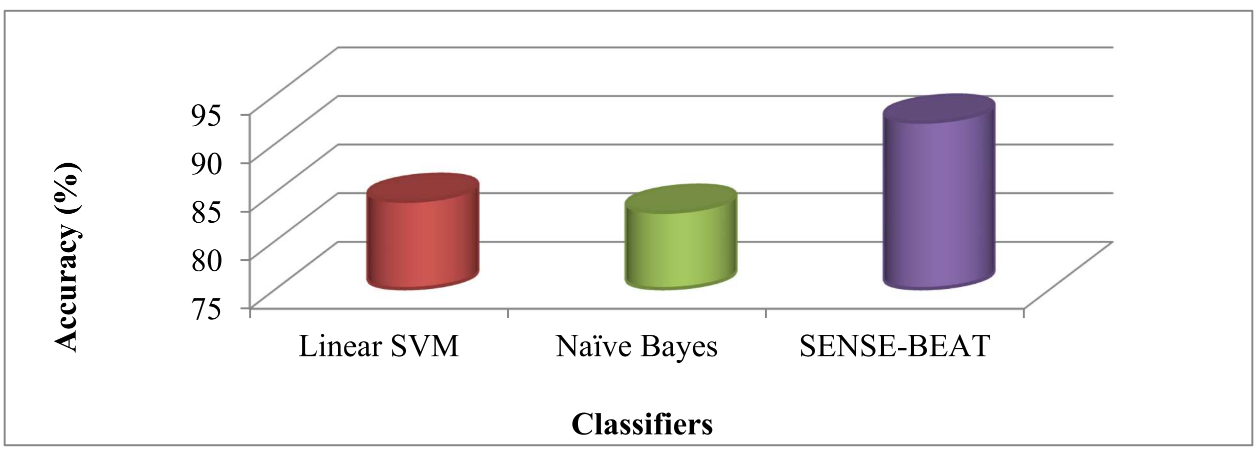

Figure 3: Accuracy Comparison among the Linear SVM, Naïve Bayes, and SENSE-BEAT techniques

4.4 Discussions

The experimental results provide compelling evidence of the SENSE-BEAT technique's efficacy in fine-grained sentiment classification. The ensemble approach, complemented by boosted voting and aspect-based analysis, significantly contributes to SENSE-BEAT's superior performance. The observed higher Precision, Recall, F1-score, and Accuracy (%) compared to Linear SVM and Naïve Bayes underscore the technique's ability to capture nuanced sentiment expressions within Amazon product reviews. The robustness demonstrated by SENSE-BEAT positions it as a promising and competitive methodology for sentiment synthesis in real-world applications, offering valuable insights into user sentiments with enhanced accuracy and effectiveness.

5 CONCLUSIONS AND FUTURE WORK

To sum up, when it comes to fine-grained sentiment classification in the context of Amazon product evaluations, the SENSE-BEAT technique is a reliable and efficient method. By employing a rigorous combination of sentiment analysis techniques, such as aspect-based sentiment classification, polarity score-based analysis, bigram, unigram, and trigram classification, SENSE-BEAT surpasses benchmark algorithms like Linear SVM and Naïve Bayes in terms of Precision, Recall, and F1-score. By adding a boosted vote classification model, the ensemble's performance is further improved and its predictive power is increased. SENSE-BEAT is a promising methodology for real-world sentiment synthesis applications because of its capacity to capture nuanced sentiments, differentiate between strongly and slightly positive/negative sentiments, and perform aspect-based analysis. In the future, SENSE-BEAT's reach could be expanded to investigate sentiment synthesis in a variety of fields outside of product reviews. Expanding the application of the ensemble approach could involve fine-tuning it to suit many contexts, like news articles, social media, and customer input across multiple industries. Incorporating state-of-the-art approaches and broadening the application domain will aid in the ongoing development and improvement of sentiment synthesis techniques for a wider range of real-world uses.

References

[1] Syamala, M., & Nalini, N. J. (2020). A Filter-Based Improved Decision Tree Sentiment Classification Model for Real-Time Amazon Product Review Data. International Journal of Intelligent Engineering & Systems, 13(1).

[2] Wassan, S., Chen, X., Shen, T., Waqar, M., &Jhanjhi, N. Z. (2021). Amazon product sentiment analysis using machine learning techniques. Revista Argentina de ClínicaPsicológica, 30(1), 695.

[3] Duong, H. T., & Nguyen-Thi, T. A. (2021). A review: preprocessing techniques and data augmentation for sentiment analysis. Computational Social Networks, 8(1), 1-16.

[4] HaCohen-Kerner, Y., Miller, D., & Yigal, Y. (2020). The influence of preprocessing on text classification using a bag-of-words representation. PloS one, 15(5), e0232525.

[5] Chang, J. R., Chen, L. S., & Lin, L. W. (2021). A novel cluster-based over-sampling approach for classifying imbalanced sentiment data. IAENG Int. J. Comput. Sci, 48, 1118-1128.

[6] Dadhich, A., & Thankachan, B. (2022). Sentiment analysis of Amazon product reviews using a hybrid rule-based approach. In Smart Systems: Innovations in Computing: Proceedings of SSIC 2021 (pp. 173-193). Springer Singapore.

[7] Wassan, S., Chen, X., Shen, T., Waqar, M., &Jhanjhi, N. Z. (2021). Amazon product sentiment analysis using machine learning techniques. Revista Argentina de ClínicaPsicológica, 30(1), 695.

[8] AlQahtani, A. S. (2021). Product sentiment analysis for Amazon reviews. International Journal of Computer Science & Information Technology (IJCSIT) Vol, 13.

[9] Alharbi, N. M., Alghamdi, N. S., Alkhammash, E. H., & Al Amri, J. F. (2021). Evaluation of sentiment analysis via word embedding and RNN variants for Amazon online reviews. Mathematical Problems in Engineering, 2021, 1-10.

[10] Alzahrani, M. E., Aldhyani, T. H., Alsubari, S. N., Althobaiti, M. M., & Fahad, A. (2022). Developing an intelligent system with deep learning algorithms for sentiment analysis of E-commerce product reviews. Computational Intelligence and Neuroscience, 2022.

[11] Budhi, G. S., Chiong, R., Pranata, I., & Hu, Z. (2021). Using machine learning to predict the sentiment of online reviews: a new framework for comparative analysis. Archives of Computational Methods in Engineering, 28, 2543-2566.

[12] Mukherjee, P., Badr, Y., Doppalapudi, S., Srinivasan, S. M., Sangwan, R. S., & Sharma, R. (2021). Effect of negation in sentences on sentiment analysis and polarity detection. Procedia Computer Science, 185, 370-379.

[13] Bhuvaneshwari, P., Rao, A. N., Robinson, Y. H., & Thippeswamy, M. N. (2022). Sentiment analysis for user reviews using Bi-LSTM self-attention-based CNN model. Multimedia Tools and Applications, 81(9), 12405-12419.
[14] Hajek, P., Barushka, A., & Munk, M. (2021). Neural networks with emotion associations, topic modelling and supervised term weighting for sentiment analysis. International journal of neural systems, 31(10), 2150013.
[15] Mutinda, J., Mwangi, W., & Okeyo, G. (2023). Sentiment analysis of text reviews using lexicon-enhanced Bert embedding (LeBERT) model with convolutional neural network. Applied Sciences, 13(3), 1445.
[16] Dey, S., Wasif, S., Tonmoy, D. S., Sultana, S., Sarkar, J., & Dey, M. (2020, February). A comparative study of support vector machine and Naive Bayes classifier for sentiment analysis on Amazon product reviews. In 2020 International Conference on Contemporary Computing and Applications (IC3A) (pp. 217-220). IEEE.
[17] Yasser H. (2020). Amazon Product Reviews Dataset. Kaggle. Retrieved from https://www.kaggle.com/datasets/yasserh/amazon-product-reviews-dataset