

Design and Development of an Efficient Ensemble Model for Aspect-Based Sentiment Analysis

Ayesha Siddiqua

Nitte Research and Education Academy, Nitte Meenakshi Institute of Technology Campus, Bengaluru, Karnataka, India | University of Mysore, Mysuru, Karnataka, India
leo.ayesha@gmail.com (corresponding author)

H. C. Nagaraj

Nitte Research and Education Academy, Nitte Meenakshi Institute of Technology Campus, Bengaluru, Karnataka, India
principal@nmit.ac.in

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ABSTRACT

Aspect-Based Sentiment Analysis (ABSA), a subfield of Natural Language Processing (NLP), aims to identify the sentiment polarity of particular features within social media content or text reviews. Unlike conventional sentiment analysis, which categorizes a whole text as positive, negative, or neutral, ABSA connects emotions to specific qualities, therefore providing more detailed insights useful for companies, product creators, and academics. Using a dataset of user-generated reviews, each tagged with aspect terms and their locations, this study focuses on aspect-term polarity estimation. Major difficulties include recording changes in context-dependent emotion caused by the surrounding language and word choices. Initially, conventional machine learning algorithms, namely Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN) were used. Acknowledging the shortcomings of single models, such as feature dependency and overfitting, this work also uses an ensemble learning technique with voting classifiers, investigating both hard (majority rule) and soft voting (probabilistic averaging). Experimental findings show that these ensemble-based voting classifiers regularly beat individual models, attaining better sentiment classification accuracy and increasing model robustness. The results confirm the efficiency of ensemble methods in promoting ABSA and enhancing sentiment analysis for practical use.

Keywords-Aspect-Based Sentiment Analysis (ABSA); NLP; RF; DT; kNN; SVM; voting-based ensemble learning

I. INTRODUCTION

Natural Language Processing (NLP) includes a vital topic called Aspect-Based Sentiment Analysis (ABSA) that aims to extract sentiment from textual data linked to certain characteristics [1]. These data might be from social media posts, reviews of products or restaurants, or even customer feedback. By linking the polarity of sentiment to specific entity attributes, ABSA offers a more nuanced understanding than conventional sentiment analysis, which simply labels texts with one sentiment. For instance, consider the sentence "The screen is nice, but the battery is pathetic." The aspects "screen" and "battery" communicate different emotions, as the former is optimistic and the latter is pessimistic. This detailed sentiment extraction allows businesses to gain actionable insights by pinpointing strengths and weaknesses in their products or services. SVM, RF, and DT are just a few of the Machine

Learning (ML) models investigated for potential use in addressing these challenges. Although these models demonstrate strong classification capabilities, they often struggle with capturing complex linguistic patterns and handling imbalanced datasets. Ensemble learning techniques, such as voting classifiers, are used to improve classification performance. Voting-based ensemble methods combine multiple classifiers to leverage their individual strengths while mitigating their weaknesses. In particular, hard voting selects the class predicted by most models, while soft voting averages the probability distributions of multiple classifiers to make a more informed decision.

Evolutionary Ensembler (EEn) [2] is a novel approach to NLP aspect-based multilabel sentiment analysis that uses SVM tuned with genetic algorithms, achieving 90-95% accuracy over seven datasets. Its efficacy is based on the quality of

preprocessed data, but could have difficulty with domain generalization. Although it relies on data quality and requires more adaptability, ABSA [3] improves consumer knowledge by providing unambiguous recommendations and reducing prejudice. In [4], it was shown how textual material affects companies, although it struggles with data quality, volume, and capture of subtle emotions. Sentiment analysis uses NLP to extract opinions from online content, particularly in the context of social media [5]. However, potential limitations include capturing nuances in sentiment expression, relying on quality data for model training, and understanding context, which could lead to misinterpretation of sentiments.

In [6], two deep-learning models were used to find review aspects and related feelings. In [7], deep learning, Reptile Search Optimisation (RSO), and Extreme Gradient Boosting (XGBoost) were combined for aspect-oriented sentiment analysis, showing issues with language complexity. Conventional models struggle with implicit aspects and domain knowledge. In [8], sentiment polarity was identified toward particular features. Although this approach had a difficult implementation and increased computational load, the dependency graphs improved classification. In [9], feature extraction with Bag of Words (BoW) and word embeddings was highlighted, and ML techniques, from Naïve Bayes to LSTM, were used for sentiment analysis. Among the constraints are reliance on datasets, little algorithm investigation, and disregard for emotional dynamics. In addition, there is still more work to be done on issues including ambiguous language and sarcasm detection. Using a two-step hybrid approach that combined rule-based extraction with ML and DL, an end-to-end ABSA framework was presented in [10] for mobile app reviews, but its complexity and inaccuracy variation might impede generalization to other fields. Examining more than 727 studies, the ABSA review in [11] showed that growth is motivated by digital opinions but pointed out low dataset and domain diversity. Among the drawbacks are a focus on English and a dependence on current research, which limits generalization.

In [12], two multilingual-BERT ensembles (mBERT-E-MV and mBERT-E-AS) were proposed for Hindi datasets, highlighting the efficiency of pre-trained models such as BERT in NLP and ABSA. Among the constraints are language generalization problems, dataset prejudices, and reliance on data quality. In [13], the CBRS architecture improved ABSA for smartphone reviews by integrating CNNs, Bi-RNNs, and SVMs but struggled with generalizability and overfitting. Although ensemble techniques can beat single models, task-specific selection remains vital even as Google's transformer model [14] pushed NLP tasks forward. The efficient market hypothesis [15] holds that stock prices reflect all information, making sentiment analysis essential for investment decisions, despite the challenges of technical financial language and insufficient labeled data. In [16], ABSA's role in classifying product-related emotions in Indian markets was highlighted, with restrictions including dataset biases and cultural diversity. In [17], a multitask learning framework was proposed to extract and classify aspect sentiments, enhancing accuracy but still struggling with aspect extraction errors. A systematic review on Arabic-ABSA [18] drew attention to a lack of thorough

research, pointing out shortcomings such as a small study pool and emphasis on 2012-2021 material. In [19], a hybrid opinion mining application used heuristic patterns for aspect extraction, but its reliance on heuristics might restrict adaptability and generalizability across various platforms and products.

By integrating ensemble approaches, this study aims to improve sentiment classification accuracy, demonstrating that ensemble-based ABSA models outperform individual classifiers in extracting fine-grained sentiment insights.

II. PROPOSED METHOD

As shown in Figure 1, the proposed architecture consists of the following five major components: Input layer (data collection and dataset preprocessing), feature engineering and vectorization, model training with individual traditional classifiers, ensemble learning using voting classifiers, and performance evaluation.

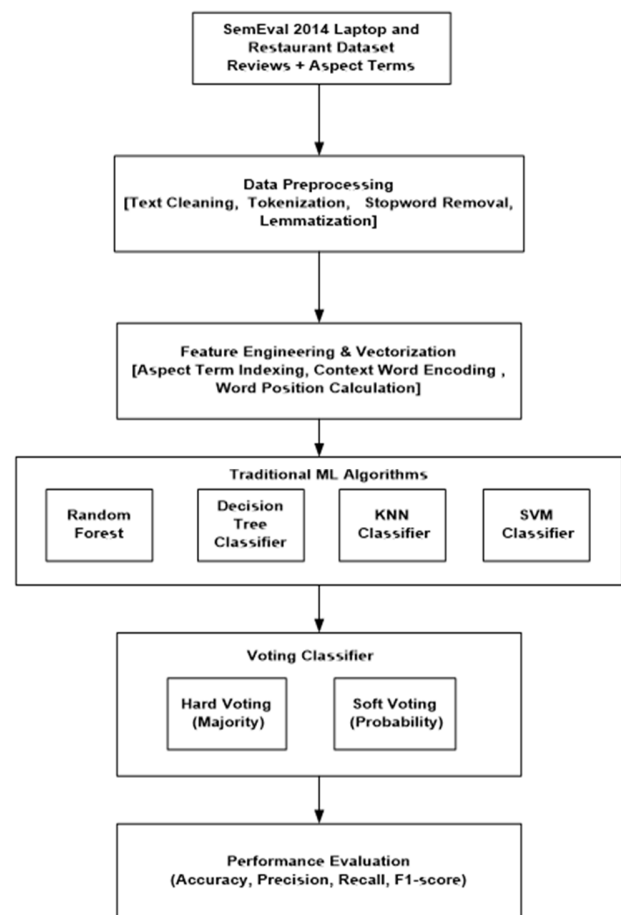


Fig. 1. Proposed architecture.

A. Data Preprocessing

Multiple preprocessing techniques were applied to the dataset to improve feature extraction, model efficiency, and overall classification performance. These steps ensure that text data are standardized and optimized for ML models:

- Replacing with "," (comma): This step preserves grammatical structure and ensures correct punctuation representation.
- Lowercasing all text: Converts all text to lowercase to eliminate case sensitivity, reducing redundant variations of the same word (e.g., "Great" and "great").
- Converting numbers to text: Enhances model interpretability by converting numerical values into their textual representations (e.g., "10" → "ten"), preventing them from being treated as outliers.
- Custom tokenization with punctuation removal: Breaks sentences into meaningful tokens while removing unnecessary punctuation, thus reducing noise in the dataset.

Additionally, stopword removal and lemmatization could be integrated to further refine the input data, ensuring that only the most relevant words contribute to sentiment classification.

B. Feature Matrix Construction

The feature matrix is a structured representation of data that serves as input to the ML models and consists of four key components:

- Source Data: The tokenized text is mapped to unique numerical IDs using the Source2idx dictionary, ensuring a structured representation of words.
- Source Location Data: Computes the relative distance of each word from the aspect term, helping the model capture context-dependent sentiment.
- Target Data: Aspect terms are replaced with unique IDs from the Target2idx dictionary, allowing for efficient and consistent model training.
- Maximum Sentence Length: Determines the fixed-length padding for all sentences, ensuring uniform input size for classification models.

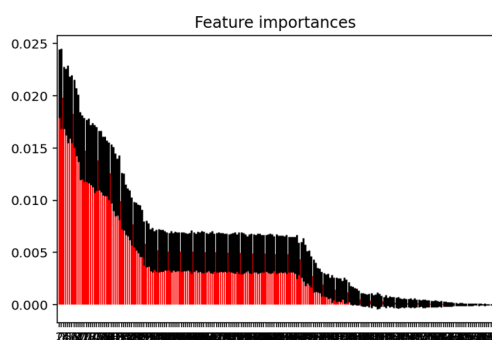


Fig. 2. Graph of feature importance for the dataset.

To further enhance feature engineering, additional techniques such as TF-IDF vectorization, word embeddings (GloVe, Word2Vec), and dependency parsing could be integrated to capture semantic and syntactic relationships more effectively. Using 250 estimators, the Extra Trees classifier ranked features according to how they affected classification.

To increase computational efficiency, the top 50 features were examined. By focusing on important predictors, this condensed feature set improves classification performance, facilitates better feature selection, and makes the model easier to understand.

C. Classification Models

1) Traditional Classifiers

To analyze aspect-based sentiment, four widely used supervised ML models were implemented:

- Random Forest (RF): An ensemble of decision trees that reduces overfitting and enhances model generalization.
- Decision Tree (DT): A tree-based model that splits features based on information gain, offering interpretable decision-making.
- K-Nearest Neighbor (KNN): A distance-based classifier that assigns sentiment labels based on similarity to nearby instances.
- Support Vector Machine (SVM): A powerful classifier that uses hyperplanes to separate classes, effective for high-dimensional text data.

Each model was trained using the preprocessed feature vectors, which include context words, location indices, and aspect word indices.

2) Voting-Based Ensemble Learning

To improve classification accuracy and robustness, an ensemble learning approach was adopted using a voting classifier. This method combines multiple classifiers to leverage their individual strengths while minimizing their weaknesses. The voting strategies were:

- Hard voting: Assigns the final class label based on the majority prediction from RF, KNN, and DT.
- Soft voting: Averages the predicted probabilities from all classifiers, leading to a more refined decision boundary.

D. Algorithm: Aspect-Based Sentiment Analysis using Ensemble Learning

1) Step 1: Data Preprocessing

A dataset D contains N textual reviews, each with an aspect term, sentiment label, and word position:

$$D = \{(S_i, A_i, y_i)\}_{i=1}^N \quad (1)$$

where $S_i = \{w_1, w_2, \dots, w_m\}$ is the textual review containing m words, A_i is the aspect term in S_i , and $y_i \in \{-1, 0, +1\}$ is the sentiment label for A_i (negative, neutral, positive). The preprocessing functions are as follows:

Lowercasing:

$$s_i^{lower} = lowercase(S_i) \quad (2)$$

Number to text conversion:

$$S_i^{num2text} = convert_numbers(s_i^{lower}) \quad (3)$$

Tokenization and punctuation removal:

$$T_i = \{t_1, t_2, \dots, t_n\} = \text{tokenize}(S_i^{\text{num2text}}) \quad (4)$$

where T_i represents the set of filtered words after removing punctuation and special characters

2) Step 2: Feature Matrix Construction

For each sentence S_i , a numerical feature matrix X is constructed. Words are mapped using indexing functions. For source text mapping, each word t_j in S_i is mapped to an index value using the vocabulary dictionary Source2idx:

$$X_{\text{source}}(i, j) = \text{Source2idx}(t_j) \quad (5)$$

For aspect term mapping, the aspect term A_j is mapped using Target2idx:

$$X_{\text{aspect}}(i) = \text{Target2idx}(A_j) \quad (6)$$

The word position relative to the aspect term is given by:

$$X_{\text{pos}}(i, j) = \text{position}(t_j, A_i) \quad (7)$$

where $X_{\text{pos}}(i, j)$ represents the distance of each word from the aspect term in the sentence. Sentence padding (Max Length = L) is performed:

$$X_{\text{padded}}(i) = \text{pad}(X_{\text{source}}(i), L) \quad (8)$$

The final feature matrix is represented as:

$$X = \{X_{\text{source}}, X_{\text{aspect}}, X_{\text{pos}}, X_{\text{padded}}\} \quad (9)$$

and the corresponding sentiment labels are:

$$Y = \{y_1, y_2, \dots, y_N\} \quad (10)$$

3) Step 3: Classification Models

Four ML classifiers are used for aspect-based sentiment classification.

- RF:

$$P_{RF}(y|X) = \frac{1}{T} \sum_{t=1}^T h_t(X) \quad (11)$$

where $h_t(X)$ represents T decision trees in the ensemble.

- DT:

$$P_{DT}(y|X) = \text{argmax}_y \sum_{j=1}^J p_j(y|X) \quad (12)$$

where $p_j(y|X)$ represents probability estimates from J nodes in the DT.

- KNN:

$$P_{KNN}(y|X) = \frac{1}{K} \sum_{k=1}^K y_k \quad (13)$$

where K is the number of nearest neighbors and y_k is the sentiment label of neighbor k ,

- SVM:

$$f(X) = \sum_{i=1}^N \alpha_i y_i K(X_i, X) + \beta \quad (14)$$

where α_i denotes Lagrange multipliers, $K(X_i, X)$ is the kernel function, and β is the bias term.

The predicted sentiment label for each classifier is given by:

$$\hat{y}_{clf} = \text{argmax}_y P_{clf}(y|X) \quad (15)$$

where clf represents RF, DT, KNN, or SVM.

4) Step 4: Ensemble Learning Using Voting Classifier

To enhance accuracy, voting classifiers were employed:

- Hard voting (majority rule):

$$\hat{y}_{hard} = \text{argmax}_y \sum_{c=1}^C \prod(\hat{y}_c = y) \quad (16)$$

where C is the total number of classifiers, and $\prod(\cdot)$ is an indicator function that returns 1 if classifier c predicts y .

- Soft Voting (probability averaging):

$$P_{soft}(y|X) = \frac{1}{C} \sum_{c=1}^C P_c(y|X) \quad (17)$$

$$\hat{y}_{soft} = \text{argmax}_y P_{soft}(y|X) \quad (18)$$

where $P_c(y|X)$ represents the probability of sentiment y predicted by classifier c .

5) Step 5: Model Evaluation and Performance Metrics

The ensemble models were evaluated using accuracy, precision, recall, and F1-score:

$$P_{\text{accuracy}} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (19)$$

$$P_{\text{Precision}} = \frac{T_P}{T_P + F_P} \quad (20)$$

$$P_{\text{Recall}} = \frac{T_P}{T_P + F_N} \quad (21)$$

$$P_{F1\text{-score}} = 2 * \frac{P_{\text{Precision}} * P_{\text{Recall}}}{P_{\text{Precision}} + P_{\text{Recall}}} \quad (22)$$

where T_P, T_N, F_P, F_N denote True Positives, True Negatives, False Positives, and False Negatives, respectively.

III. RESULTS AND DISCUSSION

A. Experimental Setting

This study used two publicly accessible benchmark datasets from SemEval-2014 Task 4: Aspect-Based Sentiment Analysis (ABSA) [20]. These datasets are commonly used for sentiment classification activities. The original datasets comprise four sentiment polarity classifications: positive, negative, neutral, and conflict. The conflict category, where comments simultaneously express positive and negative views, was omitted in this study because of its rarity, which could cause major class imbalance and influence classification performance. Thus, the sentiment classification process handled three classes.

TABLE I. DATASET STATISTICS

Dataset	Positive	Negative	Neutral
Trained data Laptop	994	870	464
Tested data Laptop	341	128	169
Trained data for Restaurant	2164	807	637
Test data for Restaurant	728	196	196

B. Performance Metrics

Table II summarizes the experimental results from the Laptop and Restaurant datasets.

TABLE II. PERFORMANCE METRICS

Algorithm	Accuracy	Precision	Recall	F1-score
RF	0.75	0.75	0.75	0.75
DT	0.74	0.73	0.74	0.73
KNN	0.72	0.71	0.72	0.71
SVM	0.76	0.76	0.76	0.76
Hard Voting	0.77	0.77	0.77	0.77
Soft Voting	0.78	0.78	0.78	0.78

DT marginally achieved 0.74 accuracy, indicating slight overfitting. RF achieved 0.75 accuracy with balanced precision and recall. Struggling with high-dimensional data, KNN had the lowest accuracy at 0.72. With 0.76 accuracy, SVM did well. Ensemble techniques surpassed single models: Hard

Voting achieved 0.77, and Soft Voting topped with 0.78 accuracy. SVM and ensemble classifiers generally performed best overall. RF provided a good balance between interpretability and performance.

C. Comparative Analysis

This study evaluated the performance of RF, DT, KNN, SVM, Hard Voting, and Soft Voting classifiers using accuracy, precision, recall, and F1-Score. As shown in Figure 3, Soft Voting beats others with the most balanced results. Particularly Hard Voting and Soft Voting ensemble techniques outperform single classifiers, stressing the benefit of model combination. KNN and DT show somewhat lower results, but SVM does well, closely matching ensemble outcomes. Table III strengthens the case for ensemble techniques, particularly Soft Voting, as they provide better classification efficiency and resilience.

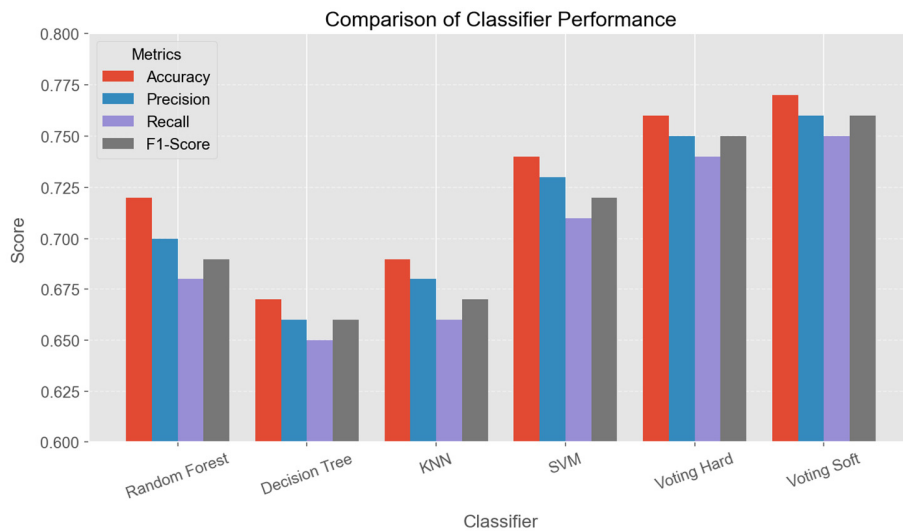


Fig. 3. Performance comparison graph.

TABLE III. COMPARISON TABLE

References	Methods/Models	Dataset focus	Advantages	Common limitations
[3], [4], [5], [16]	ABSA techniques; Sentiment analysis (general)	Consumer reviews, social media, Indian markets	Enhanced aspect-sentiment linkage; actionable insights	Dataset biases; difficulty with emotions
[6], [7], [8]	Deep Learning models	Aspect-based sentiment datasets	Improved aspect-oriented sentiment extraction	Complexity in handling language subtleties
[9], [10]	Classical ML	General and mobile app review datasets	Importance of feature extraction; end-to-end ABSA frameworks	Limited cross-domain generalization
[11], [18]	Literature Reviews (English and Arabic)	727 ABSA studies; Arabic sentiment data	Identified research growth and gaps	Language limitation; outdated data
[12], [13]	Pre-trained Models	Hindi and smartphone review datasets	Improved ABSA performance in non-English settings	Language generalization issues
[14], [15], [17], [19]	Financial Sentiment Analysis, Mining	Financial data, multi-task ABSA, social media reviews	Boosted NLP capabilities; better multi-aspect sentiment classification	Errors in aspect detection; heuristic rigidity
Proposed model	Voting Classifier Ensemble (SVM, RF, DT, KNN)	SemEval-2014 Laptop and Restaurant datasets	The ensemble approach consistently outperforms individual models; enhanced sentiment classification robustness	Sensitive to base model quality

IV. CONCLUSION

With a 78% accuracy on the ABSA task, this study shows that ensemble learning techniques, in particular the Soft Voting classifier, can greatly enhance sentiment classification performance, outperforming conventional standalone classifiers such as SVM, RF, DT, and KNN. This study combines a variety of classifiers into an ensemble framework designed for ABSA, a field where ensemble approaches have not received as much attention as deep learning architectures. By highlighting the importance of model diversity and cooperative decision-making in classification tasks, the study adds to the expanding corpus of sentiment analysis literature. Future directions include using contextual or domain-specific embeddings, Bayesian optimization, grid search for hyperparameter tuning, and context-aware deep learning techniques. The proposed ensemble-based approach shows how conventional ML techniques can still produce competitive results when carefully combined, and provides a fresh and efficient method for improving sentiment classification accuracy in ABSA.

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