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Enhanced Sentiment Analysis for Amazon Reviews Using Butterfly Optimization and Random Forest

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Abstract: In today's digital age, online shopping significantly impacts consumer purchasing behaviour. Customer reviews play a crucial role in influencing purchasing decisions, with positive feedback driving others to make similar purchases, while negative reviews deter them. Sentiment Analysis on Amazon product review data helps consumers evaluate products effectively. However, traditional machine learning methods have limitations in accuracy and feature selection, affecting sentiment classification performance. This paper introduces an Advanced Butterfly Optimization (ABO) algorithm to address these challenges, enabling the selection of the best features from the dataset and improving classification accuracy. This approach combines the Term Frequency-Inverse Document Frequency (TF-IDF) weighting scheme, the ABO algorithm, and the Random Forest (RF) algorithm. The ABO and TF-IDF algorithms extract relevant attributes from the input data, and the RF algorithm categorizes the data into positive or negative. The ABO-RF method proposed in this paper demonstrates 89.9% higher accuracy than existing methods such as Naive Bayes with GA, SVM, and Logistic Regression. The results of the simulation experiments show that the proposed approach outperforms traditional methods like Naive Bayes with GA, SVM, and Logistic Regression. Therefore, the ABO-RF algorithm is more effective in constructing a classification model for Amazon user reviews.

Keywords: Sentiment Analysis, amazon reviews, important feature identification, TF-IDF, Advanced Butterfly Optimization, Random Forest.

1. INTRODUCTION

The advancement in computers and the internet has paved the way for online marketing to become feasible. Existing user ratings and reviews are essential when purchasing any product online [1]. Additionally, it impacts the credibility of businesses that advertise their goods online. Extracting user reviews is challenging and time-consuming, as most is raw data. Social media, surveys, and reviews of e-commerce websites, among other online platforms, can be used in conjunction with Natural Language Processing (NLP) methods such as Sentiment Analysis (SA) to help entrepreneurs understand their customers' interests and views [2]. The reasons for product deterioration and factors affecting it can be understood with this information. In the early 2000s, sentiment analysis became increasingly popular. Many researchers have been interested in this field. Aspect-level sentiment analysis focuses on specific aspects of products/data as a part of sentiment analysis. The terms 'Polarity' and 'Subjectivity' are explored in sentiment analysis. In the context of polarity, subjective refers to an individual's beliefs, viewpoints, or personal feelings, while polarity refers to the sentiment expressed as positive or negative. The SA is categorized into three types: sentence level, document level, and sub-sentence level. In addition to conducting fine-grained sentiment analysis on data by comparing polarity between negative and positive, one can conduct intent-based or emotion-based sentiment analysis and aspect-level sentiment analysis. Different approaches are used in existing sentiment analysis studies to promote valid results. The absence of sentiment analysis tools and techniques makes it difficult for users to experiment and test different algorithms and optimizations based on their preferences and parameters.

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It is evident from the discussion that a sentiment analysis tool that fills the gaps delivered in the previous study is needed. Machine learning-based sentiment classification has proven to be the most effective method of understanding public sentiment [3]. Therefore, it has excellent accuracy and precision. Due to this motivation, we planned to develop a machine learning-based approach for classifying the amazon product review dataset sentiments. During the sentiment analysis research, we found that effective techniques rely more on word polarity or mood terms than on the precise meanings of the surrounding words. Many previous studies for SA missed the appropriate feature selection and improved model forecast accuracy.

1.1 Motivation and contribution

The novel contribution is to select the finest features from the sentiments via the Advanced Butterfly Optimization algorithm, which searches the elements in a multidirectional way and improves the model accuracy using Random Forest Algorithm. The TF-IDF weighting scheme supports feature extraction. The proposed method has been evaluated against existing approaches and shows high-performance results. We aim to design and develop a new feature-selection-based sentiment analysis classification system to improve our understanding of perceptions of specific products. The remains of this novel follow the sentiment analysis of existing works described in section II. Amazon reviews-based sentiment analysis (SA) detailed description presents in section III. The proposed experimental result defines in section IV. Finally, section V covered this paper's conclusion and future scope.

2. RELATED WORKS

This section analyzed different machine learning (ML) techniques for SA and learned about the pros and cons of implementing the proposed SA classification of Amazon product reviews.

Birjali et al. presented a Sentiment analysis (SA) survey where different entities are analyzed, such as topics, products, and services. Then this paper reviews and investigates the existing approaches' pros and cons. Iqbal et al. proposed developing an opinion-mining framework for measuring various public sentiments and views on terrorism, international conflicts, and social problems by utilizing Machine learning algorithms and polarity calculating techniques. Genetic Algorithm (GA) based feature reduction techniques were constructed for mining attributes and influential entities.

Deniz et al. presented sentiment analysis using entropy-based metrics and evolutionary algorithms to build a binary model classification.Hemanth et al. analyzed the product feedback of amazon products. The NB and SVMare utilized for context-based sentimental analysis with positive and negative feedback.

Mehta et al. introduced a feature selection approach that uses information gain score to select features the most appropriate and most minor demanding type for the chosen feature set. Determine the sentiment of IMDB movie reviews using lexicon-based sentiment analysis. Shah et al. evaluate the sentiments of the amazon product review. ML methods such as LR, NB, and FR are used to achieve maximum precision in classifying feedback. Parlar et al. the author explored ranking feature selection based on weighting methods in information retrieval. SVM, Naive Bays Multinomial (NBM) and Logistic Regression (LR) techniques for sentiment analysis of Turkish reviews.

Han et al. analyses the statistics of sentiment words in the Twitter dataset, where both lexical and latent semantic information is extracted from the input data. The Fisher kernel function is used to identify statistical sample sets with SVM. Dey et al. researched amazon customer reviews using sentiment analysis. The product review factor, quality, content, time, durability, and ranking determine the product factor. The customer's sentiments are analyzed through NB, and then SVM classifies the binary categories.

Arefyev et al. discovered that adding domain-specific training to the MLM aim before fine-tuning from the final data enhances performance. However, because it is done separately for each domain or work, it is relatively slow, taking several GPU days instead of a few GPU hours for the final fine-tuning task. Online comments/opinions are provided by Rafique et al. a text-free format. Comment/opinion polarity (positive/negative) can be expressed using sentiment analysis. Monali et al. the context of sentiment classification, the study compares ML techniques like NB, SVM, and ME. Three datasets are used to compare the performances of the classifiers. Elhawil et al. analyzed public sentiment on various topics. Although Arabic is one of the most commonly used languages, research on sentiment analysis in Arabic still faces several challenges. The main objective of this work is to investigate SA in Arabic by comparing SVM and NB methods as a function of dataset class.

Dubey et al. analyzed sentiment analysis using SVM classification. The smartphone product review is classified through the SVM technique, achieving 94.63% accuracy.Sharma et al. researched Twitter sentiments using peoples' opinions. In this case, MLmethodsforecastcustomers' online social activity, allowing for actively identifying positive and negative emotional states.

Rathi et al. approach machine learning to analyze the sentiments in tweets. AI techniques like SVM, ADT, and DT are effective. The proposed method classifies the tweets into positive and negative tweets and enables sentiment analysis and other decision-making. The suggested model's work has been through pre-processing and classifier learning phases.Itzcóatl et al. presented the sentiment analysis technique to understand how the impact of automated word-of-mouth, or eWOM, on user opinion formation has grown. A system for automatically analyzing these evaluations is proposed by Kauffmanna et al., which converts both positive and negative user reviews into a numerical score. The Bogus Review Detection Framework (FRDF) uses technologies for natural language processing to identify and eliminate fake reviews. Develop a review-based e-commerce product comparison decision support model, Ji et al. modelled the Decision support. Online reviews are described by the proposed model using PMVNLNs.

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Online shoppers can find desirable products using the integrated decision support model presented by Liang et al. the suggested model comprises three modules: information transformation, information gathering, and integration. The anti-LGBT campaign that was carried out among Indonesians on Twitter was analyzed by Fitri et al. NB is used in sentiment analysis since it is highly accurate at classifying sentiment analysis. This work uses SA pre-processing, processing, classification, and evaluation phases.

K. Park et al. have introduced a context-specific, meaning-based method that examines the contextual significance of product features in reviews. Their approach offers a more profound insight into the purpose of the specific product features. Nonetheless, the suggested technique falls short of grasping the genuine intentions of customers when referencing product features in their reviews.J. H. Dahooie conducted a study that combined Association Rule Mining (ARM) and Fuzzy Cognitive Map (FCM) to calculate feature weights by considering the relationships between features. They also created a decision matrix using emotion-oriented and intuitive fuzzy theory. The Interval-Value Intuitive Fuzzy (IVIF) theory ensured dependable decision-making information.

Z. Liu et al. proposed a deep learning-based SA method for generating PLTs from online reviews and ranking products accordingly. The study first utilized NLP techniques to extract product features and corresponding texts from online reviews.However, the offered method produced unsatisfactory accuracy results for SA.

Table 1: Various methods for product sentiment analysis

Author (Year)	Dataset	Technique used	Drawbacks
H. He et al. (2022)	E-commerce dataset	fusion sentiment analysis with SVM and LDA	The suggested methods didn't give proper result of SA. Therefore, it produce less accuracy result.
I. Awajan et al. (2021)	Twitter review dataset	Neutro-VADER	This method didn't identify the important features review terms.
P. Durga et al. (2023)	Twitter, Restaurant and laptop dataset.	Decision-based Recurrent Neural Network(D-RNN)	This method failed to adequately analyse sentiment terms.
N. Hussain et al. (2023)	Amazon review dataset	Rank-ify	This method ignore the negative terms of reviews in the dataset.
A. Boumhidi et al. (2023)	Social media based review dataset	aspect-based sentiment analysis	This method failed to produce high F1-score, precision and recall performance.

2.1 Problem statement

- The existing methods didn't give proper result of SA. Therefore, it produces less accuracy result.
- Traditional methods failed to produce high F1-score, precision, and recall results.
- In previously, didn't identify the significant features of customer reviews.
- The existing method ignore the negative terms of reviews in the dataset.

Nowadays, considerable efforts are being made to develop machine-based approaches to sentimental analysis, but the work in this area is not accurate enough. Therefore, this paper provides a method to perform sentiment analysis effectively. Significant contributions of our proposed work include:

- To design an effective sentiment analysis approach by combining Random Forest and Advance Butterfly Optimization algorithm (ABO) to solve the limitations of the traditional method.
- First, raw review data is pre-processed and converted into clean data.
- TF-IDF weighting scheme method is then used to extract a vital feature after pre-processing.
- We implemented a new advanced algorithm with multidirectional neighbour searching and population restart to select the best feature from the review, thus increasing classification accuracy and reducing computational time.
- Furthermore, the Random Forest classifier identifies the best features based on the positive or negative review sentiment.
- Experiments have demonstrated that the proposed system can detect sentiment very accurately.

In this work, we overcome the drawbacks of unstable outcomes in the unigram feature selection, less information gain, and improper feature extraction.

3. PROPOSED SYSTEM

Our paper proposes the ABO-RF model, which combines an advanced butterfly optimization algorithm with a random forest classifier algorithm to increase the accuracy of SA on the Amazon electronic product reviews dataset. First, the pre-processing method converts the raw data into precise data. Then the TF-IDF weighting scheme for extracting the relevance in the reviews. Then ABO selects the best features from it. In feature selection, the main goal is to decrease the number of features and the computational cost and improve the classification. Feature reduction reduces the number of unnecessary and redundant features, increasing the learning difficulty and improving sentiment classification efficiency. ABO-RF consists of four phases: pre-processing, feature extraction, feature selection, and classification. The proposed architecture diagram is described in Figure 1.

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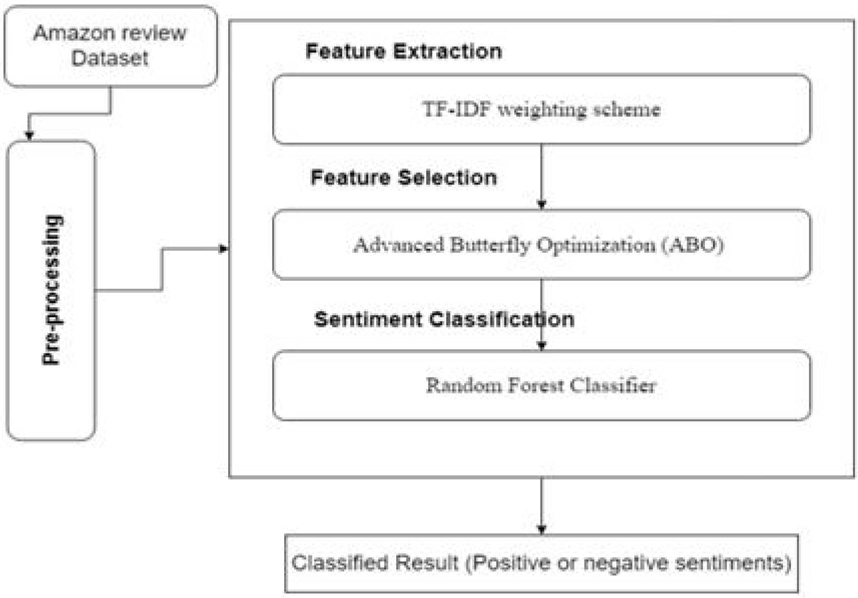

Fig 1: Architecture of proposed ABO-RF Sentiment Analysis method.

Amazon's electronic product review dataset was used to train and test ABO-RF performance in a 70:30 ratio. Incoming raw review data is extracted to a pre-processing stage and converted into clean data. Next, we extract features from the pre-processed data using the TF-IDF weighting scheme. We use the ABO algorithm to select the best features to get the best features, thereby improving the search results and optimization algorithm performance. The optimal searching and restart concept will enhance the RF classifier's accuracy. Random Forest Classifiers use ABO-based feature selection to separate the features into nodes based on fitness value. Subsequently, the ABO-RF method predicts the highest vote and determines the sentence as positive or negative.

3.1.Pre-processing

In this stage, pre-processing [12] steps are conducted as monitors:

1. Tokenizing the raw data: As a first step in pre-processing, tokenizing the data from the Amazon electronic product review dataset is required. There are multiple documents for each review. They usually consist of sentences. As a result, tokenizing data is helpful for tokenizing sentences into words. These words serve as tokens and ease the process of tokenization.
2. URL removal: All URLs must be removed from reviews to minimize the number of features.
3. ClearNumeric character: All numbers have been removed, as they do not affect sentiment analysis.
4. Punctuation Removal: In writing, punctuation enables the reader to understand the content. Firstly, we remove punctuation from all Amazon reviews since punctuation does not influence Amazon reviews.
5. Clear all Non-English words: We use the NLTK (Natural Language Tool kit) corpus to clear all non-English words, thereby reducing the features.
6. Clear non-alphabetic characters: Non-alphabetic characters were not included in this analysis because they did not influence the results.
7. Change all reviews to lowercase: To ensure there are no repeated words due to different capitalization, all reviews have been changed to lowercase.
8. Remove the words of fewer than three characters: The number of features that do not influence sentiment analysis is reduced by using words larger than two characters.
9. Stop word removal: Words lack an imperative meaning in English and should not be used within reviews. We removed all stop words from reviews since stop words return significant amounts of non-essential information.
10. Stemming: As soon as the stop words are removed from the tokenized data, they are sent to the next step. The process of converting words into their root words is known as stemming.

3.2. Feature Extraction

This feature extraction process was developed to improve sentiment classification accuracy during the feature selection step by removing irrelevant features and selecting significant ones. According to the TF-IDF, the level of importance of quality is determined by the term-document matrix. A variance score is calculated for each feature based on the TF-IDF matrix. To begin analyzing a document, TF-IDF is computed. Then, the importance of each feature in the whole document collection is explored and extracted. The below equation is described as,

$$TF\_IDF = TF * IDF \qquad (1)$$

TF is aterm frequency at which a feature appears in a document in contrast to the total number of features. Similarly, IDF evaluates how well a feature differentiates between categories. TF and IDF are expressed as follows (2) (3):

$$TF = FFTD/TFTD \qquad (2)$$

$$\mathrm{IDF} = \log(\mathrm{NDF}/\mathrm{TD}) \qquad (3)$$

TFTD is the total number of times a term seems in a document, whereas FFTD denotes the frequency of a feature appearing in a document.

3.3. Feature Selection

Each meta-heuristic algorithm has inherent limitations, making it necessary for academicians and researchers to modify its basic structure to improve its employability. Some modifications may involve merging local search techniques, incorporating the best phase of one algorithm into another's structure, or adding some parameters or self-adapting parameters depending on the nature of the problem. The Butterfly optimization algorithm is a new metaheuristic that inherits the limitations of slow convergence and low performance. Advanced Butterfly Optimization (ABO) overcomes the traditional Butterfly optimization algorithm.

Algorithm 1: Advanced Butterfly Optimization

```
Start
  Initialize the butterflies' population as n, X = {x_1, x_2, .. x_n} with the dimension d
  Define the values of the parameters p_1, p_2, p_3
  Calculate the intensity of stimulus I_i at x_n
          f = cI^a
  WhileSome termination criteria are not met do
          for Each b in X do
                  Evaluate fragrance f for b
          end for
  Identify the best b
  for Each b in X do
          Random number r = {0,1} is generated
          If r < p_3 Then
      Perform global search, Multidirectional neighbour search with the best position based on fitness value.
          else
      Perform a local search with the current position and fragrance f
          End if
          end for
  The update a's value
   end while
  Optimal results achieved
  Stop
```

Here, f is a fragrance, c is a sensor modality, and a represents the modality. The value of a and c lies between 0 and 1. The Advanced Butterfly Optimization method helps to find multidirectional neighbour features. This process of searching overcomes slow convergence, and greedy selection is used to get rid of random search results. A multidirectional search method, which finds all neighbours within a distance from different directions, is included to obtain regularly distributed neighbours. The algorithm 1 isto improve the ABO performance, a restart time and probability distribution are measured for restarting the algorithm. The lowest-fit butterflies are eliminated and added toa new group during the restart through random selection. The ABO local optimal value is improving and highly robust, represented in equation (4).

$$\mathrm{P_b} = \mathrm{rand} * \left(\mathrm{a} + \frac{\mathrm{B}}{\mathrm{NP}}\right) \qquad (4)$$

$\mathrm{P_b} \rightarrow$ propability of population
rand $\rightarrow$ random number of selection
a = 0.1
B $\rightarrow$ inding better solution
NP $\rightarrow$ population Number

Let n be the number of features with d dimension. The dimensional vector value is considered for each solution, which depends on the dataset's attributes.

3.4. Classification

The random forest method, also called random decision forest, is a method for classifying objects, predicting the future, and performing other tasks by making a cluster of decision trees at training time. In RF, the number of trees in the forest directly correlates with the accuracy. The RF algorithm is divided into two steps, which are as follows:

1. RF trees are first constructed. They are further developed in the five essential levels:

- Let K be the number of random features taken from entire features m where $K < m$
- Based on the selected features, the best split point is used to determine node d
- Using the best split, the nodes are distributed and split into daughter nodes.
- Till the number of nodes is obtained, the steps mentioned above will be looped
- The loop repetition is carried on till the number of tree generations.

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2. Then the data is classified based on the RF tree created in step 1
- Based on randomly formulated rules, the decision tree features data is classified
- For each target, the vote is estimated
- The highest vote target is considered the final result in the RF algorithm.

Algorithm 2: Random Forest

Input: Selected features
Output: Product review classification P_{rc}
Start function
    Import selected features
    For $\wp_d \in \mathcal{L}_d$ do
        For $\mathbb{U}_r \in \mathcal{Q}$ do
            If $\mathbb{U}_r \in \wp_d$
                Calculate review important feature score $\mathbb{F}_{sco}$

$$\mathbb{F}_{sco} = \frac{w c(\mathcal{F}_{pos}) - w c(\mathcal{F}_{neg})}{w c(\mathcal{F}_{pos}) + w c(\mathcal{F}_{neg})}$$

            End if
        End for
    End for
    Return Product review classification $P_{rc} \leftarrow \mathbb{F}_{sco}$
Stop function

The algorithm 2 efficiently analysis the product review classification in the dataset. Let assuming that, $c(\mathcal{F}_{pos})$ and $c(\mathcal{F}_{neg})$denotes the count of positive and negative features in the dataset, w denotes the weight, $\wp_d$ lies the product, $\mathcal{L}_d$ list of product,$\mathbb{U}_r$user queries $\mathcal{Q}$in the dataset. Figure 2 defines the detailed flowchart for sentiment analysis for amazon product.

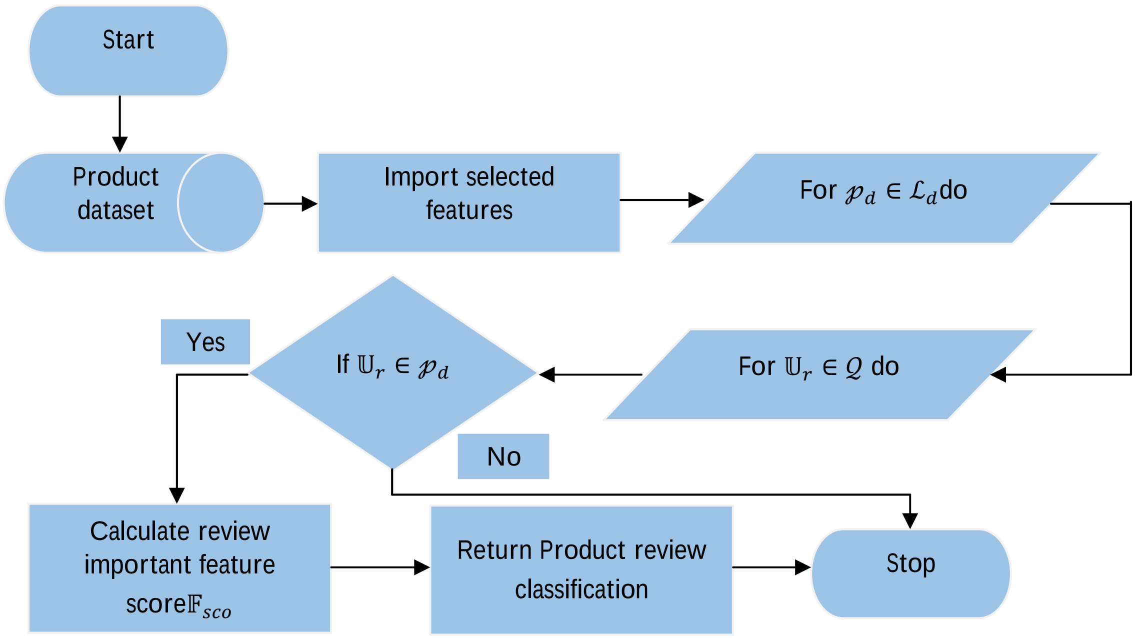

Fig 2: Overview of product review classification

4. EXPERIMENT RESULT ANALYSIS

In this result of the implementation, we examine the performance of the proposed ABO-RF algorithm for classifying sentiments in the Amazon electronic product review dataset with advanced butterfly optimization. This research used Windows 10 OS with an i5 processor and 4GB of RAM to evaluate the simulation result. Python is the language used to implement the proposed model.

Table 2: Experimental setup

Parameters	Details
Language	Python
Environment tool	Anaconda
Dataset name	Amazon product sentiment analysis

4.1. Dataset

The dataset engaged in this paper is the Consumer Reviews of Amazon Products dataset from Kaggle, which contains separate training and testing data with 34,000 feedbacks of Amazon electronic products consumer reviews like the Kindle, Fire TV, etc. [11].

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The data can be used to investigate Amazon's most popular consumer electronics product releases to understand consumers' thoughts and develop machine learning algorithms. More labels are available from Datafiniti's Product Database. It consists of Customer reviews and star ratings, input text and output labels in sentiment analysis.

4.2. Performance Metrics

We evaluate the SA classification accuracy performance, precision, recall and F1 score using a confusion matrix. The quality of the suggested framework utilizes the Binary-classes confusion matrix, and it classifies, namely, False Negative (FN), True Positive (TP), False Positive (FP), and True Negative (TN). The following are the possible results of the confusion matrix. Below equation (5), the predicted reviews class is split by the number of reviewclasses available in the dataset.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Precision: In the dataset equation (6), the ratio of predicted positive reviews to the total predicted positive reviews.

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (6)$$

Recall: The ratio of positive reviews predicted to actual categories in the dataset as defined in equation 7.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (7)$$

F1 Score: It preserves a harmonic balance between precision and recall equation (8).

$$\text{F1 score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

Table 3: Accuracy performance for proposed ABO-RF sentiment analysis

Machine Learning methods/ Parameter	Accuracy (%)
Naïve Bayes with GA [5]	77.9
SVM [15]	82.6
Logistic Regression [16]	83.89
Proposed ABO-RF	89.9

Based on the previous discussion, we evaluate three existing approaches, including Naive Bayes with GA [5], Support Vector Machine [15], and Logistic Regression [16], and compare their performance with the proposed ABO-RF method, as shown in Table 3.

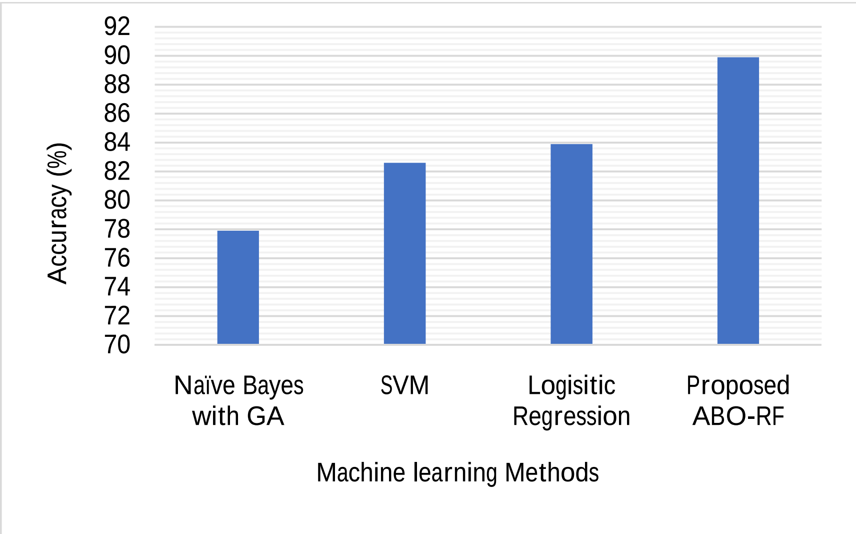

Fig 3: Accuracy Obtained for each sentiment analysis method with Amazon review dataset.

Figure 3 illustrates the analysis of accuracy performance with amazon review dataset. The proposed method efficiently identifies appropriate review sentences using non-English terms, stemming, and tokenization. After that, the proposed ABO method selects the essential features of sentiment terms from the Amazon review dataset. As a result, the proposed method performs better than other methods. Using the important features, we classify the sentiment into positive and negative terms using the Random Forest method.

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Table 4: Evaluating Performance metric for proposed ABO-RF sentiment analysis

Comparison methods/ Metrics	Precision (%)	Recall (%)	F1 score (%)
Naïve Bayes with GA [5]	0.78	0.77	0.78
SVM [15]	0.827	0.81	0.84
Logistic Regression [16]	0.83	0.80	0.81
Proposed ABO-RF	0.89	0.85	0.87

Table 4 discusses the performance metrics for the proposed ABO-RF and compares them to approaches like NB, SVM, and LR.

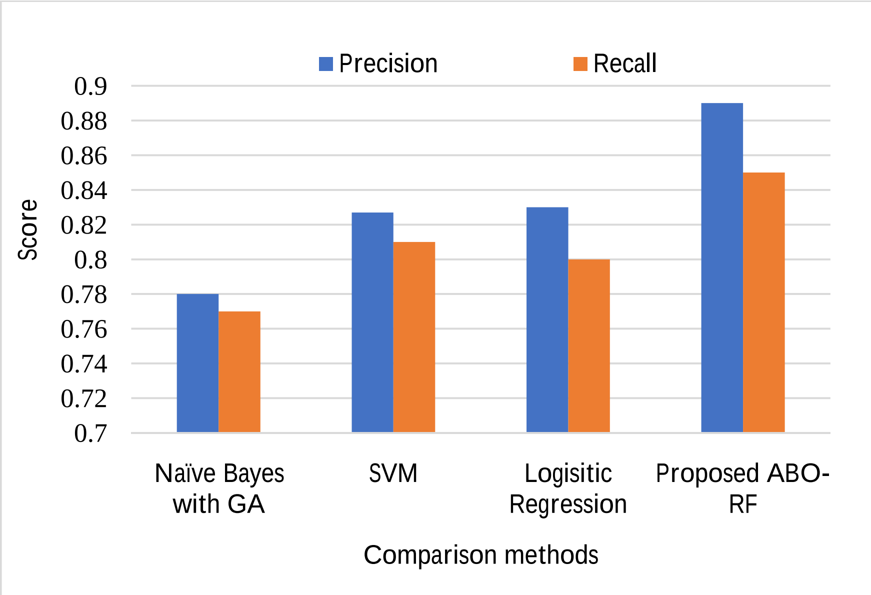

Fig 4: Precision and Recall obtained for each sentiment analysis method with Amazon review dataset.

Figure 4 describes the analysis of precision and recall performance with amazon review dataset. The proposed method proficiently identifies customer reviews based on non-English terms, stemming, tokenization etc. Then, the proposed ABO method selects the important features of sentiment terms in the amazon review dataset. Therefore, the proposed method attains the high performance than other methods.

Fig 5: Analysis of F1-score performance with Amazon review dataset

Figure 5 describes the impact of F1-score performance with amazon review dataset. The proposed method efficiently selects the features of sentiment terms using Advanced Butterfly Optimization (ABO) method. Based on the important features, we classify the sentiment into positive and negative terms using Random forest. Therefore, the proposed method attained 0.87 of F1-score performance.

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4.3 Discussion

The proposed ABO-RF achieves 0.89 precision, 0.85 recall, and 0.87 F1 Score, which is higher than the NB-GA (0.78 precision, 0.77 recall, 0.78 F1 Score), SVM (0.827 precision, 0.81 recall, 0.84 F1 Score), LR (0.83 precision, 0.80 recall, 0.81 F1 Score). As shown in Figure 2, the proposed ABO-RF method achieves 89.9% more accuracy than the existing methods (Naive Bayes with GA - 77.9%, SVM -82.6%, Logistic Regression -83.89%), as presented in table 3 and 4.In addition, the proposed ABO-RF outperformed other performance metrics. Based on our experiments, we have found that the ABO-RF model performs better than other existing models. As a result of ABO novelty, feature selection has also improved, increasing classification accuracy.

5. CONCLUSION

This paper introduced the ABO-RF algorithm for Sentiment Analysis (SA) using the amazon product feedback dataset. The user is interested in reading feedback about the product. In the Pre-processing step, raw data is converted into precise data, which is then used for feature extraction using the TF-IDF weighting scheme. Using the ABO, the best features are selected from the extracted features and then classified.Random Forest Classifier categorizes the result into positive and negative reviews. The training and testing datasets are divided 70:30. The proposed ABO-RF method achieves an accuracy of 89.9% more than the existing methods (Naive Bayes with GA - 77.9%, SVM - 82.6%, Logistic Regression -83.89%). Therefore, it can be regarded as a robust feature selection for sentiment analysis. We plan to implement a deep learning-based algorithm for further research to improve accuracy.

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