Sentiment Analysis for Online Product Reviews and Recommendation Using Deep Learning Based Optimization Algorithm

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Abstract— Recently, online shopping is becoming a popular means for users to buy and consume with the advances in Internet technologies. Satisfaction of users could be efficiently improvised by carrying out a Sentiment Analysis (SA) of larger amount of user reviews on e-commerce platform. But still, it is a challenge to envision the precise sentiment polarity of the user reviews due to the modifications in sequence length, complicated logic, and textual order. In this study, we propose a Hybrid-Flash Butterfly Optimization with Deep Learning based Sentiment Analysis (HFBO-DLSA) for Online Product Reviews. The presented HFBO-DLSA technique mainly aims to determine the nature of sentiments based on online product reviews. For accomplishing this, the presented HFBO-DLSA technique applies data pre-processing at the preliminary stage to make it compatible. Besides, the HFBO-DLSA model uses deep belief network (DBN) model for classification. The HFBO algorithm is used as a hyperparameter tuning process to improve the SA performance of the DBN method. The experimental validation of the presented HFBO-DLSA method has been tested under a set of datasets. The experimental results reveal that the HFBO-DLSA approach surpasses recent techniques in terms of SA outcomes. Specifically, when compared to various existing models on the Canon dataset, the HFBO-DLSA technique achieves remarkable results with an accuracy of 97.66%, precision of 98.54%, recall of 94.64%, and an F-score of 96.43%. In comparative analysis, other approaches such as ACO, SVM, and NN exhibit poorer performance, while TextCNN, BiLSTM, and RCNN approaches yield slightly improved SA results.

Keywords- Sentiment analysis; Product reviews; Product recommendation; Deep belief network; Metaheuristics

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1. INTRODUCTION

As there were several brands in the market; choosing one among them is considered a difficult task for the user. The progression of E-Commerce had a great influence on buying routine of consumers [1]. Purchasers make favourable decisions based on the reviews in E-commerce (e.g., summary of related text and ratings). Also, the reviews regarding the product can be seen on social media websites. Recently, social networking sites gains more popularity; so, the data expansion could not be controlled in upcoming years. As everybody is posting comments that results in immense continual augmentation in the online information and the online data [2]. Therefore, it becomes tough to precisely derive appropriate data from the internet. The customer and manufacturer would experience positive and negative comments regarding all product that is attained through SA [3]. SA will stand as main task in NLP. By using SA, the attitude or mood of the critic could be ascertained as positive or negative [4]. In SA, every product review is concise and sentiments will be classified.

The major focus of SA was sentence-level SA. The accuracy of emotion analysis is enhanced through identification of the relationships between product feature words, predominantly appropriate to online reviews on complicated goods [5]. Initially, the reviews were accumulated in the procedure, their sentiment recognized, sentiments classified, features selected, and finally, ascertained or sentiment polarizing computed [6]. Systems should execute analysis steps mechanically to evaluate subjective information effectively and help to produce aspect and sentiment dictionaries. Such reviews undergo assorted procedures and classifier methods for mining the sentiments officially. Such reviews and ratings will be positive as well as negative descriptions [7]. Therefore, it is important to recognize the nature of consumers' feelings, negative, or neutral, being positive, on social networking sites. Also, the real noisy textual data which includes informal words, idioms, sarcasm, phrases, additionally spelling mistakes cannot be understood by the SA's present techniques [8]. Therefore, Cluster Computing mechanically examines the individual feeling in text data and shortens the decision-making procedure of consumers to process the unstructured online reviews having intellectual technology [9]. Currently, it has appeared as a hot study topic in the domain of computer science. Recently, Deep Learning (DL) approaches play a major part were a subdomain of ML in many SA mechanisms and several authors began to study them to improve manipulating data procedures [10].

The several significant contributions to the field of sentiment analysis and e-commerce are as follows: The study introduces the HFBO algorithm as a novel hyperparameter tuning technique, specifically designed for improving sentiment analysis using deep learning models. This contribution enhances the efficiency and accuracy of sentiment classification in online product reviews. By incorporating a deep belief network (DBN) model, the research contributes to the advancement of sentiment analysis methodologies. DBN is a powerful neural network architecture that can capture intricate patterns and relationships within textual data, leading to more accurate sentiment predictions. The research conducts a thorough comparative analysis of the proposed HFBO-DLSA technique with various existing sentiment analysis methods, including traditional techniques like Support Vector Machines (SVM) and neural network approaches such as TextCNN, BiLSTM, and RCNN. This contribution provides insights into the relative strengths and weaknesses of different methods in the context of sentiment analysis for online product reviews. The experimental results clearly demonstrate that the HFBO-DLSA approach consistently outperforms other methods in terms of accuracy, precision, recall, and F-score. This improvement in sentiment analysis performance is a significant contribution, as it directly impacts the quality of user recommendations in e-commerce platforms.

In this study, we propose a Hybrid-Flash Butterfly Optimization with Deep Learning related Sentiment Analysis (HFBO-DLSA) for Online Product Reviews. The presented HFBO-DLSA technique mainly aims to determine the nature of sentiments based on online product reviews. For accomplishing this, the presented HFBO-DLSA technique applies data pre-processing at the preliminary stage to make it compatible. Besides, the HFBO-DLSA model uses deep belief network (DBN) model for classification. The HFBO algorithm is used as a hyperparameter tuning process to improvising the SA performance of the DBN method. The experimental validation of the presented HFBO-DLSA algorithm has been tested under a set of datasets.

2. LITERATURE REVIEW

Onan [11] introduces a DL-oriented technique to SA on product reviews obtained from Twitters. The proposed structure will combine TF-IDF weighted Glove word implanting with CNN-LSTM structure. The presented structure has 5 layers the dense layer, weighted embedding layer, Maxpooling layer, LSTM, and convolution layer. In the experimental study, the prediction accuracy of various word embedding techniques having numerous weighting functions was assessed in conjunction with standard DNN structures. Yadav et al. [12] modeled an enhanced Feature Based Algorithm (FBA) for SA of product reviews when developing a tree structure of elements, products, and related features. Further, assessment of negative sentences, identifying emotions and questions from reviews were measured that rises efficacy of FBA technique. AL-Sharuee et al. [13] present temporal SA through the implementation of the automated context analysis and ensemble clustering (ACAEC) technique. This aforementioned was a clustering technique that uses clustering ensemble learning and contextual analysis. The authors devise chronological SA utilizing segregated window clustering (SWC) and window sequential clustering (WSC). It was a dynamic analysis, where SWC can be solely dependent upon the temporal feature of reviews.

Zhao et al. [14] proposed a novel optimized ML technique named the Local Search Improvised Bat Algorithm related Elman Neural Network (LSIBA-ENN) for the SA. The presented work of SA has four stages they are polarity or Sentiment Classification (SC) Data Collection (DC), Term Weighting (TW) or FE, preprocessing, and Feature Selection (FS). Primarily, the Web Scrapping Tool (WST) can be used for extracting the user reviews of the products for which the data can be collected from the E-commerce website. Next, pre-processing can be taken placed on the web scrap derived data. Such pre-processed data undergoes FS and TW for further processing by utilizing the Hybrid Mutation based Earth Warm Algorithm (HMEWA) and Log Term Frequency-based Modified Inverse Class Frequency (LTF-MICF). Verma et al. [15] introduce a way of FS issue for classifying sentiments that employ ensemble-related classifier. It involves a hybrid method of maximum relevance (mRMR) and minimal redundancy technique and Forest Optimization Algorithm (FOA). Before implementing the FOA on SA, it was employed as FS method enforced on ten distinct classifier datasets publically available on UCI-ML repository.

Karthik and Ganapathy [16] introduce an innovative fuzzy logic-related product recommendation mechanism that dynamically forecasts most applicable goods to the users in online shopping in accordance with the user present interest. A new technique was devised in this study to compute the product's sentimental score with the linked end user target class. At last, the ontology-based recommendation system and presented fuzzy rules utilize ontology alignment to make decisions that are highly precise and forecast dynamically on the basis of the search context. In [17], a novel product ranking score, filtering, and hybrid DT techniques were enforced. Primarily, real-time amazon product review data was considered utilizing the Document Object Model (DOM) parser. The attributes from review comments have been derived from AFINN and lexicon Feature Dictionary (FD), and Normalized Product Review Score (NPRS) were produced for computing the class label for product review sentiment estimation. The presented filter-related enhanced DT sentiment classification method for practical amazon product review data will recommend product on the basis of the user query by estimation utilizing a new normal product reviewed sentiment score and ranked FS measure.

The primary research objective of this study is to enhance the accuracy and efficiency of sentiment analysis for online product reviews in e-commerce platforms. The specific objectives includes Precise Sentiment Polarity Determination, Integration of Deep Learning, Optimized Hyper parameter Tuning, Comparative Evaluation. To accurately determine the sentiment polarity (positive, negative, or neutral) of user reviews, despite challenges posed by varying sequence lengths, complex language, and textual structures. To leverage the capabilities of deep learning, particularly the deep belief network (DBN) model, for sentiment analysis. Deep learning can capture subtle nuances and context within reviews, leading to more nuanced sentiment classification. To introduce the Hybrid-Flash Butterfly Optimization (HFBO) algorithm as a novel hyperparameter tuning process. This optimization mechanism aims to fine-tune the deep learning model's parameters, enhancing its performance in sentiment analysis tasks. To conduct a comprehensive comparative analysis of the proposed HFBO-DLSA technique against existing sentiment analysis methods, providing empirical evidence of its superiority. Ultimately, the overarching objective is to contribute to improved user satisfaction and engagement in online shopping platforms by providing more accurate sentiment-based product recommendations.

3. The Proposed Model

In this article, a new HFBO-DLSA algorithm was projected for determining the nature of sentiments based on online product reviews. Initially, the presented HFBO-DLSA technique applies data pre-processing at the preliminary stage to make it compatible. Besides, the HFBO-DLSA model applied the DBN model for classification. For improving the SA performance of the DBN method, the HFBO algorithm is used as a hyperparameter tuning process. Fig. 1 depicts the block diagram of HFBO-DLSA system.

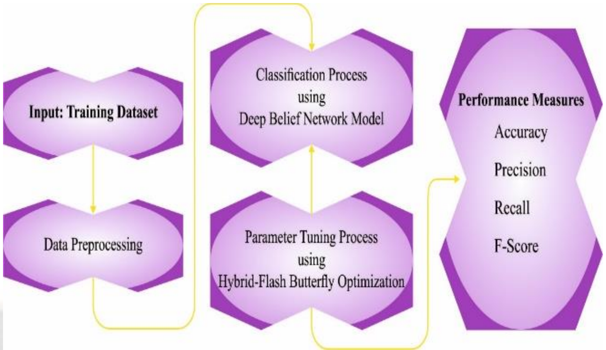

Fig. 1. Block diagram of HFBO-DLSA algorithm

3.1. Data Pre-processing

Here, the presented HFBO-DLSA technique applies data pre-processing at the preliminary stage to make it compatible.

- Restore “@Username” with “usr” through regular expression matching.
- Eliminate the URL by using routine expression mapping.
- Avoid parenthesis, forward slash (/), backward slash (\), and-.
- As “hash-tag(#)” provides useful details, it removes #, and retains the similar word. i.e., “#Lee” is restored with “Lee.”
- Change the input dataset to lowercase.
- Remove more than one white space by replacing single white space.
- Retain the word that begins with alphabet.
- Restore the short form with concerned abbreviation
- Remove the stop words such as a, is, the, etc. by involving with stop word dictionary.
- Restore the sequence of duplicate words by single character, i.e., “hellooooo” is transformed into “Hello.”

3.2. Sentiment Classification using DBN Model

The DBN model is exploited for the detection and classification of sentiments. DBN is stacked by a sequence of RBM layer-wise [18]. RBM is classified into visible and hidden layers. Among them, every visible and hidden neuron is interconnected with connection weight however the neuron in the layer is not interconnected. An RBM contains three learning hyperparameter $\theta = \{b, c, w\}$. b_i indicates the visible layer bias. Hidden layer offset refers to $c_j.w_{ij}$ signify the connection weight among visible units and hidden cells. The amount of neurons in visual and hidden layers is i and j. RBM shows the energy based mechanism, and the energy function is determined as follows:

$$E(v,h;\theta) = -\sum_i b_i v_i - \sum_j c_j h_j - \sum_{ij} v_i w_{ij} h_j \qquad (1)$$

Joint probability distribution of RBM based on the energy function is defined as follows:

$$Z(\theta) = \sum_{vh} e\,xp\big(-E(v,h;\theta)\big) \qquad (2)$$

$$p(v,h;\theta) = \frac{1}{Z(\theta)} exp\big(-E(v,h;\theta)\big) \qquad (3)$$

The marginal probability distribution of RBM has been given below:

$$p(v;\theta) = -\sum_h p\,(v,h;\theta) \qquad (4)$$

Consequently, the conditional probability of RBM is attained:

$$p\big(h_j|v;\theta\big) = \frac{p(v,h;\theta)}{p(v;\theta)} \qquad (5)$$

$$p(v_i|h;\theta) = \frac{p(v,h;\theta)}{p(h;\theta)} \qquad (6)$$

$$p\big(h_j = 1|v;\theta\big) = sigmoid\left(\sum_{i=1}^{n} v_i w_{ij} + c_j\right) \qquad (7)$$

$$p(v_i = 1|h;\theta) = sigmoid\left(\sum_{j=1}^{m} w_{ij} h_j + b_i\right) \qquad (8)$$

The loss function of RBM:

$$J(\theta) = \langle\, \frac{1}{N}\sum_i l\,ogp(x_i;\theta)\,\rangle_{data} - \langle\, logZ(\theta)\,\rangle_{model} \qquad (9)$$

K-step Gibbs sampling (CD-K algorithm) is utilized for initializing the network weight. To attain the top network super parameter, viz., the distribution $\langle\, logZ(\theta)\,\rangle_{model}$ of the algorithm is extremely closer to the distribution $\langle\, \frac{1}{N}\sum_i l\,ogp(x_i;\theta)\,\rangle_{data}$ of the sampled dataset, the maximal likelihood approximation of the algorithm is performed. Utilize the SGD model for updating the hyperparameter, as demonstrated in Eq. (10), whereas η indicates the learning rate, θ^t shows the gradient of RBM at the $t\text{-}th$ training:

$$\theta^{t+1} = \theta^t - \nabla_\theta J(\theta^t) \qquad (10)$$

In real time application, the capability of single RBM to characterize complex raw data is frequently not optimistic and needs various RBMs for stacking into a depth confidence network to extract features layer-wise to simulate original distribution. The architecture of DBN has been demonstrated in Fig. 2. The training procedure of DBN is classified into forwarding unsupervised pre-learning and reverse finetuning. Initially, the model adopted the hierarchical greedy learning mechanism. Then, add a classification layer to final hidden layer, and the weight of DBN is finetuned via minimalizing the error between the label data and the estimated output value through backpropagation. At last, the training is done and performance of the network is tested through a testing dataset.

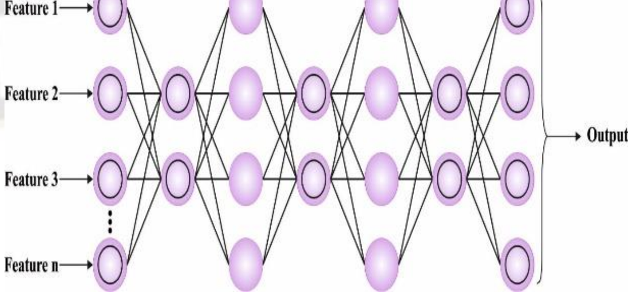

Fig. 2. Architecture of DBN

3.3. Hyperparameter Tuning using HFBO algorithm

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To improve the SA performance of the DBN method, the HFBO algorithm is used as a hyperparameter tuning process. Considered the searching approach of the FA, and utilized vision of butterfly for local optimization in HFBO [19]. The initialization, optimization, witch parameter setting, local, and global search phases of HFBO are given below.

Initialization Phase

The initial population position of butterfly is randomly set, now, the initial position can be formulated using Eq. (11):

$$X_{i,j} = X_{lb,j} + rand \times \left(X_{ub,j} - X_{lb,j}\right) \qquad (11)$$

Let $x_{i,j}$ be the $i\text{-}th$ solution for $j\text{-}th$ parameter, $i \in [1,2,3,\cdots,n], j \in [1,2,3,\cdots,Dim]$. $x_{ub,j}$ and $x_{lb,j}$ represents the upper and lower limits of the search space, correspondingly, and $rand$ indicates a uniformly distributed random number within [0, 1]. Usually, this strategy is utilized for initializing the location of the population of SI algorithm.

Optimization Phase

Especially, F_i^t characterizes the fragrance of $i\text{-}th$ butterfly in $t\text{-}th$ iterations as follows:

$$F_i^{t+1} = c \cdot (F_i^t)^a \qquad (12)$$

In Eq. (12), c shows sensory modality it is fixed to a arbitrary value within (0, 1). Because of the interval (0,1) of variable c, we apply the chaotic approach for updating the value with 1D chaotic mappings, called logistic mapping. The power exponent a is fixed to 0.1.

Global Search

The parameter r is considered such that α is utilized for replacing it. Therefore, the mathematical modelling of the butterfly global search movement is as follows:

$$X_i^{t+1} = X_i^t + (\alpha^2 \times g_{best} - X_i) \times F_i^t \qquad (13)$$

In Eq. (13), X_i^t signifies the solution vector X_i of $i\text{-}th$ butterfly at $t\text{-}th$ iteration and α shows a random value within (0,1). g_{best} shows the present optimal solution amongst every solution in the present phase. To a certain degree, variable α is considered a scaling factor that is exploited for adjusting the distance between the optimum solution and the $i\text{-}th$ butterflies.

Local Search

Two stages of HFBO must be swapped while the individual search for the optimum values. Then, the vision of butterfly is considered in the local search stage. Therefore, this searching phase stage of butterfly is expressed in the following:

$$X_i^{t+1} = X_i^t + \beta \times (X_i^k - X_j^t) + \alpha \cdot \epsilon \qquad (14)$$

In Eq. (14), X_j^t and X_i^k denotes $j\text{-}th$ and $k\text{-}th$ agents that are selected arbitrarily from the solution space. Furthermore, e shows a random number so that $\epsilon \in [-0.5,0.5]$. α indicates a random value within [0,1]:

$$\beta = \beta_0 \cdot e^{-R_i}j \qquad (15)$$

In Eq. (15), β_0 indicates the attractiveness while $R = 0$. The initial values of variable β are generally fixed as 1, viz., $\beta_0 = 1$. R_{ij} characterizes the distance between X_i and X_j that is evaluated using the 2-norm:

$$R_{ij} = ||X_i - X_j||_2 \qquad (16)$$

Switch Parameter sp

In this phase, sp is set to transform the intensive local and the normal global search. In all the iterations, it arbitrarily produces value within [0, 1] that is equated to the switch probability sp for deciding either to conduct a local or global search. Whereas the value of sp is fixed as 0; viz., the local search stage is implemented. In contrast, the global search stage is performed by the values sp assumed as 1. The proposed HFBO-DLSA method excels in sentiment analysis by harnessing the power of deep learning, achieving high accuracy and relevance in the e-commerce domain. However, it introduces complexity due to hyperparameter optimization, potentially demanding significant computational resources, and relying on effective data pre-processing. Model interpretability and parameter tuning may also pose challenges. Nevertheless, its superior performance and tailored applicability to online product reviews make it a valuable addition to sentiment analysis techniques, particularly when accuracy and customer satisfaction are paramount.

4. RESULTS AND DISCUSSION

The experimental validation of the HFBO-DLSA approach has been tested under two datasets namely Canon and iPod datasets [20]. Table 1 depicts the sample reviews on products. The details relevant to these datasets are shown in Table 2. The first Canon dataset holds 636 instances, comprising 500 instances under Canon class and 136 instances under negative class. Next, the iPod dataset includes 1811 instances with 380 positive instances and 1431 negative instances [21-25]. The core concept underlying AI and machine learning technologies is that developers should not be constrained to writing programs manually. As a result, it should be possible to design a computer system capable of autonomously learning how to generate code [29-28].

Table 1 Sample Reviews on Products

S. No	Product	Sample Reviews
1	Canon	before i decided to get these players, i did my research
2	ipod	i was a little concerned to be the black sheep buying these players rather than the incredibly overpriced apple i-pod
3	ipod	hopefully, these players will out sell the ridiculously over-hyped i-pod

Table 2 Dataset details

Class	Dataset	
	Canon	iPod
Positive	500	380
Negative	136	1431
Total No. of Instances	**636**	**1811**

The existing system provides the contribution and its complexity in terms of SVM, **TextCNN, BiLSTM, HFBO-DLSA**

SVM is a traditional machine learning technique used for sentiment analysis. It is known for its effectiveness in binary classification tasks. SVM models typically require feature engineering, such as text vectorization, which can be complex and time-consuming. Tuning SVM hyperparameters may also involve manual intervention. TextCNN is a neural network architecture designed for text classification. It captures local patterns effectively through convolutional layers. TextCNN models are less complex than recurrent models like LSTM and require less computational resources. However, tuning hyperparameters and choosing an appropriate architecture can still be challenging. BiLSTM models capture sequential dependencies in text data and are well-suited for sentiment analysis tasks. BiLSTM models are more complex than traditional machine learning methods like SVM. They require careful tuning of hyperparameters and can be computationally intensive. RCNN combines the strengths of both recurrent and convolutional layers, making it capable of capturing contextual information effectively. RCNN models are moderately complex, sitting between simpler models like TextCNN and more complex ones like deep belief networks (DBN). HFBO-DLSA is a novel approach that integrates a hyperparameter tuning algorithm (HFBO) with deep learning (DBN) for sentiment analysis. HFBO is specifically designed to optimize the DBN model's performance. HFBO-DLSA introduces an additional layer of complexity by incorporating the HFBO algorithm, which requires optimizing hyperparameters in the deep learning model. While this adds complexity, it enhances model performance and represents a valuable contribution in improving sentiment analysis outcomes.

The SA results of the HFBO-DLSA technique are reported interms of confusion matrix on Canon dataset is given in Fig. 3. With 80% of TR data, the HFBO-DLSA technique has identified 392 instances into positive class and 102 instances

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into negative class. Next, with 20% of TS data, the HFBO-DLSA system has identified 100instances into positive class and 25 instances into negative class. Additionally, with 70% of TR data, the HFBO-DLSA technique has recognized 340 instances into positive class and 87 instances into negative class. Finally, with 30% of TS data, the HFBO-DLSA methodology has recognized 147 instances into positive class and 36 instances into negative class.

A comprehensive SA outcome of the HFBO-DLSA technique on Canon dataset. With 80% of TR data, the HFBO-DLSA technique has attained average $accu_y$ of 97.24%, $prec_n$ of 95.61%, $reca_l$ of 96.22%, F_{score} of 95.91%, and G_{mean} of 96.21%. Simultaneously, with 20% of TS data, the HFBO-DLSA system has gained average $accu_y$ of 97.66%, $prec_n$ of 98.54%, $reca_l$ of 94.64%, F_{score} of 96.43%, and G_{mean} of 94.49%. Concurrently, with 70% of TR data, the HFBO-DLSA approach has achieved average $accu_y$ of 95.96%, $prec_n$ of 93.70%, $reca_l$ of 94.36%, F_{score} of 94.02%, and G_{mean} of 94.32%. Finally, with 30% of TS data, the HFBO-DLSA system has reached average $accu_y$ of 95.81%, $prec_n$ of 94.51%, $reca_l$ of 92.90%, F_{score} of 93.68%, and G_{mean} of 92.76%.

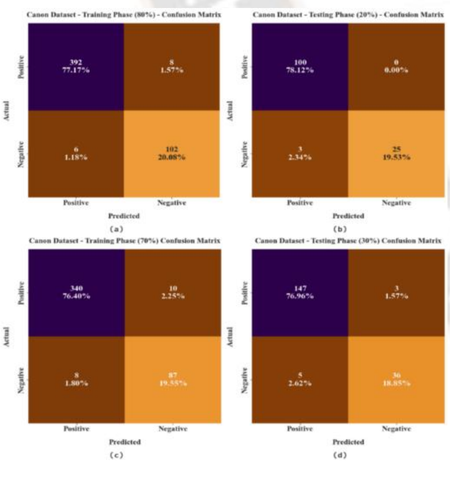

Fig. 3. Confusion matrices of HFBO-DLSA methodology under Canon dataset (a) 80% of TR data, (b) 20% of TS data, (c) 70% of TR data, and (d) 30% of TS data

The training accuracy (TRA) and validation accuracy (VLA) acquired using the HFBO-DLSA system under Canon dataset is illustrated in Fig. 4. The results stated that the HFBO-DLSA algorithm has realized higher values of TRA and VLA. Especially the VLA appeared superior to TRA.

The training loss (TRL) and validation loss (VLL) realized by the HFBO-DLSA methodology under Canon dataset are displayed in Fig. 5. The result pointed out that the HFBO-DLSA method has obtained minimum values of TRL and VLL. Specifically, the VLL is lesser than TRL.

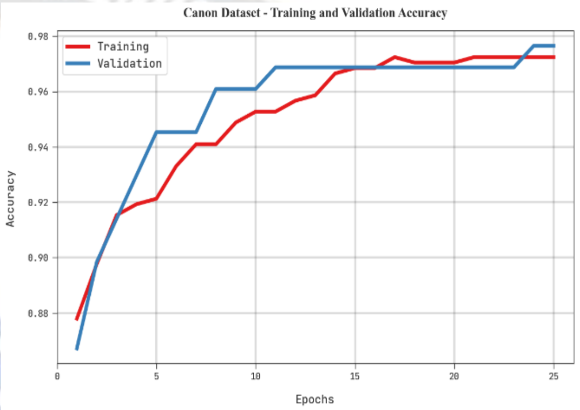

Fig. 4. TRA and VLA analysis of HFBO-DLSA methodology under Canon dataset

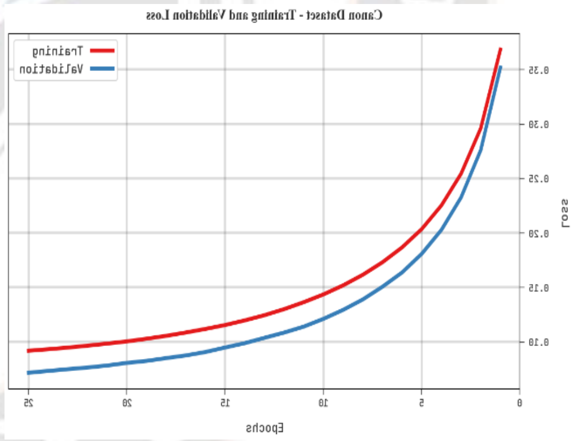

Fig. 5. TRL and VLL analysis of HFBO-DLSA methodology under Canon dataset

The SA results of the HFBO-DLSA approach are reported with respect to confusion matrix on ipod dataset provided in Fig. 6. With 80% of TR data, the HFBO-DLSA system has identified 234 instances into positive class and 977 instances into negative class. Besides, with 20% of TS data, the HFBO-DLSA algorithm has identified 113 instances into positive class and 408 instances into negative class. Then, with 70% of

TR data, the HFBO-DLSA methodology has recognized 281 instances into positive class and 1133 instances into negative class. Eventually, with 30% of TS data, the HFBO-DLSA algorithm has recognized 78 instances into positive class and 277 instances into negative class.

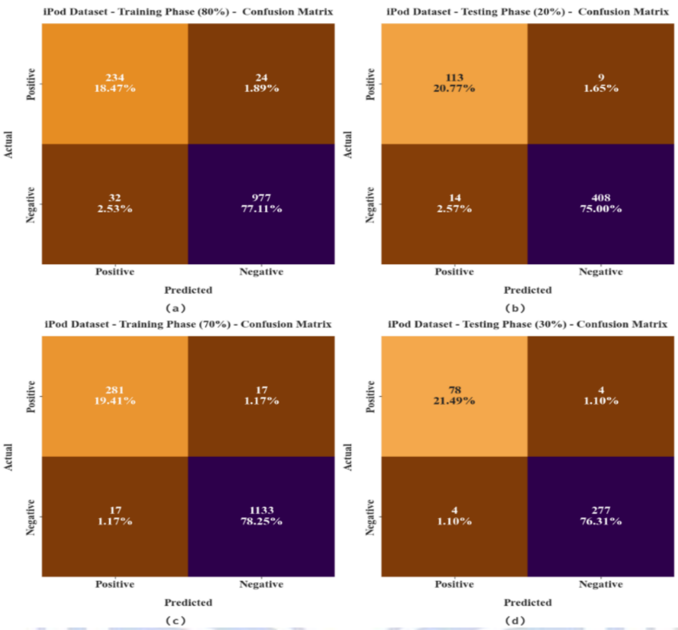

Fig. 6. Confusion matrices of HFBO-DLSA approach under iPod dataset (a) 80% of TR data, (b) 20% of TS data, (c) 70% of TR data, and (d) 30% of TS data

Table 3 provides a comprehensive SA outcome of the HFBO-DLSA methodology on ipod dataset. With 80% of TR data, the HFBO-DLSA approach has gained average $accu_y$ of 95.58%, $prec_n$ of 92.79%, $reca_l$ of 93.76%, F_{score} of 93.26%, and G_{mean} of 93.71%. Likewise, with 20% of TS data, the HFBO-DLSA system has achieved average $accu_y$ of 95.77%, $prec_n$ of 93.41%, $reca_l$ of 94.65%, F_{score} of 94.01%, and G_{mean} of 94.63%. At the same time, with 70% of TR data, the HFBO-DLSA approach has reached average $accu_y$ of 97.65%, $prec_n$ of 96.41%, $reca_l$ of 96.41%, F_{score} of 96.41%, and G_{mean} of 96.39%. Lastly, with 30% of TS data, the HFBO-DLSA methodology has accomplished average $accu_y$ of 97.80%, $prec_n$ of 96.85%, $reca_l$ of 96.85%, F_{score} of 96.85%, and G_{mean} of 96.83%.

Table 3 Result analysis of HFBO-DLSA method with varying measures under iPod dataset

Training / Testing (80:20)					
Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	G_{mean}
Training Phase					
Positive	95.58	87.97	90.70	89.31	93.71
Negative	95.58	97.60	96.83	97.21	93.71
Average	**95.58**	**92.79**	**93.76**	**93.26**	**93.71**
Testing Phase					
Positive	95.77	88.98	92.62	90.76	94.63
Negative	95.77	97.84	96.68	97.26	94.63
Average	**95.77**	**93.41**	**94.65**	**94.01**	**94.63**
Training / Testing (70:30)					
Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	G_{mean}
Training Phase					
Positive	97.65	94.30	94.30	94.30	96.39
Negative	97.65	98.52	98.52	98.52	96.39
Average	**97.65**	**96.41**	**96.41**	**96.41**	**96.39**
Testing Phase					
Positive	97.80	95.12	95.12	95.12	96.83
Negative	97.80	98.58	98.58	98.58	96.83
Average	**97.80**	**96.85**	**96.85**	**96.85**	**96.83**

The TRA and VLA achieved by the HFBO-DLSA system under iPod dataset are shown in Fig. 7. The result exposed that the HFBO-DLSA methodology has reached enhanced

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values of TRA and VLA. Particularly, the VLA appeared superior to TRA.

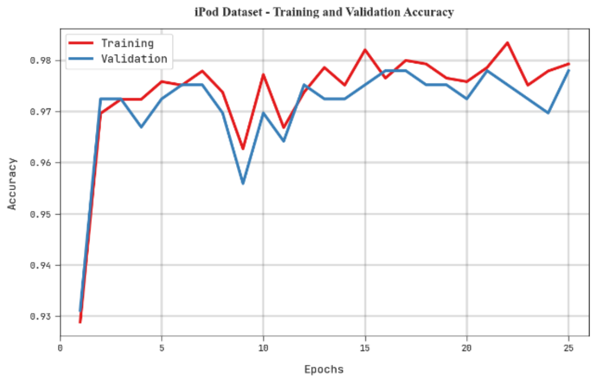

Fig. 7. TRA and VLA analysis of HFBO-DLSA methodology under iPod dataset

Fig. 8. TRL and VLL analysis of HFBO-DLSA methodology under iPod dataset

The TRL and VLL realized by the HFBO-DLSA algorithm under iPod dataset are demonstrated in Fig. 8. The outcome stated that the HFBO-DLSA system has been able lesser values of TRL and VLL. In certain, the VLL is lesser than TRL.

The selection of comparison methods, including BiLSTM, TextCNN, and RCNN, is likely based on several reasons such as Relevance to the Problem Domain, Benchmarking Against State-of-the-Art, Baseline Comparison, Diversity of Architectures and Comparability with Prior Research.

BiLSTM, TextCNN, and RCNN are all well-established neural network architectures for natural language processing tasks, including sentiment analysis. They have been widely used in the literature for such tasks, making them relevant choices for comparison in a sentiment analysis study. These models are often considered as benchmarks or state-of-the-art methods for sentiment analysis. By comparing the proposed HFBO-DLSA method against these well-known architectures, the paper aims to demonstrate whether it can outperform or compete with the current best-performing methods. BiLSTM, TextCNN, and RCNN represent different neural network architectures with distinct strengths and characteristics. BiLSTM excels at capturing sequential dependencies, TextCNN is efficient at learning local features through convolution, and RCNN combines both convolutional and recurrent layers to capture context. Including these diverse architectures allows for a comprehensive assessment of the proposed method's performance under various modeling approaches. These models can serve as strong baselines for evaluating the proposed method. Researchers often compare their novel techniques against established methods to assess whether their approach provides significant improvements or innovations in terms of accuracy, precision, recall, or other performance metrics. Since these models are widely used in sentiment analysis research, comparing the proposed HFBO-DLSA method to them allows for comparability with prior studies. It enables readers to contextualize the paper's findings and understand how the new method performs relative to existing literature. This selection enables a comprehensive assessment of the proposed method's performance and its potential contributions to the sentiment analysis domain.

Table 5 reveal a comparison of SA outcomes of the HFBO-DLSA technique with existing models on Canon dataset [20]. The experimental value indicates that the ACO, SVM, and NN approaches have shown poor performance over other techniques. Then, the TextCNN method reported slightly enhanced SA outcomes. Then, the BiLSTM and RCNN approach have accomplished closer SA outcomes. On the other hand, the HFBO-DLSA technique has reached maximum performance with $accu_y$ of 97.66%, $prec_n$ of 98.54%, $reca_l$ of 94.64%, and F_{score} of 96.43%.

Table 5 Comparative analysis of HFBO-DLSA approach with recent algorithms under Canon dataset

Canon Dataset				
Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
The Proposed Model	97.66	98.54	94.64	96.43
BiLSTM[4]	92.79	75.73	74.72	74.44
TextCNN[10]	91.49	83.59	83.21	83.33
RCNN[5]	92.44	82.09	81.29	81.35
ACO[8]	89.46	92.23	89.93	91.56
SVM[1]	90.50	91.58	90.86	90.53
NN[20]	89.05	90.59	91.63	91.49

Table 6 demonstrate a comparison SA outcome of the HFBO-DLSA system with existing techniques on ipod dataset. The experimental values exposed that the ACO, SVM, and NN techniques have shown least performance over other techniques. Afterward, the TextCNN approach has reported somewhat improved SA outcomes. Besides, the BiLSTM and RCNN techniques have obtained closer SA outcomes.

Table 6 Comparative analysis of HFBO-DLSA approach with recent algorithms under iPod dataset

iPod Dataset				
Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
The Proposed Model	95.81	94.51	92.9	93.68
BiLSTM[4]	88.65	92.48	88.83	92.03
TextCNN[10]	91.85	88.09	91.54	89.07
RCNN[5]	89.52	89.57	91.15	90.12
ACO[8]	92.06	91.04	90.14	92.26
SVM[1]	88.01	91.00	87.86	89.17
NN[20]	88.62	91.35	87.02	90.98

But, the HFBO-DLSA methodology has achieved maximal performance with $accu_y$ of 95.81%, $prec_n$ of 94.51%, $reca_l$ of 92.9%, and F_{score} of 93.68%. These results indicated the proficient SA outcomes of the HFBO-DLSA technique.

5. CONCLUSION

In this article, a new HFBO-DLSA algorithm was devised for determining the nature of sentiments based on online product reviews. Initially, the presented HFBO-DLSA technique applies data pre-processing at the preliminary stage to make it compatible. Besides, the HFBO-DLSA model applied DBN model for classification. The HFBO algorithm is used as a hyperparameter tuning process to improve the SA performance of the DBN method. The experimental validation of the presented HFBO-DLSA method has been tested under a set of datasets. The experimental results reported the enhanced outcomes of the HFBO-DLSA method over recent techniques. Hence, the presented HFBO-DLSA algorithm can be utilized for SA in real time databases. In upcoming days, hybrid DL model was designed to boost the classification performance.

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