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Artificial Fish Swarm Optimization with Deep Learning Enabled Opinion Mining Approach

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Abstract: Sentiment analysis or opinion mining (OM) concepts become familiar due to advances in networking technologies and social media. Recently, massive amount of text has been generated over Internet daily which makes the pattern recognition and decision making process difficult. Since OM find useful in business sectors to improve the quality of the product as well as services, machine learning (ML) and deep learning (DL) models can be considered into account. Besides, the hyperparameters involved in the DL models necessitate proper adjustment process to boost the classification process. Therefore, in this paper, a new Artificial Fish Swarm Optimization with Bidirectional Long Short Term Memory (AFSO-BLSTM) model has been developed for OM process. The major intention of the AFSO-BLSTM model is to effectively mine the opinions present in the textual data. In addition, the AFSO-BLSTM model undergoes pre-processing and TF-IFD based feature extraction process. Besides, BLSTM model is employed for the effectual detection and classification of opinions. Finally, the AFSO algorithm is utilized for effective hyperparameter adjustment process of the BLSTM model, shows the novelty of the work. A complete simulation study of the AFSO-BLSTM model is validated using benchmark dataset and the obtained experimental values revealed the high potential of the AFSO-BLSTM model on mining opinions.

Keywords: Sentiment analysis; opinion mining; natural language processing; artificial fish swarm algorithm; deep learning

1 Introduction

With recent advancements of the Internet, people groups, social networks, the ascent in their applications, and number of clients of interpersonal organizations, the volume of information produced has expanded [1]. In this way, it makes significant data extraction really testing. Then again, individuals are eager and glad to share their lives, information, and experience, and the immense measure of data has turned into an alluring asset for associations to screen the opinions of clients, and interpersonal organizations have been a suitable system for offering clients' viewpoints and thoughts in different applied fields and a rich asset for clients' opinions mining (OM) and sentiment analysis (SA) [2]. Thus, mining such information helps extricate pragmatic examples which are valuable for business, applications, and shoppers [3].

Since the world has been immersed with the rising measure of traveller information, the travel industry associations and businesses should keep side by side about vacationer experience and perspectives about the business, item, and administration [4]. Acquiring bits of knowledge into these fields can work with the improvement of the power system that can upgrade traveller experience and further lift vacationer dedication and suggestions. Generally, businesses depend on the organized quantitative methodology, for instance, rating vacationer fulfilment level in view of the Likert Scale [5]. Albeit this approach is viable to demonstrate or negate existing speculation, the shut finished questions can't uncover accurate traveller experience and sensations of the items or administrations, which hampers acquiring bits of knowledge from sightseers. All things considered, businesses have previously applied complex and progressed approaches, for example, text mining and SA, to unveil the examples taken cover behind the information and the primary subjects [6].

OM is an exploration field that arrangements with data recovery and information location from the text utilizing information mining and regular language handling strategies [7]. Information mining is an interaction that utilizes information examination apparatuses to reveal and observe examples and connections among information that might prompt extraction of new data from an enormous data set. The motivation behind OM is research on opinions and contemplations, recognizable proof of arising social polarities in light of the perspectives, sentiments, states of mind, mentalities, and assumptions for the recipient gatherings or most individuals. By and large, the goal is to perceive clients' mentalities involving investigation of their sentences in substance shipped off networks [8]. The mentalities are grouped by their polarities, in particular sure, unbiased and negative. Programmed help from the investigation interaction is vital, and because of the great volume of data, this sort of help is one of the fundamental difficulties. OM can be considered as a programmed information location whose objective is to track down secret examples in numerous thoughts, web journals, and tweets [9]. Lately, many examinations have been acted in various fields of OM in interpersonal organizations. By researching the techniques proposed in this space was defined that the principal challenges are maximum preparation cost in light of time or memory utilized, absence of advanced dictionaries, maximum elements of highlights' space, and vagueness in sure or negative discovery of certain sentences in these strategies [10].

Zervoudakis et al. [11] propose OpinionMine, a Bayesian based structure for OM, developing Twitter Data. Primarily, the structure imports Tweets extremely by utilizing Twitter application programming interface (API). Afterward, the import Tweet is more managed automatically to construct the group of untrained rules and arbitrary variables. Next, the training method is utilized to estimate of novel Tweet. At last, the created method is retraining incrementally, so developing further robust. In [12], analysis of many tweets compared with the no plastic campaign has been executed for predicting the degree of polarity and subjectivity of tweets. The analysis was separated as to stages namely removing data, pre-processed, cleaning, eliminating stop word, and computation of sentiment score. The Machine Learning (ML) technique was executed on data set compared with the no plastic campaign and analysis was completed.

Yadav et al. [13] purposes for predicting the outcome of vote from Haryana in the tweet written in the English language. It can be utilized the Twitter Archiving Google Sheet (TAGS) tool and Twitter API utilizing R for obtaining the tweet. R is an extremely strong programming language and is satisfyingly employed from data interpretation and SA. Eshmawi et al. [14] concentrate on the scheme of automated OM method utilizing deer hunting optimization algorithm (DHOA) with fuzzy neural network (FNN), named as DHOA-FNN technique. The presented DHOA-FNN approach contains 4 various phases pre-processed, feature extracting, classifier, and parameter tuning procedures. Also, the DHOA-FNN approach contains 2 phases of feature extracting like Glove and N-gram techniques. Furthermore, the FNN system was employed as a classifier method, and parameter optimized procedure occurs by GTOA.

In this paper, a new Artificial Fish Swarm Optimization with Bidirectional Long Short Term Memory (AFSO-BLSTM) model has been developed for OM process. The major intention of the AFSO-BLSTM model is to effectively mine the opinions present in the textual data. In addition, the AFSO-BLSTM model undergoes pre-processing and TF-IFD based feature extraction process. Besides, BLSTM model is employed for the effectual detection and classification of opinions. Finally, the AFSO algorithm is utilized for effective hyperparameter adjustment process of the BLSTM model. A complete simulation study of the AFSO-BLSTM model is validated using benchmark dataset and the obtained experimental values revealed the high potential of the AFSO-BLSTM model on mining opinions.

2 Working of AFSO-BLSTM Model

In this article, a novel AFSO-BLSTM model has been developed for OM process. The AFSO-BLSTM model undergoes pre-processing and TF-IFD based feature extraction process. Moreover, BLSTM model is employed for the effectual detection and classification of opinions. Then, the AFSO algorithm is utilized for effective hyperparameter adjustment process of the BLSTM model. Fig. 1 illustrates the block diagram of proposed AFSO-BLSTM technique.

2.1 Pre-processing and TF-IDF Model

At the initial stage, the AFSO-BLSTM model undergoes pre-processing and TF-IFD based feature extraction process [15]. TF-IDF is most generally employed feature extracting manner on text analysis. Amongst the 2 important tasks of index and weighted to text analysis, TF-IDF controls the weighting. It defines the weighted of offered term t in the given document D. The TF-IDF was established in TF and IDF that were various terms and is computed as [15]:

$$TF(t) = \frac{t_D}{N_D} \tag{1}$$

$$IDF(t) = log\frac{d}{dt} \tag{2}$$

whereas t_D, d and dt refer the total count of t occurrence from the document D, whole count of documents, and the count of documents that include term t.

The weighted of every term employing the TF-IDF is calculated by:

$$W_{t,d} = TF_{t,d}\left(\frac{t_D}{d_{f,t}}\right) \tag{3}$$

In which $TF_{t,d}$ and $d_{f,t}$, signifies the frequency of term t in the document d and count of documents that comprise t.

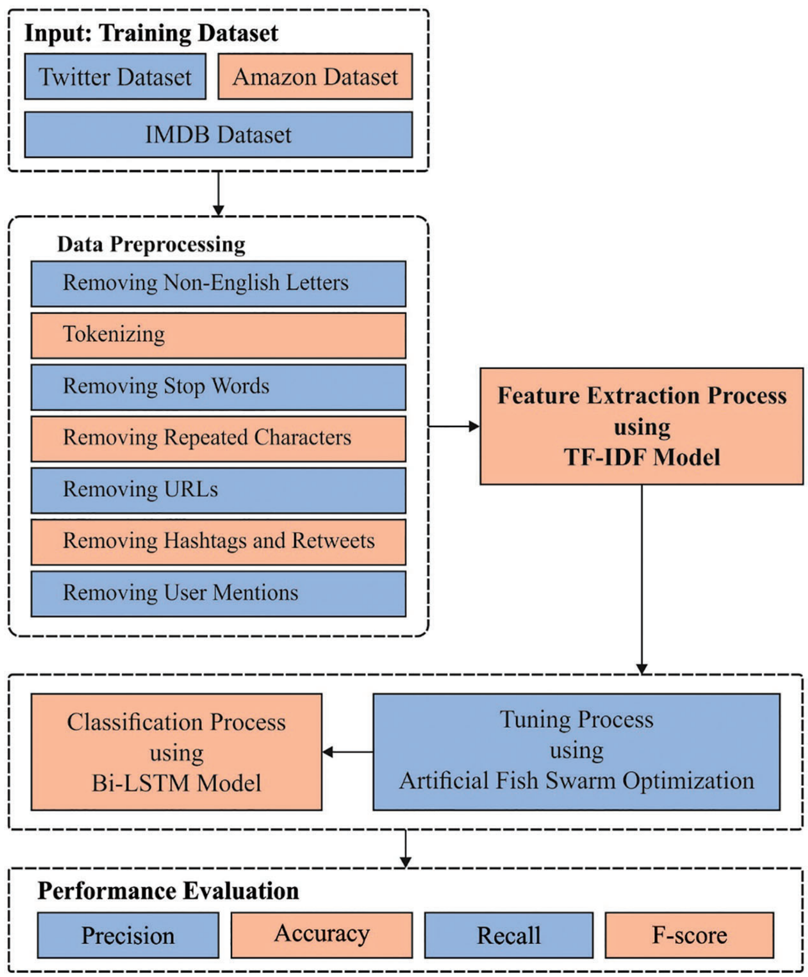

Figure 1: Block diagram of AFSO-BLSTM technique

2.2 Process Involved in BLSTM Model

Next to feature extraction, the BLSTM model is employed for the effectual detection and classification of opinions [16,17]. The BLSTM approach receives the feature is input for recognizing the class label of activities. The LSTM improves Memory Cell infrastructures from the neural nodes of hidden layer of RNN to store the previous data and added 3 gate infrastructures such as Forget, Output, and Input gates, to handle the procedure of previous data [16]. LSTM is transfer useful information from the subsequent time computation. The c_t refers the existing state and $\widetilde{c_t}$ refers the temporary state. i_t, f_t and 0_t correspondingly defines the forget, output, and input gates, $h_{\tau-1}$ refers the hidden state of previous time and x_τ implies the existing input.

The calculation equation is provided from the subsequent formulas:

$$i_\tau = o(W_i \cdot [h_{\tau-12}x_\tau] + b_i) \tag{4}$$

$$f_T = o\left(W_f \cdot [h_{\tau-12}x_\tau] + b_f\right) \tag{5}$$

$$o_\tau = o(W_o \cdot [h_{\tau-12}x_\tau] + b_o) \tag{6}$$

$$h_\tau = 0_\tau \odot tanh(c_\tau) \tag{7}$$

$$c_\tau = f_T \odot c_{t-1} + i_t \odot \tilde{c} \tag{8}$$

$$\tilde{c} = tanh(W_c \cdot [h_{\tau-1}, x_t] + b_c) \tag{9}$$

$$o(x) = \frac{1}{1+e^{-\chi}} \tag{10}$$

$$tanh\ (x) = \frac{e^{\chi} - e^{-\chi}}{e^{\chi} + e^{-\chi}} \tag{11}$$

In which W_i, W_f & W_o signifies the weighted of 3 gates connection correspondingly, b stands for the offset, σ and tanh implies the activation function. Fig. 2 depicts the framework of BLSTM.

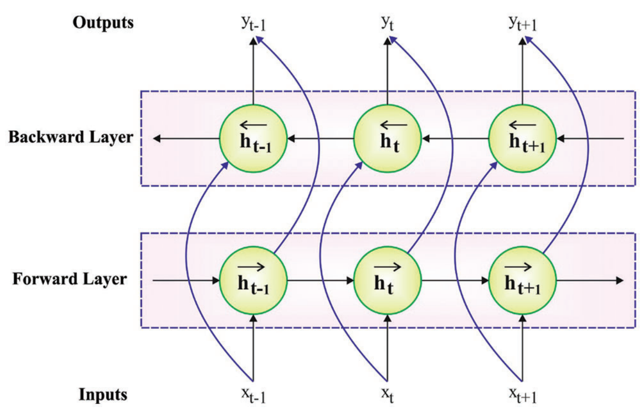

Figure 2: Framework of BiLSTM

Long short term memory (LSTM) is only learned from the abovementioned data of time sequence, BLSTM generates a more increase dependent upon LSTM, for instance, developed up of reverse as well as forward LSTM network, offering the context data of time sequence. At this point, $\chi_1, \chi_2, \ldots \chi_t$ signifies the input sequence, $\vec{h}_t$ & $\overleftarrow{h_t}$ refers the forward as well as reverse output calculated at every moment correspondingly, and then the reverse as well as forward outputs were estimated to reach the final result y_t. Proceeds the forward output $\vec{h}_t$ at time t as sample, the calculation equation of backward as well as forward ways were consistent with LSTM, for instance, by "(1)" to "(8)", the reverse as well as forward temporary cell states $\overrightarrow{\tilde{c}_t}$ & $\overleftarrow{\tilde{c}_t}$, input gates $\overrightarrow{l_t}$ & $\overleftarrow{l_t}$, forget gates $\overrightarrow{f_t}$ & $\overleftarrow{f_t}$, output gates $\overrightarrow{o_t}$ and $\overleftarrow{o_t}$ are measured correspondingly.

The final outcome y_t at time t is:

$$y_t = \left[\overrightarrow{h_t},\ \overleftarrow{h_t}\right] \tag{12}$$

In the abovementioned formulas, it calculates the outcome at every moment, and later reach the final output $Y = [h_0,\ h_1,\ h_t]$.

2.3 Process Involved in AFSO Based Parameter Optimization

At the final stage of OM, the AFSO algorithm is utilized for effective hyperparameter adjustment process of the BLSTM model [17]. AFSO algorithm is a type of SI technique depending upon the performance of animals. Is baseline being the stimulation of clustering, collision, and foraging behaviors of fish and the cooperative provision in a fish swarm to understand a global optimal point. The maximum distance passed by the artificial fish technique is defined as *Step*, the obvious distance passes by the artificial fish is defined as *Visual*, the repeat quantity signifies the *Try_Number* the factor of crowd total characterize η. The place of ingle artificial fish can be described as the resultant vector $X = (X_1, X_2, \ldots, X_n)$, and the distance amongst artificial fishes i and j represents $d_{ij} = |X_i - X_j|$. Consider that the fish observes the food through the eye, the existing position is X_i, along with a subjectively designated place is X_j with the perception,

$$X_j = X_i + Visual \ \times rand(0 \sim 1) \tag{13}$$

while *rand* (0–1) characterizes an arbitrary value amongst zero & one. After $Y_i > Y_j$, the fish moves in that path. Otherwise, the technique subjectively chooses a novel place X_j for arbitrating it accomplishes the moving conditions:

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} \times Step \times rand(0 \sim 1) \tag{14}$$

After it does not *Try_Number* times, an arbitrary motion is created as:

$$X_i^{t+1} = X_i^t + Visual \times rand(0 \sim 1) \tag{15}$$

To avoid over-crowding, an artificial current place X_i is set. Following, the sum of fish in its n_f firm and X_c center in the area (viz., $d_{ij} < Visual$) are described. Once $Y_c/n_f < \eta \times Y_i$, the place of companion characterizes an ideal quantity of food and lesser crowd. Next, the fish move towards the companion centre:

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\|X_c - X_i^t\|} \times Step \times rand(0 \sim 1) \tag{16}$$

Otherwise, it begins to accomplish the prey behavior.

The current place of artificial fish swarm is described as X_i. The swarm determines foremost firm Y_j as X_j in the area (viz. $d_{ij} < Visual$). Once $Y_j/n_f < \eta \times Y_i$, the location of company characterizes an optimum quantity of food and slighter crowding. Then, the swarm moved to X_j:

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} \times Step \times rand(0 \sim 1) \tag{17}$$

It allows artificial fish to accomplish food and company over a great region. A place is subjectively selected, along with artificial fish moved to them.

Through the searching region of D dimension, very likely distance amid 2 artificial fishes is exploited for energetically restraining the *Visual* & *Step* of an artificial fish. It can be described as *MaxD*:

$$MaxD \ = \sqrt{(x_{\max} - x_{\min})^2 \times D} \tag{18}$$

In which $x_{\min}$ and $x_{\max}$ indicates the lower and upper boundaries of the optimization, and D designates the dimension of the searching region.

3 Experimental Validation

In this section, the performance validation of the AFSO-BLSTM model is tested using three benchmark datasets namely IMDB Dataset [18], Amazon Products Dataset [19], and Twitter Dataset [20]. All these three datasets comprises two class labels namely positive and negative.

Tab. 1 and Fig. 3 illustrate a comprehensive comparative study of the AFSO-BLSTM model on the test IMDB dataset [21,22]. The outcomes indicated that the AFSO-BLSTM model has showcased enhanced performance over the other models under distinct feature extraction techniques. With unigram features, the AFSO-BLSTM model has offered $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.97%, 99.90%, 99.21%, and 99.87% respectively. In line with, with bigram features, the AFSO-BLSTM model has offered $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.68%, 99.79%, 99.22%, and 99.60% respectively. Followed by, with trigram features, the AFSO-BLSTM model has depicted $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.53%, 99.65%, 99.54%, and 99.48% respectively. At last, with TF-IDF features, the AFSO-BLSTM model has provided $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.61%, 99.17%, 98.95%, and 99.53% respectively.

Table 1: Comparison study of AFSO-BLSTM model on IMDB dataset

Methods	Measures	Feature extraction techniques			
		Unigram	Bigram	Trigram	TF-IDF
A-boost algorithm	Accuracy	80.21	65.90	58.34	81.88
	Precision	80.67	72.00	68.05	82.67
	Recall	79.71	64.43	57.31	82.11
	F-score	79.92	69.61	62.72	82.40
Support Vector Machine (SVM) algorithm	Accuracy	86.70	85.84	72.49	87.15
	Precision	85.25	84.77	75.31	88.28
	Recall	85.12	86.15	72.57	87.91
	F-score	86.43	86.24	73.66	87.91
Logistic Regression (LOR) algorithm	Accuracy	87.12	85.60	72.67	89.03
	Precision	88.18	84.42	73.73	87.56
	Recall	87.70	85.79	72.99	89.26
	F-score	87.74	85.62	72.11	87.51
DH-FNN	Accuracy	98.82	99.60	99.41	99.85
	Precision	99.49	99.63	99.28	99.50
	Recall	99.02	98.97	99.31	99.02
	F-score	99.65	99.02	99.37	99.20
AFSO-BLSTM	Accuracy	99.97	99.68	99.53	99.61
	Precision	99.90	99.79	99.65	99.17
	Recall	99.21	99.22	99.54	98.95
	F-score	99.87	99.60	99.48	99.53

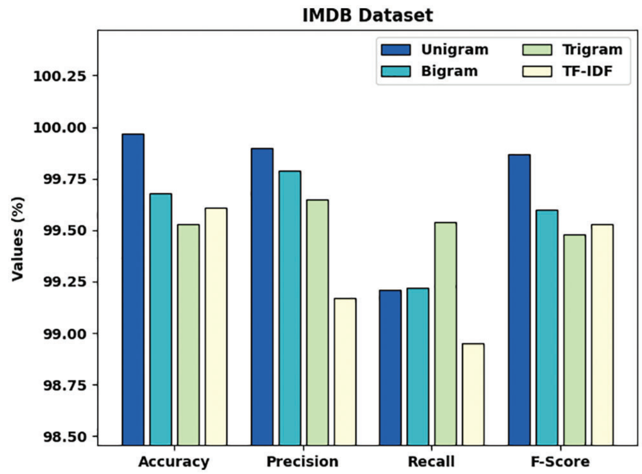

Figure 3: Comparative analysis of AFSO-BLSTM technique on IMDB dataset

Fig. 4 illustrates the training and validation accuracy inspection of the AFSO-BLSTM model on IMDB dataset. The figure conveyed that the AFSO-BLSTM model has offered maximum training/validation accuracy on classification process.

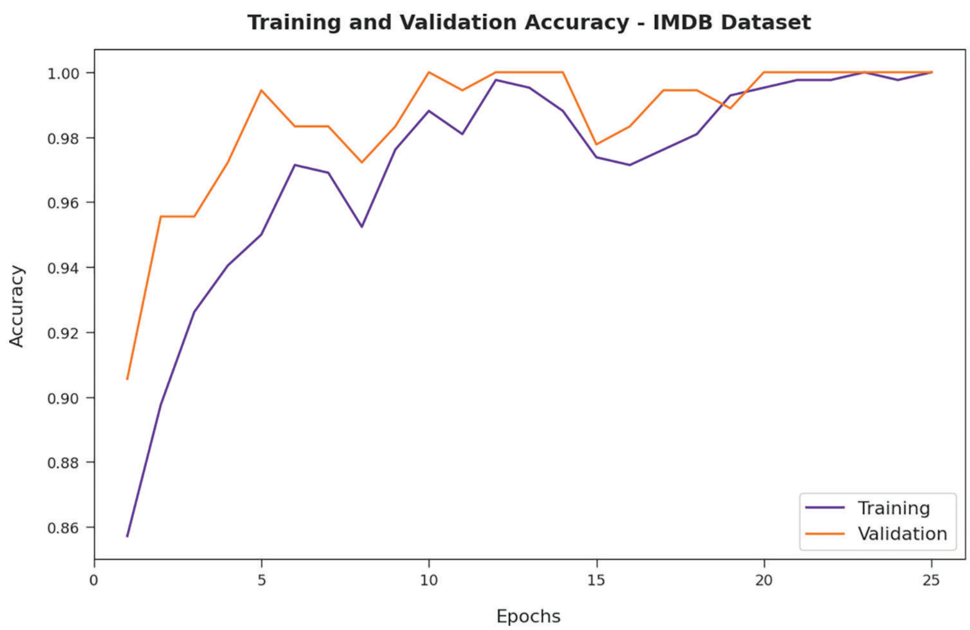

Figure 4: Accuracy analysis of AFSO-BLSTM technique under IMDB dataset

Next, Fig. 5 exemplifies the training and validation loss inspection of the AFSO-BLSTM model on IMDB dataset. The figure reported that the AFSO-BLSTM model has offered reduced training/accuracy loss on the classification process of test data.

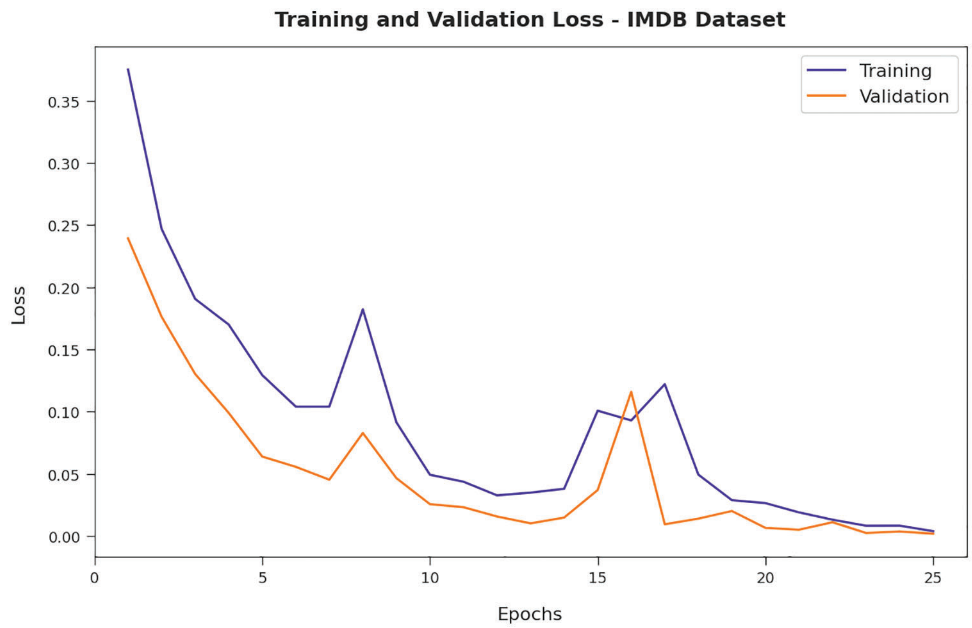

Figure 5: Loss analysis of AFSO-BLSTM technique under IMDB dataset

Tab. 2 and Fig. 6 demonstrate a comprehensive comparative study of the AFSO-BLSTM model on the test Amazon dataset. The outcomes referred that the AFSO-BLSTM model has showcased enhanced performance over the other models under distinct feature extraction techniques. With unigram features, the AFSO-BLSTM method has offered $accu_y$, $prec_n$, $recal_l$, and F_{score} of 99.95%, 99.95%, 99.44%, and 99.78% respectively. Along with that, with bigram features, the AFSO-BLSTM system has offered $accu_y$, $prec_n$, $recal_l$, and F_{score} of 98.91%, 99.07%, 99.86%, and 99.77% respectively. Followed by, with trigram features, the AFSO-BLSTM approach has depicted $accu_y$, $prec_n$, $recal_l$, and F_{score} of 90.12%, 94.63%, 97.52%, and 96.93% correspondingly. Eventually, with TF-IDF features, the AFSO-BLSTM methodology has provided $accu_y$, $prec_n$, $recal_l$, and F_{score} of 99.09%, 99.45%, 99.34%, and 99.41% respectively.

Table 2: Comparison study of AFSO-BLSTM model on amazon dataset

Methods	Measures	Feature extraction techniques			
		Unigram	Bigram	Trigram	TF-IDF
A-boost algorithm	Accuracy	84.18	64.26	55.00	86.36
	Precision	85.12	77.37	75.72	85.63
	Recall	84.38	64.92	54.81	85.27
	F-Score	84.19	70.53	64.83	85.85
SVM Algorithm	Accuracy	78.53	68.14	52.07	81.31
	Precision	78.82	73.40	64.57	81.02
	Recall	80.16	66.75	52.56	82.16
	F-score	78.92	70.83	56.84	80.11

(Continued)

Table 2 (continued)

Methods	Measures	Feature extraction techniques			
		Unigram	Bigram	Trigram	TF-IDF
LOR algorithm	Accuracy	80.95	66.26	51.33	83.07
	Precision	80.83	73.51	64.97	84.65
	Recall	81.11	66.30	51.03	81.83
	F-score	80.47	69.59	58.17	82.35
DH-FNN	Accuracy	99.87	98.46	88.83	98.75
	Precision	99.84	98.66	90.73	99.17
	Recall	99.19	97.71	89.59	98.93
	F-score	99.26	98.36	89.86	99.18
AFSO-BLSTM	Accuracy	99.95	98.91	90.12	99.09
	Precision	99.95	99.07	94.63	99.45
	Recall	99.44	99.86	97.52	99.34
	F-score	99.78	99.77	96.93	99.41

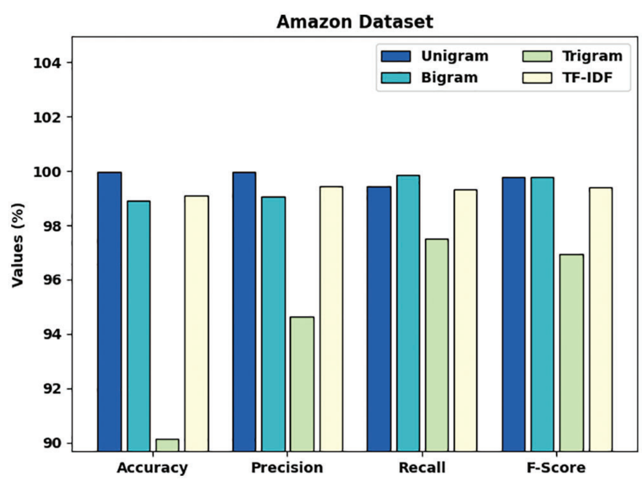

Figure 6: Comparative analysis of AFSO-BLSTM technique on Amazon dataset

Fig. 7 showcases the training and validation accuracy inspection of the AFSO-BLSTM method on Amazon dataset. The figure exposed that the AFSO-BLSTM model has offered maximum training/validation accuracy on classification process.

Afterward, Fig. 8 exemplifies the training and validation loss inspection of the AFSO-BLSTM technique on Amazon dataset. The figure revealed that the AFSO-BLSTM system has offered reduced training/accuracy loss on the classification process of test data.

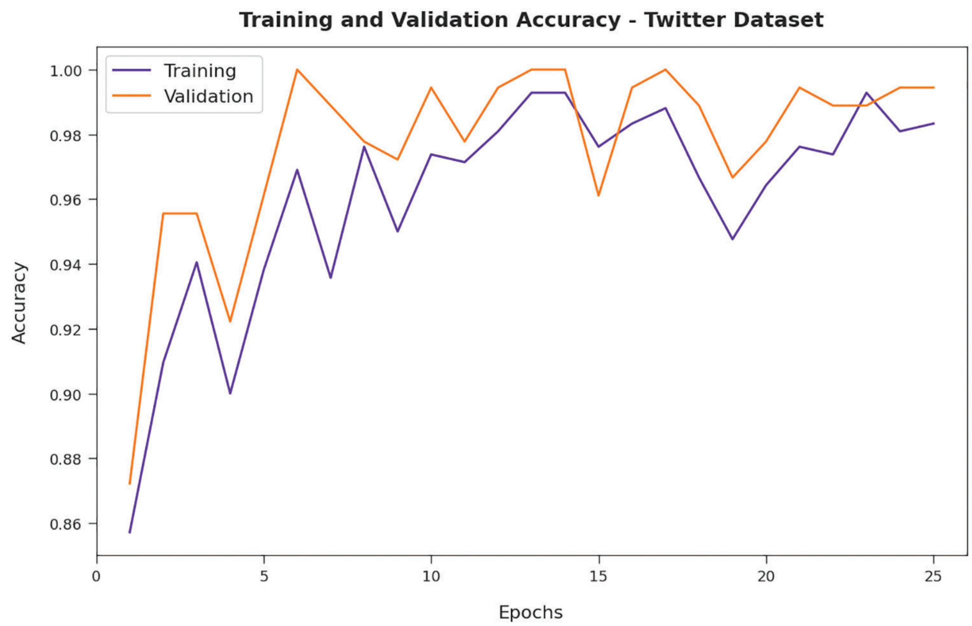

Figure 7: Accuracy analysis of AFSO-BLSTM technique under Amazon dataset

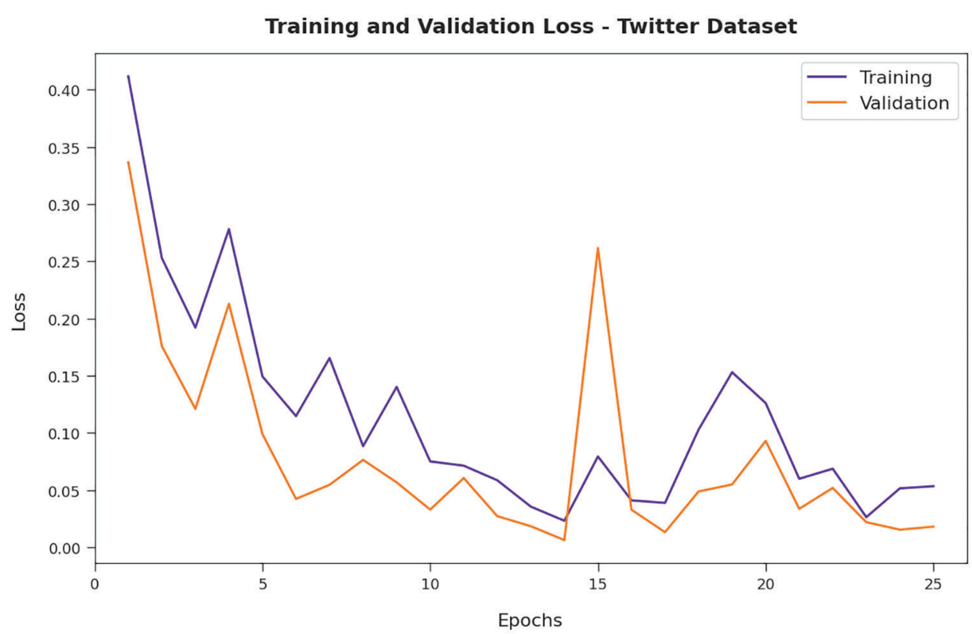

Figure 8: Loss analysis of AFSO-BLSTM technique under Amazon dataset

Tab. 3 and Fig. 9 demonstrate a comprehensive comparative study of the AFSO-BLSTM approach on the test Twitter dataset. The outcomes represented that the AFSO-BLSTM model has showcased enhanced performance over the other techniques under distinct feature extraction techniques. With unigram features, the AFSO-BLSTM model has offered $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.87%, 99.93%, 99.91%, and 99.63% correspondingly. Also, with bigram features, the AFSO-BLSTM model has offered $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.51%, 99.36%, 99.55%, and 99.54% correspondingly. Similarly, with trigram features, the AFSO-BLSTM approach has depicted $accu_y$, $prec_n$, $reca_l$, and F_{score} of 97.37%, 98.37%, 98.57%, and 98.29% correspondingly. At last, with TF-IDF features, the AFSO-BLSTM technique has provided $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.68%, 99.74%, 99.95%, and 99.29% correspondingly.

Table 3: Comparison study of AFSO-BLSTM model on twitter dataset

Methods	Measures	Feature extraction techniques			
		Unigram	Bigram	Trigram	TF-IDF
A-boost algorithm	Accuracy	64.77	51.99	51.31	68.76
	Precision	65.62	67.82	62.97	71.39
	Recall	65.26	52.18	51.74	66.59
	F-score	66.74	59.20	56.17	68.90
SVM Algorithm	Accuracy	75.81	66.25	52.61	75.64
	Precision	74.81	67.37	62.32	75.20
	Recall	75.77	64.88	52.53	76.56
	F-score	74.14	65.07	57.38	74.17
LOR algorithm	Accuracy	73.18	64.59	54.34	72.67
	Precision	72.71	65.63	60.66	72.98
	Recall	74.61	65.52	53.45	73.97
	F-score	73.49	65.86	57.91	73.54
DH-FNN	Accuracy	93.33	99.41	96.77	91.48
	Precision	93.55	99.10	97.59	92.98
	Recall	94.56	99.21	97.42	91.97
	F-score	93.10	99.38	96.78	93.46
AFSO-BLSTM	Accuracy	99.87	99.51	97.37	99.68
	Precision	99.93	99.36	98.37	99.74
	Recall	99.91	99.55	98.57	99.95
	F-score	99.63	99.54	98.29	99.29

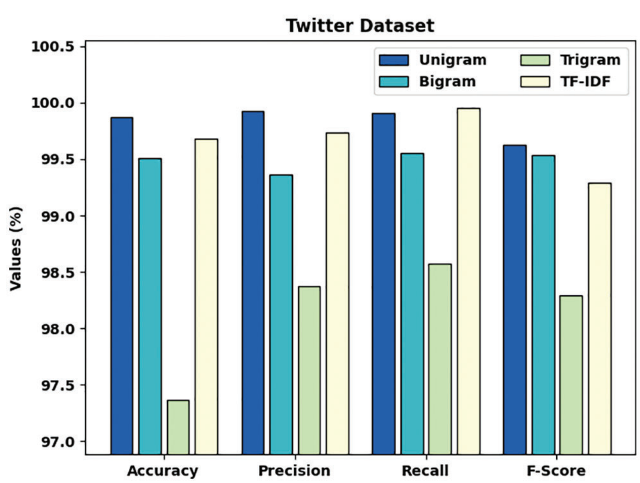

Figure 9: Comparative analysis of AFSO-BLSTM technique on Twitter dataset

Fig. 10 depicts the training and validation accuracy inspection of the AFSO-BLSTM approach on Twitter dataset. The figure conveyed that the AFSO-BLSTM model has offered maximal training/validation accuracy on classification process.

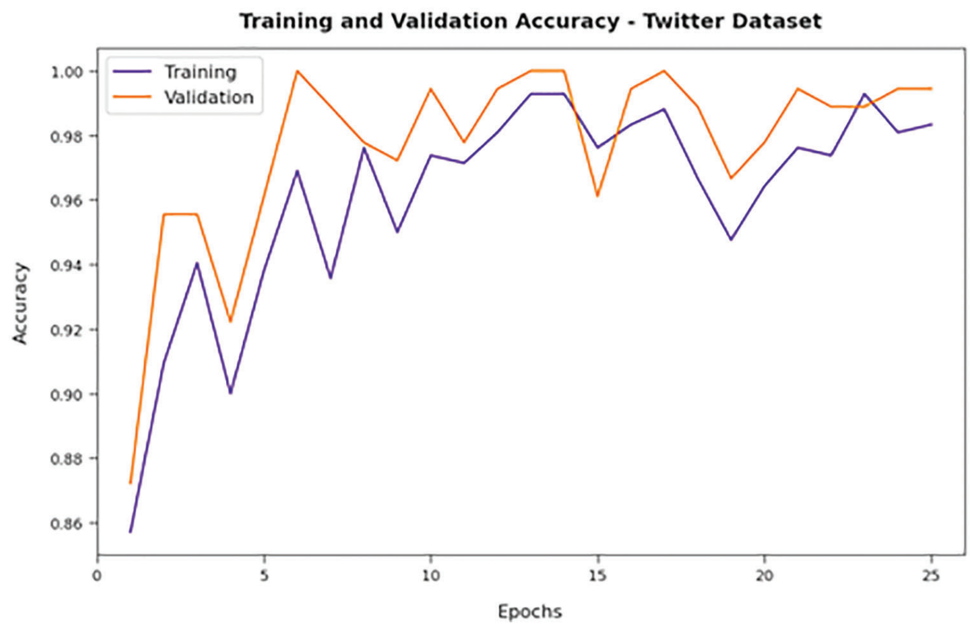

Figure 10: Accuracy analysis of AFSO-BLSTM technique under Twitter dataset

Then, Fig. 11 typifies the training and validation loss inspection of the AFSO-BLSTM approach on Twitter dataset. The figure reported that the AFSO-BLSTM model has offered reduced training/accuracy loss on the classification process of test data.

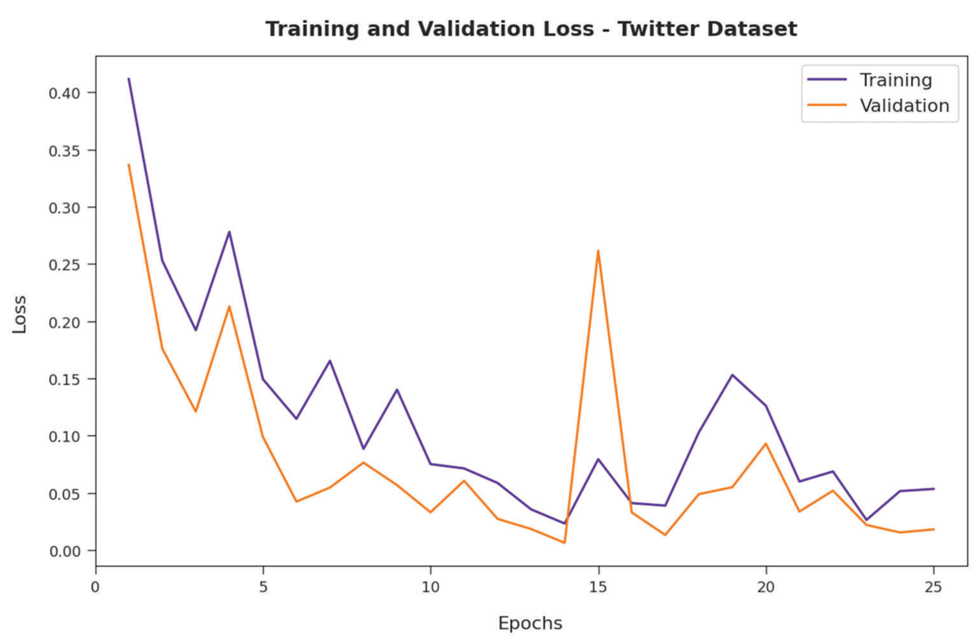

Figure 11: Loss analysis of AFSO-BLSTM technique under Twitter dataset

The above mentioned results and discussion indicated the supremacy of the AFSO-BLSTM model on the OM tasks.

4 Conclusion

In this article, a novel AFSO-BLSTM model has been developed for OM process. The major intention of the AFSO-BLSTM model is to effectively mine the opinions present in the textual data. In addition, the AFSO-BLSTM model undergoes pre-processing and TF-IFD based feature extraction process. Besides, BLSTM model is employed for the effectual detection and classification of opinions. Finally, the AFSO algorithm is utilized for effective hyperparameter adjustment process of the BLSTM model. A complete simulation study of the AFSO-BLSTM model is validated using benchmark dataset and the obtained experimental values revealed the high potential of the AFSO-BLSTM model on mining opinions. In future, hybrid DL models can be included to further boost the classification efficiency of the BLSTM model.

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