Fusion of Artificial Intelligence Based Deep Learning Model for Product Reviews on E-Commerce Environment

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Abstract

The emergence of e-commerce is introduced in the golden era. E-commerce product reviews are comments generated by customers of online shopping to estimate the service and product qualities having purchased; these remarks aid users in identifying the facts of the product. The sentiment polarity of e-commerce product analyses is the optimal method to get consumer opinions on a service or product. Hence, sentiment analysis (SA) of product remarks on e-commerce platforms is much more influential. Deep learning (DL) analysis of online consumer feedback can identify user behavior toward a sustainable future. Artificial intelligence (AI) can acquire perceptions from product evaluations to develop efficient products. The main challenge is that numerous ethical products do not satisfy customers' expectations owing to the gap among users' expectations and their perception of sustainable products. This paper focuses on the design of the Fusion of Artificial Intelligence Deep Learning Model for Product Reviews on E-Commerce (FAIDLM-PREC) model. The main intention of FAIDLM-PREC method is to appropriately distinguish the dissimilar types of sentiments that occur in the e-commerce reviews. Initially, data preprocessing is executed to increase the product review quality with Glove based word embedding method. For product reviews classification, the FAIDLM-PREC approach evolves fusion of dual DL methods namely Bidirectional Long Short-Term Memory (Bi-LSTM) and gated recurrent unit (GRU) methods. Eventually, the parameters relevant to the two DL methods are perfectly modified utilizing the Archimedes optimization algorithm (AOA). An extensive experiment of the FAIDLM-PREC technique was conducted utilizing customer review database and outcomes indicated that the FAIDLM-PREC technique highlighted betterment over other recent methods to several measures.

Keywords: Archimedes Optimization Algorithm; Gated Recurrent Unit; Bidirectional Long Short-Term Memory; Product Reviews; Artificial Intelligence

1. Introduction

Most of the customers wish to use e-commerce sites, with the growing number of e-commerce web pages [1]. Corresponding to manual shopping in actual stores, consumers can purchase anytime with shorter timing and energy and the products in e-commerce platforms were different. Consumers can buy the wanted products in the home itself. Currently, green habits are influencing customer choices to select goods while there are many of the difficulties in the commodities sold in online mediums namely the divergence between the real merchandise and the sustainability, low attributes, and lacking consumer services [2]. Therefore, that is significant to use lexical investigation of the retail estimation with e-commerce platforms. In the interior of the enormous data quantity created over the Internet, essential information was unseen. The data mining methods were applied to remove data and resolve numerous difficulties [3]. Online product analyses need two main features in that information is kept on the Internet. Moneymaking webpages are forums where customers express their opinions or sentiments on various areas. Sentiment analysis (SA) denotes a wide range of text mining, natural language processing (NLP),

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and computational linguistics [4]. These methods usage results in the analysis and extraction of the view on particular products. Opinion mining describes opinions either negative or positive, and SA expresses the value of polarity a customer's opinion in specific services or products. The aim is to decide the polarity of the text in natural languages transcribed in product analyses [5].

Deep learning (DL) models have achieved important study growth in the e-commerce field, particularly in solving SA, customer behaviour, and purchase intention prediction [6]. This approach proceeds the complete benefit of the great features of deep neural networks (DNN) like automated feature extraction, large-scale data process, and context modelling for understanding and predicting customer buying choices [7]. Additionally, there a various emotional levels and semantic data in e-commerce product assessments that need DL methods for enhanced capturing and understanding [8]. In the DL study during the e-commerce field, model varieties were broadly utilized for solving problems like SA and purchase intention prediction. Convolutional neural network (CNN) is a DL technique initially applied to image processing [9]. The main goal is to effectually seize local features with pooling layers and convolutional layers, and slowly construct worldwide data for achieving progressive feature learning. During the NLP field, CNN has been presented for SA and the classification of text [10].

This article focuses on the design of Fusion of Artificial Intelligence Based Deep Learning Model for Product Reviews on E-Commerce (FAIDLM-PREC) model. The main intention of FAIDLM-PREC method is to appropriately distinguish the dissimilar types of sentiments that occur within the e-commerce reviews. Initially, data pre-processing is executed to increase the product review quality with Glove based word embedding method. For product review classification, the FAIDLM-PREC approach evolves fusion of dual DL methods namely gated recurrent unit (GRU) and Bidirectional Long Short-Term Memory (Bi-LSTM) methods. Eventually, the parameters relevant to the two DL methods are perfectly modified utilizing the Archimedes optimization algorithm (AOA). An extensive experiment of the FAIDLM-PREC technique was conducted utilizing customer review database and outcomes indicated that the FAIDLM-PREC technique highlighted betterment over other recent methods in several measures.

2. The Related Works

In [11], the DL CNN and LSTM combined by LSTM (CNN-LSTM) methods are applied for SA review within the e-commerce fields. Data pre-processing stages, such as stop word removal, punctuation deletion, tokenization, and lower-case process are utilized for the cleaning of data. The cleaned data is processed by the LSTM and CNN-LSTM methods for the classification and detection of the users' sentiments as negative or positive. Rasappan et al. [12] propose a novel improved ML method called Enhanced Golden Jackal Optimizer-based LSTM (EGJO-LSTM) to execute SA of e-commerce product review. The first stage involves using a tool for web scrapping to collect consumer product reviews from different e-commerce sites. The gathered information is subject to a pre-processing stage to fine-tune the scrape data. The pre-processed information later undergoes feature selection (FS) and term weighting process by using Improved Grey Wolf Optimizer (IGWO) and Log term Frequency based Modified Inverse Class Frequency (LF-MICF). In the last phase, the fine IGWO data is served into the EGJO-LSTM method that identifies the sentimentality of the consumer reviews into neutral, negative, or positive types. Zhao et al. [13] propose BERT Fusion DNN, new framework combining BERT for mining text features and a DNN for incorporating the arithmetical features. We evaluate the efficiency of our method by utilizing a Females Cloths E-Commerce dataset, evaluating it against recognized methods. Our technique efficiently mines useful information from the reviews of the consumers, stimulating e-commerce suggestion system by overcoming obstacles connected with decoding both numerical intricacies and textual nuances.

In [14], the authors present a new structure that uses the influence of DL systems to improve CRM in e-commerce. Creating a complete earlier article review, we detect the necessity for innovative analytic techniques to open perceptions from difficult data patterns. Our method contains the evaluation and development of DNN and ANN personalized to CRM tasks like recommendation systems, churn prediction, and consumer segmentations. Leveraging an accurately organized dataset containing different transaction histories and consumer attributes, we meticulously assess and train our methods. Li and Esquivel [15] introduce locality-sensitive hashing (LSH) in neighbour-based embedded learnings. Using adverse methods, LSH provides effective searching of neighbour. Acquiring multi-view embeddings from various data behaviours improves the precision of forecasts. Because of utilizing multi-view preferred embeddings, customer priorities could be shown intimately. In LSH, neighbour-centred embedding, interactions aware embedding, and self-embedding are all utilized to complete this task. Additionally, to provide effectual similar search abilities, adversarial search, and neighbour-based embedding learning provides strong protection of privacy. Mamta and Sangwan [16] present an ensemble framework for analyzing the behavior of customers to improve satisfying experiences and customized suggestions. The presented structure contains two components such as abandonment analysis (AA) and purchasing intention (PI) that use

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integration of 3 DL methods, LSTM-RNN, CNN, and generative adversary networks (GANs). This ensemble forecast method gives useful perceptions of consumer behaviours and communication with e-commerce sites. Huang, Lin, and Wang [17] develop a SA method ERNIE Bi-LSTM Att (EBLA). In this, the dynamic word vector is created by utilizing the Enhanced Representations using Knowledge Integration (ERNIE) word embedding method and is an entry for the (BiLSTM) to mine the feature of the texts. At that time, the Att is utilized to enhance the hidden layer weight. At last, softmax is employed as being output layer as sentiment classifications.

3. The Proposed Model

In this research, we have presented a FAIDLM-PREC model. The main intention of FAIDLM-PREC method is to appropriately distinguish the dissimilar types of sentiments that occur in the e-commerce reviews. It contains distinct processes such as pre-processing word embedding, fusion of DL models, and parameter tuning are illustrated in Figure 1.

A. Pre-Processing

Initially, the FAIDLM-PREC technique utilized a pre-processing model [18]. In NLP tasks, the data pre-processing is a fundamental step, enhancing the efficacy of knowledge evolution. It contains methods such as integration, data cleaning, reduction, and transformation, each designed to improve and prepare the dataset for improved analysis.

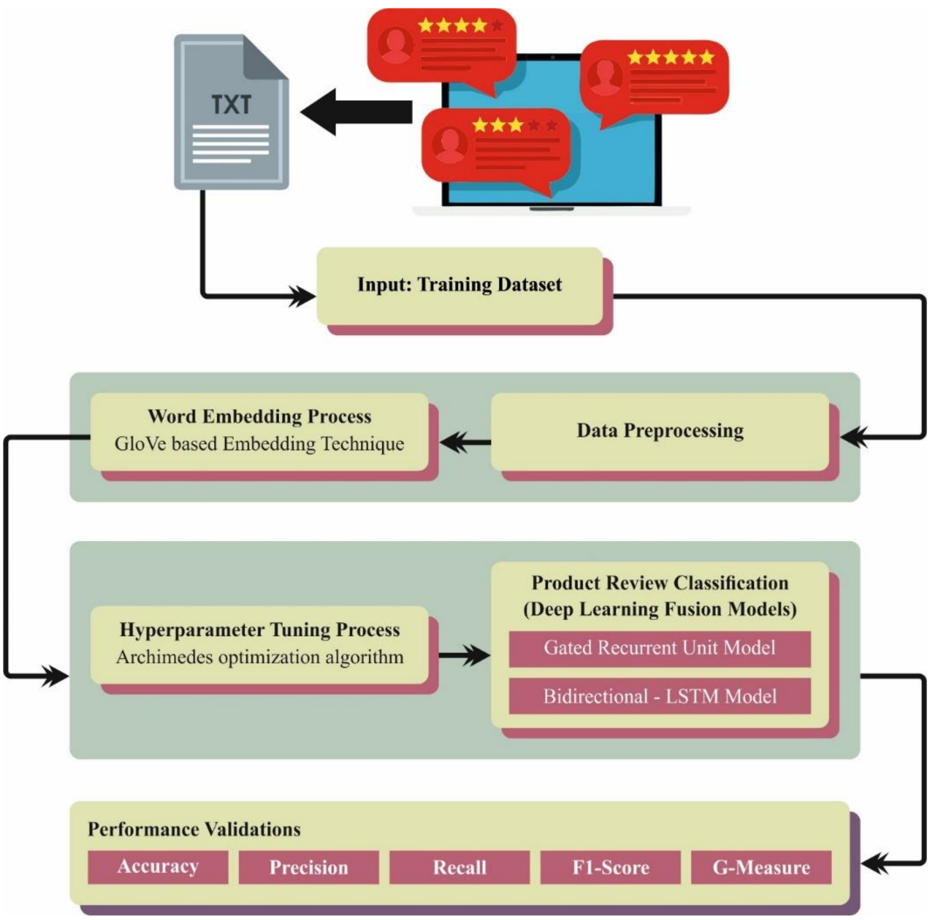

Figure 1. Overall process of FAIDLM-PREC model

i, Handling Missing Value

While approaching the problem of missing values in the data set, our main attention relies on handling the missing entry in the features of star ratings and body reviews. These are focused on positioned owing to the feature's impact on thoughts and their equivalent output.

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For object features, we used the fillna() model obtainable in Python for populating the void values. Moreover, for feature of star rating, we applied the Interpolate model. This technique computes an average depending upon the value that encompasses the empty cell, either below or above it, so helps in the accusation of missing data.

ii, Lower-case Conversion

At this stage, we transform every comment word into the lower-case. For instance, Amazing and Great are changed to amazing and great. Lowercase aids in normalizing the text and decreases the data size by handling each word in a lowercase method.

iii, Elimination of Stop Words

Generally, the stop words are fundamental in sentences that have no meaning over every zone within the text-mining field. Hence, so removed every punctuation mark, stop word, and tag of HTML from the analyses in our study. This pre-processing stage aids in decreasing noise and enhancing computation efficacy in the data.

iv, Tokenization

In this work, we used word tokenization and sentence tokenization. In general, tokenization is a method where a text sequence is divided in order to distinct modules recognized as tokens. It includes solitary phrases, words, or complete sentences. Then, it helps as an input for numerous methods like parsing and text mining. It aids methods to concentrate on the significance of distinct units instead of handling the complete text as a distinct series.

B. Word Embedding

Next, the GloVe is a prevalent word embedding method in NLP [19]. It builds a word vector by examining the global concurrence word statistics in a great text corpus. The impartial function of GloVe's diminishes the alteration amongst the logarithm of their co-occurrence likelihoods and dot products of word vectors, resulting in dense vector representation whereas semantically connected words were nearer together. Pre-trained GloVe embeddings are obtainable for numerous languages and have been established as effective in NLP tasks like machine translation and sentiment analysis. However GloVe acquires global word relationships efficiently, it might need extensive computation sources for training and might not attain delicate semantic inferences.

C. Fusion of DL Models

At this stage, The FAIDLM-PREC approach utilizes fusion of dual DL methods namely Bi-LSTM and GRU for the classification of product reviews.

i, BiLSTM Model

Similar to RNN, a conventional LSTM analyses and records the data as it propagates [20]. The core component of LSTM has various cell states and gates, with dissimilar cell activities enabling it to store or ignore data based on the activity level. The neural network acts as a gate and controls the data that may be utilized in a cell's state during the processing. The cell state is a memory channel that is used for transmitting pertinent information during cell processing. The gates learn what data to store and ignore during the training. LSTM cell exploits input, output, and forget gates for the data transmission. The gate defines what data is added to the existing state that can be stored from the prior state, and to the existing state. The succeeding equation describes the input and output at t and $t-1$ time.

$$\zeta_\iota = \vartheta\left[\left(\varsigma_{\varrho\zeta} * \varrho_\iota\right) + \left(\varsigma_{v\zeta} * v_{\iota-1}\right) + \left(\varsigma_{v\zeta} * v_{\iota-1}\right) + \kappa_\zeta\right] \tag{1}$$

$$\eta_\iota = \vartheta[(\varsigma_{\varrho\eta} * \varrho_\iota) + (\varsigma_{\iota\eta} y * v_{\iota-1}) + (\varsigma_{v\eta} * v_{\iota-1}) + \kappa_\eta \tag{2}$$

$$\gamma_\iota = (\eta_\iota * \gamma_{\iota-1}) + \zeta_\iota tanh\left[\left(\varsigma_{tJ} y * v_{\iota-1}\right) + \left(\varsigma_{v\gamma} * v_{\iota-1}\right) + \kappa_\gamma\right] \tag{3}$$

$$\varphi_\iota = \theta\left[\left(\sigma_{\varrho\varphi} * \varrho_\iota\right) + \left(\varsigma_{v\varphi} J * v_{\iota-1}\right) + \left(\varsigma_{v\varphi} * v_{\iota-1}\right) + \kappa_\varphi\right] \tag{4}$$

$$\sigma_\iota = \varphi_\iota tanh(\sigma_\iota) \tag{5}$$

Where ζ_ι is the input gate, ϱ is the input vector, φ is the output gate, v_ι is the output, and η_ι is the forgetting function. γ_ι is expressed as cell state, γ, and K are bias and weight, correspondingly.

The usage of Bi-LSTM as a supplement to classical LSTM enhances classifier accuracy.

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Both LSTMs are trained with the input dataset. Both sets of input datasets were trained with the original and reversed input datasets. This makes the network more effective, and the outcomes are quickly attained. It is quite straightforward to understand how the BiLSTM works. It is necessary to create a duplicate recurrent layer in the network, transmitting the input dataset from the original layer to the duplicate layer in reverse order before returning to the original layer. In traditional RNNs, there is a gradient vanishing problem due to these concepts.

The BiLSTM is trained by the present and past datasets. BiLSTM is trained using backward and forward shifts of the input dataset (from left to right and from right to left). Python's Keras library implements BiLSTM as a bidirectional layer wrapper that accepts an LSTM layer as an input. The integrated forward and backward output could be transmitted to the following layer by specifying the fusion mode. It is emerging from the forward HL $\overrightarrow{\lambda_\tau}$ and the backward HL $\overleftarrow{\lambda_\tau}$ is given below:

$$\overrightarrow{\Sigma_\imath} = L\left(\varsigma_\varrho \vec{l}\varrho_\iota + \varsigma_{\vec{l}\vec{l}} \vec{l}_{\iota-1} + \kappa_{\vec{l}}\right) \quad (6)$$

$$\overleftarrow{\Sigma_\iota} = L\left(\varsigma_\varrho \overleftarrow{l}\varrho_\iota + \varsigma_{\overleftarrow{l}\overleftarrow{l}} \overleftarrow{l}_{\iota-1} + \kappa_{\overleftarrow{l}}\right) \quad (7)$$

$$z_i = \varsigma_{\vec{l}_z} \vec{l}_\iota + \varsigma_{\vec{l}_z} \vec{l}_\iota + \kappa_z \quad (8)$$

Where l denotes the HL, and the matrices of input weights, σ and the vectors of the hidden weight bias for both directions. Both vectors are represented as $\kappa(\kappa_{\vec{l}}$ and $\kappa_{\overleftarrow{l}})$. Figure 2 describes the infrastructure of BiLSTM.

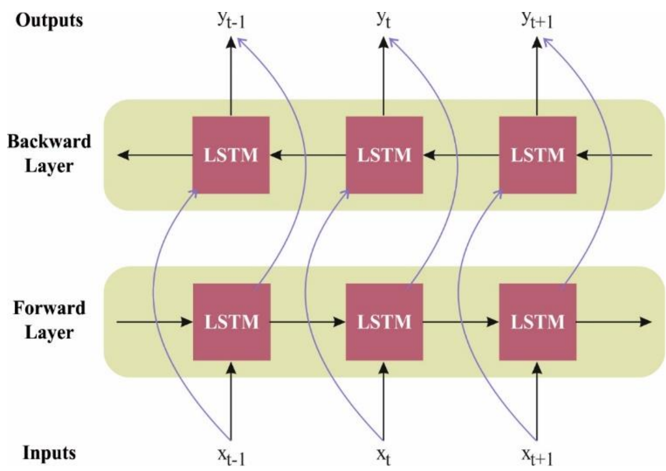

Figure 2. Structure of BiLSTM

ii, GRU Model

The GRU model is also utilized in combination with BiLSTM for the classification of the product reviews [21]. For an assumed state h_{t-1} at the preceding moment and input X_t of the present nodes, the dual gates state is computed as per the Eqs. (9) and (10), while r_t represents the reset gate and z_t refers to the present update gate state:

$$z_t = \sigma(W_z \cdot [h_{t-1'} x_t] + b_z) \quad (9)$$

$$r_t = \sigma(W_r \cdot [h_{t-1'} x_t] + b_r) \quad (10)$$

After attaining the gate signal, they initially utilize the reset gate for obtaining the reset data and later join it with an input signal X_t and lastly, transform the data to an interval of $(-1,1)$ over the activation function $tanh$ to get the $\tilde{h}_t$; Eq. (11) is expressed below:

$$\tilde{h}_t = tanh(W \cdot [r_t * h_{t-1}, x_t] + b) \quad (11)$$

Lastly, the component is upgraded utilizing the gate of update, as exposed in Eq. (12) below:

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$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (12)$$

D. Hyper parameter Tuning Process

Eventually, the AOA is implemented for the hyper parameter tuning process [22-24]. Hashim et al developed AOA a physics-inspired approach, especially Archimedes' law that is a member of the metaheuristics class. The solution is encoded in the way the uniqueness of this algorithm is found that involves three basic auditory signals: volume (V), density (D), and acceleration (Γ). Consequently, a randomly produced number of the initial agent's group in Dim dimension. Then, all the items are estimated to define which is the finest (O_{best}).

In the AOA procedure, updates to volume and density change the acceleration depending upon concept of the collision among objects.

Initialization: the position of object is initialized using:

$$O_i = lb_i + rand \times (ub_i - lb_i); i = 1,2, \dots, N \quad (13)$$

In Eq. (13), O_i denotes the i^{th} object amongst N total objects. ub_i, and lb_i are the upper and lower boundaries of the search range correspondingly.

The volume (vol) and density (den) for i^{th} objects are shown below:

$$den_i = rand$$

$$vol_i = rand \quad (14)$$

Then, the acceleration (acc) of the i^{th} object can be initialized by the Eq. (15), where $rand$ is a D-dimensional vector that generates a random value within [0,1].

$$acc_i = lb_i + rand \times (ub_i - lb) \quad (15)$$

The initial population is evaluated and objects with the optimum fitness values are selected in this stage. $x_{best}, den_{best}, vol_{best}$, and acc_{best} must be allocated.

Update density and volume: The volume and density of i^{th} objects for the $t + 1$ iteration are adapted as follows:

$$den_i^{t+1} = den_i^t + rand \times (den_{best} - den_i^t)$$

$$vol_i^{t+1} = vol_i^t + rand \times (vol_{best} - vol_i^t) \quad (16)$$

In Eq. (16), $rand$ is a uniformly distributed random integer and vol_{best} and den_{best} are the volume and density related to the better item?

The density scalar and transfer coefficient: object collides with each other until equilibrium is obtained. Shifting from exploration to exploitation is the main objective of the transfer function (T_c) based on Eq. (17):

$$T_c = \exp\left(\frac{t - T}{T}\right) \quad (17)$$

T and t are the maximum and existing iteration counters, and T_c exponentially grows over time until it reaches 1. Furthermore, the reduction in density scalar d_s in AOA is based on Eq. (18) to search for the optimum solution:

$$d_s^{t+1} = \exp\left(\frac{t - T}{T}\right) - \left(\frac{t}{T}\right) \quad (18)$$

Exploration stage: random selection of material (Mr) is used to bring agents into contact with each other. If the transfer function values are lesser than or equivalent to 0.5, then the acceleration object can be updated as follows:

$$\Gamma_i^{t+1} = \frac{D_{Mr} + V_{Best} \times \Gamma_{Best}}{D_i^{t+1} \times V_i^{t+1}} \quad (19)$$

Exploitation stage: This stage does not lead to agent collision. It is used for updating the acceleration object once the transfer coefficient values are higher than 0.5.

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$$\Gamma_i^{t+1} = \frac{D_{Best} + V_{Best} \times \Gamma_{Best}}{D_i^{t+1} \times V_i^{t+1}} \quad (20)$$

In Eq. (20), Γ_{Best} denotes the acceleration of the optimal object O_{Best}.

Normalization of acceleration: here, the acceleration is normalized to define the rate of change as follows:

$$\Gamma_{i-norm}^{t+1} = \alpha \times \frac{\Gamma_i^{t+1} - \Gamma^{\text{Min}}}{\Gamma^{\text{Max}} - \Gamma^{\text{Min}}} + \beta \quad (21)$$

In Eq. (21), α and β are constants of 0.9 and 0.1, correspondingly. Γ_{i-norm}^{t+1} determines the step percentage that all the agents will change. The high values of acceleration imply that the object understands the exploration operation; otherwise, the exploitation is active.

Update process: If $T_c \leq 0.5$ then exploration phase takes place which updates the location of j^{th} objects at $t+1$ iteration using Eq. (22), If $T_c > 0.5$, then exploitation phase takes place which updates the position of the object using Eq. (23).

$$O_i^{t+1} = O_i^t + c_1 \times r_5 \times \Gamma_{i-norm}^{t+1} \times d_s \times (O_{rand} - O_i^t) \quad (22)$$

Where c_1 is equal to 2.

$$O_i^{t+1} = O_{Best}^t + F \times c_2 \times r_6 \times \Gamma_{i-norm}^{t+1} \times d_s \times (\delta \times O_{Best} - O_i^t) \quad (23)$$

Where c_2 equals 6.

δ is a parameter positively related to time and proportionally related to the transfer coefficient T_c, viz., $\delta = 2 \times T_c$. The objective is to preserve a good balance between exploitation and exploration operations. The margin between the superior object and the other objects are greater in the initial iteration, which results in a higher random walking. But at the last iteration, the margin is reduced and provides a lower random walking.

F represents flagging which defines the search direction:

$$F = \begin{cases} +1 & if P \leq 0.5 \\ -1 & if P \geq 0.5 \end{cases} \quad (24)$$

where $P = 2 \times \text{rand} - C_4$.

Evaluation: the score index Sc is used for assessing the new population and other data including D_{Best}, V_{Best}, and Γ_{Best} for identifying the better object.

The AOA offers a fitness function for achieving a better performance of classification. It defines a positive number for representing the enhanced performance from the candidate results. In the proposed work, the reduction of the error rate classification is measured for the fitness function, as described in Eq. (25).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no.of\ misclassified\ instances}{Total\ no.of\ instances} * 100 \quad (25)$$

4. Results and Discussion

The simulation analysis of the FAIDLM-PREC model can be tested using Amazon product reviews dataset [25]. The dataset has 500 samples under 5 class labels as represented in Table 1. Table 2 shows rating samples.

Table 1: Details on Dataset

Class	No. of Samples
Rating-1	100
Rating-2	100
Rating-3	100
Rating-4	100
Rating-5	100
Total Samples	500

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Table 2: Sample of ratings

Score (Ratings)	Summary
1	Not as Advertised
2	Poor taste
3	Better price for this at Target
4	Delight says it all
5	Good Quality Dog Food

Figure 3 determines the classifier results of the FAIDLM-PREC technique under the test database. Figs. 3a-3b depicts the confusion matrices presented by the FAIDLM-PREC approach under 70:30 of TRAP/TESP. This outcome indicated that the FAIDLM-PREC techniques have classified and recognized every class label precisely. Similarly, Fig. 3c authenticates the analysis of PR in the FAIDLM-PREC approach. This result indicated that the FAIDLM-PREC method has obtained better PR performance under each class label. Finally, Fig. 3d displays the ROC examination of the FAIDLM-PREC technique. These results represented that the FAIDLM-PREC techniques have resulted in efficient results with maximal ROC values under dissimilar classes.

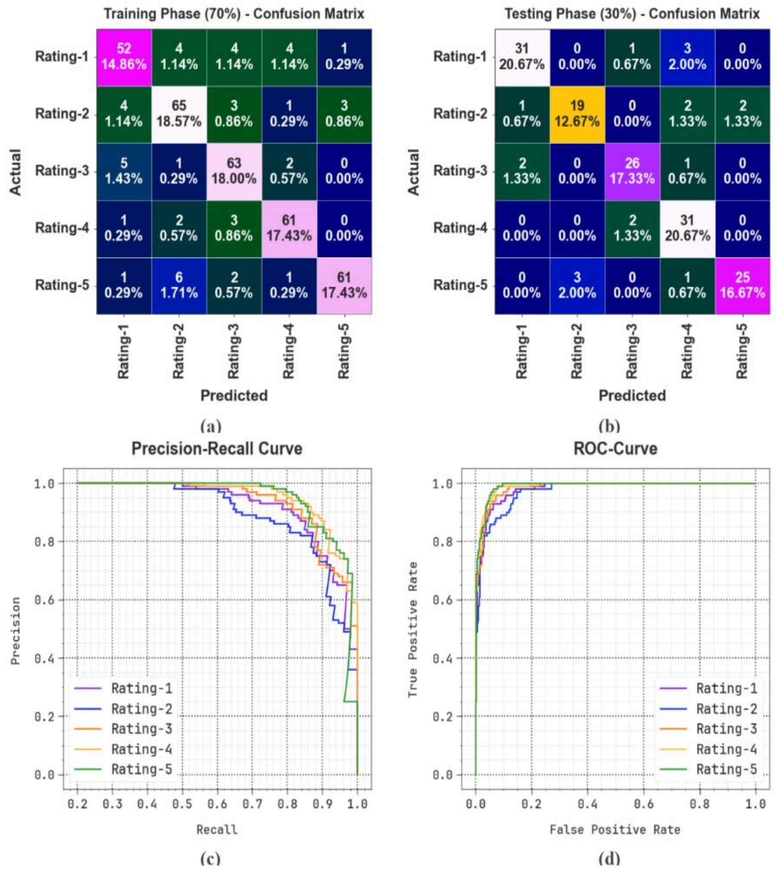

Figure 3. Classifier outcome of (a-b) 70%TRAP and 30%TESP confusion matrices and (c-d) PR and ROC curves

Table 3 illustrates the product reviews investigation of the FAIDLM-PREC system under 70%TRAP and 30%TESP. In Fig. 4, the average outcomes provided by the FAIDLM-PREC method on 70% of TRAP are emphasized. The outcomes showed that the FAIDLM-PREC system has correctly recognized the samples. On 70%TRAP, the FAIDLM-PREC approach gains average $accu_y$ of 94.51%, $prec_n$ of 86.42%, $reca_l$ of 86.24%, F_{score} of 86.28% and $G_{Measure}$ of 86.31%.

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In Figure 5, the average outcomes presented by the FAIDLM-PREC method on 30% of TESP are underscored. The outcomes demonstrated that the FAIDLM-PREC technique has appropriately recognized the instances. On 30%TESP, the FAIDLM-PREC approach obtains average $accu_y$ of 95.20%, $prec_n$ of 88.27%, $reca_l$ of 87.51%, F_{score} of 87.75% and $G_{Measure}$ of 87.82%.

Table 3: Product reviews analysis of FAIDLM-PREC technique under 70%TRAP and 30%TESP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$G_{Measure}$
TRAP (70%)					
Rating-1	93.14	82.54	80.00	81.25	81.26
Rating-2	93.14	83.33	85.53	84.42	84.42
Rating-3	94.29	84.00	88.73	86.30	86.33
Rating-4	96.00	88.41	91.04	89.71	89.72
Rating-5	96.00	93.85	85.92	89.71	89.79
Average	94.51	86.42	86.24	86.28	86.31
TESP (30%)					
Rating-1	95.33	91.18	88.57	89.86	89.86
Rating-2	94.67	86.36	79.17	82.61	82.69
Rating-3	96.00	89.66	89.66	89.66	89.66
Rating-4	94.00	81.58	93.94	87.32	87.54
Rating-5	96.00	92.59	86.21	89.29	89.34
Average	95.20	88.27	87.51	87.75	87.82

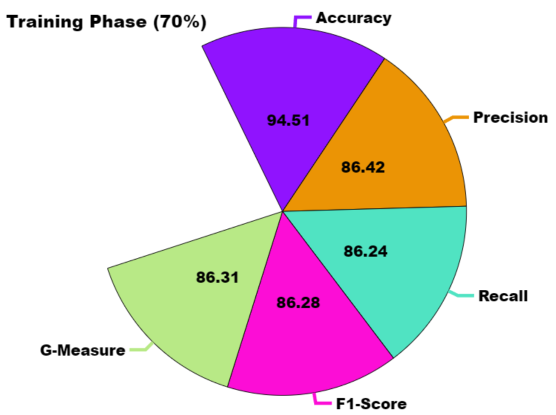

Figure 4. Average of FAIDLM-PREC technique under 70%TRAP

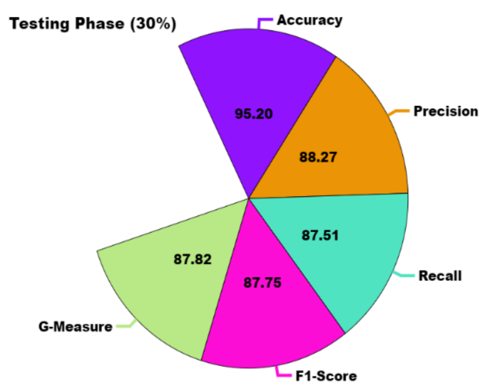

Figure 5. Average of FAIDLM-PREC technique under 30%TESP

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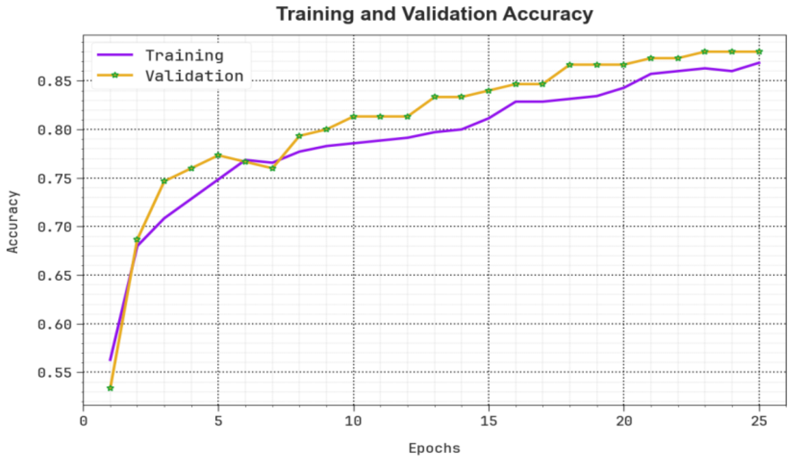

Figure 6. $Accu_y$ Curve of FAIDLM-PREC technique

In Fig. 6, the training and validation accuracy outcomes of the FAIDLM-PREC system are displayed. The precision values are computed throughout 0-25 epoch counts. This figure underlined that the training and validation accuracy values show an increasing trend that informed the capacity of the FAIDLM-PREC approach with enhanced performance over numerous iterations. Furthermore, the training accuracy and validation accuracy remain nearer over the epoch counts that reported the least minimum overfitting and displayed better performance of the FAIDLM-PREC methods, assuring continuous prediction on hidden samples.

In Figure 7, the training and validation loss graph of the FAIDLM-PREC system is demonstrated. The loss values are calculated for 0-25 epoch counts. It is portrayed that the training and validation accuracy values described a lowering trend, reporting the ability of the FAIDLM-PREC technique to balance a trade-off between generalization and data fitting. The consistent decrease in loss values also assurances the superior performance of the FAIDLM-PREC approach and tuning of the prediction outcomes in time.

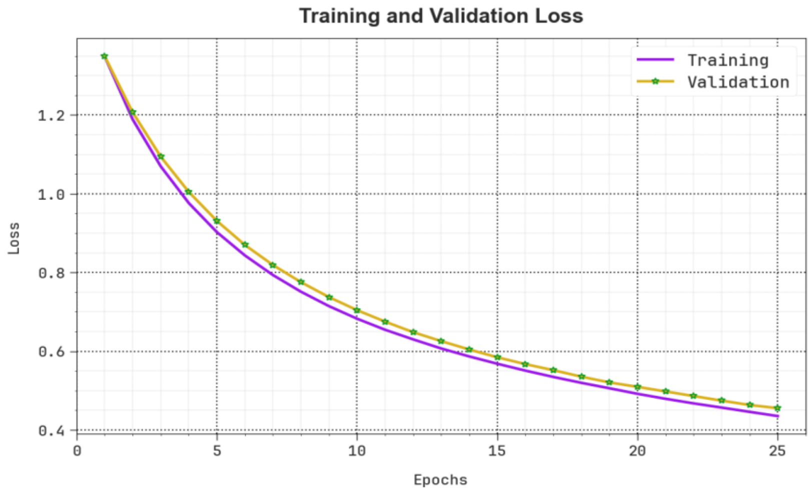

Figure 7. Loss curve of FAIDLM-PREC technique

The comparison study of FAIDLM-PREC system with recent techniques is depicted in Table 4 and Figure 8 [18, 27]. The experimental results portrayed that the FAIDLM-PREC approach exceeds superior performances. Depend upon $accu_y$, the FAIDLM-PREC model has greater $accu_y$ of 95.20% whereas the RoBERTa, TextCNN, MNB, RF, DT, BiLSTM, and LR techniques have lower $accu_y$ of 93.62%, 93.49%, 90.84%, 83.80%, 84.20%, 85.40%, and 78.90%, correspondingly. Also, depending on F_{score}, the FAIDLM-PREC system has superior F_{score} of 87.75% but the MNB, DT, RoBERTa, RF, BiLSTM, LR, and TextCNN methods take lesserF_{score} of 85.75%, 86.97%, 79.64%, 81.70%, 82.70%, 83.70%, and 78.40%, accordingly. In the end, based on $prec_n$, the FAIDLM-PREC techniques have maximum $prec_n$ of 88.27% through the LR, TextCNN, RoBERTa, BiLSTM, DT, MNB, and RF models have the least $prec_n$ of 78.63%, 85.64%, 79.69%, 80.80%, 81.20%, 82.90%, and 78.00%, appropriately.

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Table 4: Comparative analysis of FAIDLM-PREC technique with other models

Methodology	$Accu_y$	F_{score}	$Prec_n$	$Reca_l$
FAIDLM-PREC	95.20	87.75	88.27	87.51
TextCNN Classifier	93.62	85.75	78.63	78.78
BiLSTM Model	93.49	86.97	85.64	79.98
RoBERTa	90.84	79.64	79.69	80.21
MNB Algorithm	83.80	81.70	80.80	83.80
Random Forest	84.20	82.70	81.20	84.20
Logistic Regression	85.40	83.70	82.90	85.40
Decision Tree	78.90	78.40	78.00	78.90

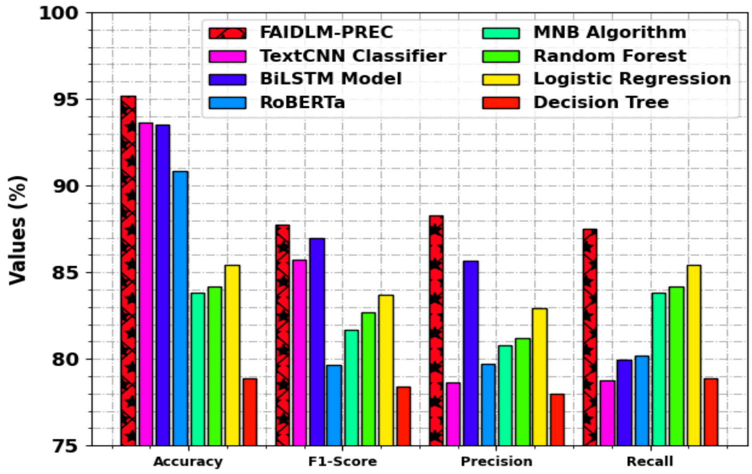

Figure 8. Comparative analysis of FAIDLM-PREC technique with other models

5. Conclusion

In this research, we have presented a FAIDLM-PREC model. The main intention of FAIDLM-PREC method is to appropriately distinguish the dissimilar types of sentiments occur in the e-commerce reviews. Initially, data pre-processing is executed to increase the product reviews quality with Glove based word embedding method. For product reviews classification, the FAIDLM-PREC approach evolves fusion of dual DL methods namely Bi-LSTM and GRU methods. Eventually, the parameters relevant to the two DL methods are perfectly modified utilizing the AOA. An extensive experiment of the FAIDLM-PREC technique was conducted utilizing customer review database and outcomes indicated that the FAIDLM-PREC technique highlighted betterment over other recent methods in several measures.

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