Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 32s (2025)
https://www.jneonatalsurg.com

Sentiment Analysis Of E-Commerce Product Reviews Using An Attnetion Based Deep Learning Model

Sathya.P[1], Anuratha.V[2], Elamparithi.M[3]

[1]Research Scholar, Department of Computer Science, Kamalam College of Arts and Science, Anthiyur, Affiliated to Bharathiar University, Coimbatore, Tamil Nadu, India,

Email ID: sathyakamalraj1234@gmail.com

[2]Associate Professor ,Department of Computer Science, Kamalam College of Arts and Science, Anthiyur, Affiliated to Bharathiar University, Coimbatore, Tamil Nadu, India,

Email ID: profanuratha@gmail.com

[3]Associate Professor ,Department of Computer Science, Kamalam College of Arts and Science,Anthiyur, Affiliated to Bharathiar University, Coimbatore, Tamil Nadu, India,

Email ID: profelamparithi@gmail.com

.Cite this paper as: Sathya.P, Anuratha.V, Elamparithi.M, (2025) Sentiment Analysis Of E-Commerce Product Reviews Using An Attnetion Based Deep Learning Model. *Journal of Neonatal Surgery*, 14 (32s), 1507-1515.

ABSTRACT

Mawkishness study of a big amount of operator appraisals on e-commerce podiums can efficiently advance user consummation. Numerous methods have been future to get understandings from these statistics. Here are still tests in dealing with the text of huge size; precise sen5timent analysis of E-commerce product appraisals is an ongoing and thrilling problematic. This paper suggests a sentimentality analysis of E-commerce creation reviews by by novel deep knowledge model. The proposed system mainly involves three phase such as data preprocessing, word embedding, and sentiment classification. To begin, the collected data from Amazon review 2018 dataset is preprocessed to improve the quality of data. After that, the word embedding is performed by using Period Occurrence Converse Text Incidence and Glove methods. Finally, the sentiment classification is done by hybrid Residual Network 50-Gated Recurrent Unit with Self attention (HRN50-GRUSA) that classifies the review as positive or negative. The experiential fallouts designate that the future cross profound education with courtesy construction outdoes the conservative approaches in footings of correctness, drumming, memory, and damage metrics.

Keywords: *Sentiment Analysis, E-commerce product reviews, Amazon dataset, Deep Learning (DL), Data Preprocessing, Word Embedding, and Sentiment Classification.*

1. INTRODUCTION

These days, due to advancements in science and information technology, the world is known as a global village. Over half of the worldwide population is using social media. Social media is not only used for fun and entertainment purposes but also they use it for information, Marketing, and other online activities etc. So, this is a digital world, and we hugely rely on it because of information technology. This reliance generates a greater amount of statistics in terms of chirps, poles, and client reviews made for different crops [1]. Sentiment analysis, a task to assign sentiment labels that reflect the viewpoint of people from text against given topics called views, is useful in obtaining insights into public sentiments across different domains like business, government and biomedicine as well [2], With the potential use of wide amount of E-commerce data available. Now, sentiment analysis offers an opportunity for organizations to determine the perception of customers in this worldwide marketplace towards their products and services. Negative sentences or negation use really affect the detection of sentiment polarity. Misclassification of sentiment and the emergence of biases due to inappropriate processing bert-based [3] In this regard, sentiment analysis uses lexica-based and natural language processing (NLP) approaches for opinion extraction from text, polarity classification, agreement detection, subjectivity-objectivity detection [4, 5] Such approaches include lexical affinity, and keyword spotting, which are the various lexicon-based approaches of sentiment analysis [6].

This theme has paying courtesy substantial quantity of courtesy as some investigation identifications absorbed on this focus and countless diverse tactics have stood planned to study on paper verbal. But, the gush investigation turf is mounting knowingly, and its devices are immobile embryonic [7]. From that, NLP is typically used locomotive facts means to appreciate, observe, and improvement in-depth denotation from a hominid philological with aptitude [8]. The commonly used ML algorithms are Immature Bayes, Sustenance Course Engine, Accidental Woodland, Result Bush, Logistic Deterioration, K-Nearest national (KNN), and etc. [9, 10]. These ML-based methods provide satisfactory classification results, but they require lots of labeled data. Unfathomable education is a sub-branch of engine education that customs profound neural grids. Newly, DL systems must remained broadly useful for mawkishness examination. The key lead of DL is that it is able to recall the arrangement of historical data i.e. disputes in our instance in direction to make an precise choice on the sentimentality. This is driven to recommend a fresh DL tactic with consideration apparatus for mawkishness investigation of E-commerce artifact estimations. The key objectives of the paper are structured as follows:

- The system proposes a TF-IDF and GloVe to characterize the transcript statement S as a biased expression course medium.
- Educating the accurateness by emergent a hybrid profound education classical uniting the RN50 and GRU models with self-attention for the produce connected mawkishness cataloging, in which the self-attention extracts deeper features to improve the classification rate with less loss.

The rest of the weekly is deliberate as shadows: Unit 2 presents the prose surveys linked to our effort. Section 3 gives the future practice. Section 4 examines the presentation of the future work and finally section 5 concludes the future work with future research.

2. RELATED WORK

This piece surveys the recently published work related to the proposed methodology. **Huiliang Zhao *et al.* [11]** recommended a Indigenous Exploration Unplanned Paddle Procedure based Elman Neural System grounded mawkishness study of scheduled invention appraisals with a new time allowance (TW) and feature medley (FS) tactic. Originally, the Net Struggling Instrument was used to excerpt the client appraisals of the crops for which the statistics was met as of the E-commerce websites. Next, preprocessing was carried out on the web scrap removed statistics. Those preprocessed data go finished TW and FS for added dispensation by incomes of Log Term Incidence founded Adapted Opposite Lesson Incidence and Cross Change founded Soil Sincere Process. Finally, the HM-EWA facts were reduced to the LSIBA-ENN, which secret the client appraisals' mawkishness as optimistic, negative, and unbiased. The scheme attained 87.79% memory for measure datasets than the present approaches. **Murat Demircan *et al.* [12]** developed Turkish sentimentality examination mockups founded on ML and e-commerce data. The system was initially collected data from hepsiburada.com. After that, the system was applied Total Vectorizer and Period Incidence to represents the text into vector form. Finally, the classification was performed based on SVM, RF, DT, LR, and KNN. From that, the SVM achieved maximum f1-score of 87, 0.77, and 0.94 for undesirable, impartial, and confident review.

M.P. Geetha and D. Karthika Renuka [13] introduced a perfected Bert base uncased classical to improve the performance of aspect based sentiment analysis. Initially, the product reviews was collected from the Amazon dataset. Next, the tokenization could be complete by isolating sequence of contribution manuscript statistics addicted to marks. Then, the feature extraction was done by Basket of words (BoW) and TF-IDF. Finally, the sentiment classification was done by Naïve Bayes (NB), SVM, long short term memory (LSTM), and bidirectional encoder representations from transformers (BERT). The experimental results showed that the system achieved 88.48% accuracy than the existing methods. **Gagandeep Kaur and Amit Sharma [14]** suggested a deep learning-based model based on hybrid feature extraction approach for consumer sentiment analysis. Next, the organization used a cross way encompassing appraisal connected landscapes and facet connected topographies to extract features. Finally, the mawkishness arrangement was did based on the profound erudition classifier LSTM. The system experimentally assessed the system based on three datasets such as SemEval-2014 cafeteria evaluations dataset, Sentiment 140, and STS-Gold datasets.

Naveen Kumar Gondhi *et al.* [15] presented an efficient LSTM-based sentiment analysis of E-commerce reviews. The dataset was generated from the Amazon review 2018 dataset with preprocessing. Word2vec embeddings represent a critical preprocessing step of the data. The Word2vec model was trained on the database. It was used to extract the feature vector, which would then be fed into the LSTM mode, serving as the embedding layer and classifying to get its sentiments. Results indicated that the accuracy achieved by the system was 89% higher than that of existing methods.

Although those surveys yield satisfying results, they have some drawbacks. Many authors show the efficiency of the employed ML models for classifying the product reviews as they fit ML models to classify the reviews M. However, the ML model does have some limitations. Because the reviews are becoming larger, the traditional ML models need help to grasp all the context of sentences or reviews fully. Deep learning technology addresses the limitations of the current machine learning-based sentiment analysis model of product reviews. Deep learning doesn't require human intervention features but rather requires extremely large data to help it out. It features different kinds of neural networks and pulls what is learned from its own mistakes. However, enhancement is still critical to deepening features from input. This paper aims to extract sentiment, context, and multi-deeper features to enhance the accuracy of the proposed work.

3. PROPOSED METHODOLOGY

The hunk figure of the complete procedure used for sentimentality uncovering in evaluations is shown in numeral 1. Three main ladders are occupied in instruction to sense mawkishness in E-commerce evaluations: 1. Statistics pre-processing, 2. Expression inserting, and 3. Mawkishness cataloging. The first step is used to preprocess the collected dataset by removal of hash tags and hyperlinks, lowercase conversion, stop word removal, lemmatization, and tokenization. The second step performs word embedding on the collected dataset by TF-IDF and GloVe. At last, the third step classifies the sentiment as positive or negative by HRN50-GRUSA model.

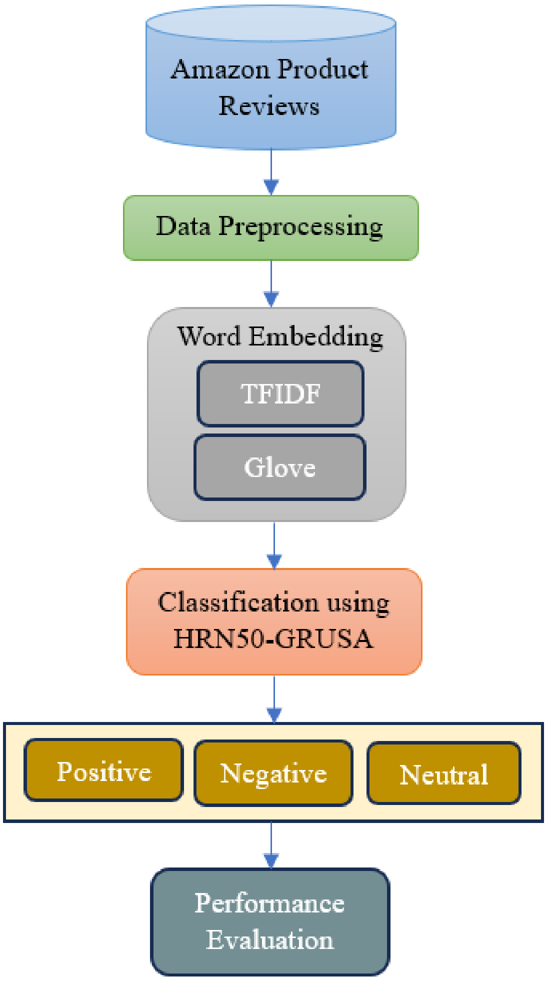

Figure 1: Workflow of the proposed methodology

3.1 Data Preprocessing

Firstly, the data was taken from the Amazon Review 2018 dataset, which is available publicly. Once all of that is done, the preprocessing eliminates any ambiguity or redundancy. In this regard, the proposed system performs some preprocessing steps (removal of hashtags and hyperlinks, lowercase conversion, stop word removal, lemmatization and tokenization) to get the data in the desired form. These are shortly described as follows:

i) **Removal of hyperlinks and hash tags:** Hyperlinks have lost their meaning in the acetate set. Hence, it is very important to remove the associations from the datasets. Another trending highlight is hashtagging. It is a common practice to hashtag consumer reviews. Hashtags occupy a considerable amount of memory. All hashtags are removed from the resulting datasets, and training data is cleaner with no keyword noise.

ii) **Lowercase conversion:** It needs renovating complete disputes of the assessment manuscript into lowercase arguments.

iii) **Stop word removal:** Stopwords are broadly used disagreements in a verbal, such as "the," "a," "an," "is," and "are". As these disagreements do not transport any gen noteworthy for the classical, they stood uninvolved since the happy of the appraisal.

iv) **Lemmatization:** The course of federation associated name methods that are since the meticulous disagreements is identified as Lemmatization, and with Lemmatization, we investigate folks disputes as a lone word.

v) **Tokenization:** Tokenization is when separate sequences of input text data are dispersed into tokens. A token can be a single word, keywords, digits or punctuation. To increase the precision of the analysis, punctuation and special characters in the input data are dropped during tokenization as they do not seem to be paid attention to.

Thus, the preprocessed data were input into the word embedding layer as

$$WE = we_1, we_2, we_3, \ldots\ldots we_k \tag{1}$$

Where we_k indicates a word in statement WE.

3.2 Word Embedding

Once preprocessing was completed on the collected dataset, then word embedding is performed in this phase. Name implanting is a symbol method of a manuscript that can change a text into courses of telling image. Here, the proposed system uses a combination of two-word embeddings practices such as TF-IDF and GloVe as input to the classification model.

- **Term Frequency-Inverse Document Frequency**

TF-IDF is a rudimentary period used for changing the tweet text data into figures before smearing any organization model. It follows two ways: first, TF, which is the total term amount entrance in a article; the subsequent process is IDF that denotes to the whole relations existences in the document. The bulk is based on the product of TF and IDF to portion the importance and how the term is central in a given article. It is mathematically given as follows:

$$\underline{TF}(T,D) = \frac{a_T}{a} \tag{2}$$

$$\underline{IDF}(D) = \frac{A_D}{A} \tag{3}$$

$$\underline{TF} - \underline{IDF}\,(T,D) = \underline{TF}(T,D) \times \underline{IDF}(D) \tag{4}$$

Where, T refers to the period with incidence a, D characterizes the article, and A refers to files' frequency, D, comprising the tenure, T.

- **Glove**

Worldwide Courses is extra general word implanting procedure. In the Glove expression inserting process, the proposed system has three steps to harvest term paths for both article's detailed term. First, a terminology role will hoard and estimate each everyday word short of retelling. Next, the word-to-word co-occurrence system will form a atmosphere for determining the occurrence of in the whole kit and entirety of each pair of difference of opinion and scatter a mass to it and store into medium, the medium quantity is identical to the sum of all different words appear in the dataset. Finally, the GloVe train the dataset with the matrix of cooccurrences of disagreements to make a word trajectory for each word that comprises the occurrences heft for every happening with other arguments and they will be stowed in a file or inside reminiscence ram to be treated in the next actions. Final course form of the GloVe is expressed as follows:

$$\ddot{G}\ddot{V} = Glove(WE) \tag{5}$$

Finally, weigh the word vectors using sentiment weight as shown in equation (6).

$$\underline{FE_v} = \underline{TF} - \underline{IDF}\,(T,D) \times \ddot{G}\ddot{V} \tag{6}$$

Where, $\ddot{G}\ddot{V}$ indicates s a word vector matrix obtained by Glove, $\underline{TF} - \underline{IDF}\,(T,D)$ refers the TF-IDF weighing of document D and term T, and $\underline{FE_v}$ signifies the biased expression path atmosphere, which is the production of the entrenched layer.

3.3 Sentiment Classification

Finally, the sentiment classification is done in this step from the embedded word. In this work, the proposed system uses a hybrid Residual Network 50-Gated Recurrent Unit with Self attention (HRN50-GRUSA) to cutting the key gush landscapes and situation landscapes in the assessments and copiously allied film pigeonholes the mawkishness. ResNet50 (RN50) is a different of the ResNet classical, which has 50 coatings, which entail of 48 convolutional coats, one pass with flying colors Lake Coat, and one regular combining coating. It efficiently extracts the sentiment features in embedded word. Also, the GRU is used to excerpt the situation geographies in the sequence of data. When extracting these sentiment features and context features, it didn't take any deep features, so the performance of the classification is affected only by concentrating on the sentiment and context features. So the Self-attention mechanism is included in the hybrid RN50 and GRU to extract the deeper features. These improvisations included in the proposed work are called as HRN50-GRUSA. The classical entails of six layers: an fixed layer, a convolutional coat, a mutual coating, a GRU coating, an care coat, and a entirely associated deposit. The perfect assembly is shown in Figure 2.

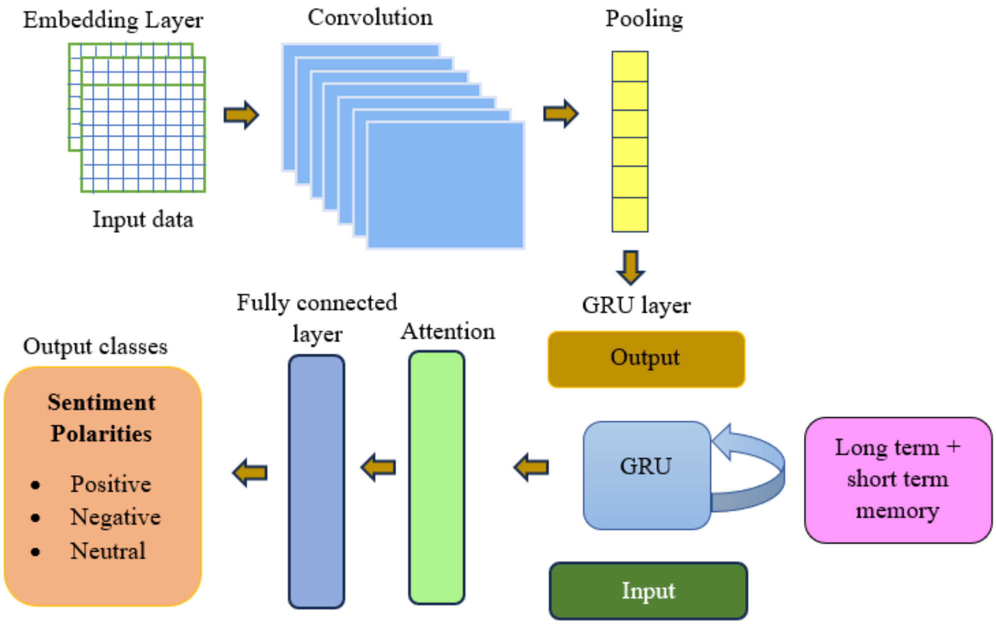

Figure 2: Structure of HRN50-GRUSA

i) Embedding layer

This is the chief coating of the HRN50-GRUSA perfect that is secondhand to alter every term in the isometrics dataset into an real respected trajectory by cross TF-IDF-GloVe. The output from the TF-IDF-GloVe that is shown in equation (6) is fed into the convolutional layer.

ii) Convolutional layer

The RN50' convolutional coat takings the input from the embedded layer. Its purpose is to retrieve the record momentous local nose from the say atmosphere. In NLP, the word vector representation of a word is generally an integer number. As a result, the specific example kernel expanse in the convolutional layer typically adapts the perimeter of the word vector and thus with "1x1, 64, step 2" denotes that the length of input kernel is 1 ×1, number out of articles maps is 64 shapes so size workspace momentum for firm output. It is literally pronounced like tracks:

$$\overrightarrow{CL} = \eta^{*}\left(\ddot{W} \,.\, \underline{FE}_{v} + \ddot{B}\right) \qquad (7)$$

Where, $\overrightarrow{CL}$ indicates the output features of the convolutional layer, $\underline{FE}_{v}$ refers the input embedded vector, $\ddot{W}$ and $\ddot{B}$ refers the weight and bias value, and η^{*} signifies the ReLU beginning meaning. A cured line element is an initiation meaning that announces the stuff of nonlinearity to a RN50 and cracks the waning slopes matter. If the meaning accepts any undesirable effort, it earnings 0; but, if the meaning accepts any confident price $\underline{FE}_{v}$, it revenues that price. As a effect, the yield has a choice of 0 to countless. It is precisely totaled as follows:

$$\eta^* = \max\left(0, \underline{FE}_v\right) \quad (8)$$

iii) Pooling layer

The chief persistence of this coating is to down-sample the typescript topographies that we got from the convolutional coating and cutting noticeable topographies. Assembling actions are normally considered hooked on normal assembling and be very effective pooling. In the case of text gush analysis, max pooling is used in this system since, typically, only one or two words play an important role in crucial the sentimentality of a ruling. It takings the supreme complete landscapes of the lake from every filter grain. It has elected two 2-sized strides.

iv) GRU layer

Outputs of the pooling layer, which are feature maps fed to the Gated Recurrent Unit (GRU) layer. The memory requirement is less than that of LSTM and other DL calculations; additionally, GRU calculation is easier, which makes it perform faster calculations. GRU systems course successive data, like time sequences or normal linguistic, resounding the veiled state since the existing time step to the next one. The clandestine national is a path brief the past of what has been seen throughout past while ladders that are applicable to the existing period phase. The apprise gate is the grouping of the overlook gate + input gate. It is also mutual with the cell state and unseen national. The second model is less complex than a traditional LSTM model and a super popular form of the short-term that it uses. The mathematical formulations of GRU are expressed as follows:

$$\ddot{R}\ddot{G}_\tau = \eta^* \left(\ddot{W}_{\ddot{R}\ddot{G}}\, \ddot{E}_\tau + \ddot{X}_{\ddot{R}\ddot{G}}\, \ddot{H}_{\tau-1}\right) \quad (9)$$

$$\ddot{U}\ddot{G}_\tau = \eta^* \left(\ddot{W}_{\ddot{U}\ddot{G}}\, \ddot{E}_\tau + \ddot{X}_{\ddot{U}\ddot{G}}\, \ddot{H}_{\tau-1}\right) \quad (10)$$

$$\overline{\ddot{H}}_\tau = \eta^* \left(\ddot{W}_{\ddot{H}}\, \ddot{E}_\tau + \ddot{X}\left(\ddot{R}\ddot{G}_\tau \,\Theta\, \ddot{H}_{\tau-1}\right)\right) \quad (11)$$

$$\ddot{H}_\tau = \left(1 - \ddot{U}\ddot{G}_\tau\right)\ddot{H}_{\tau-1} + \ddot{U}\ddot{G}_\tau\, \overline{\ddot{H}}_\tau \quad (12)$$

In this above equations, $\ddot{E}$ refers the input vector at time step τ, $\ddot{R}\ddot{G}$ and $\ddot{U}\ddot{G}$ refers the reset gate and update gate, $\ddot{W}$ and $\ddot{X}$ indicates the weight matrices, Θ denotes the element wise product, η^* signifies the ReLU activation function, which is computed using equation (8), $\overline{\ddot{H}}$ denotes the candidate output, and $\ddot{H}$ indicates the output feature vector (context feature vector).

v) An Self-attention layer

After leveraging both sentiment features and context features fusing RN50 layer and GRU layer from the input embedded vector, the proposed system uses self-attention layer to the deep feature on the GRU-generated features. Once the effort mouth chart go in the self-attention component, it will pass finished three difficulty seeds with a size of 1 × 1 to make diverse profounder ear atlases. It routines the Softmax meaning to attain the self-attention hefts of unlike networks in the fusion nose map. Precisely, the self-attention is really a plotting meaning composed of Query $\left(\widehat{q}\right)$, Key $\left(\widehat{k}\right)$, and Value $\left(\widehat{v}\right)$ in the feature map and extracts higher quality feature map. Initially the Query is combined with each Key to calculate the attention weight. It is expressed as follows:

$$f\left(\widehat{q}, \widehat{k}\right) = \widehat{k}^T\, \widehat{q} \quad (13)$$

Following, the softmax job is used to regulate the kindness heaviness gotten in equation (13), as shown in equation (14).

$$\hat{N}_w = soft\max\left(f\left(\widehat{q}, \widehat{k}\right)\right) \quad (14)$$

Where, $\hat{N}_w$ refers the normalized weight. The final attention deep feature vector $\left(\overrightarrow{AT}_o\right)$ is the weighted sum of normalized weights $\hat{N}_w$ and corresponding values, which is shown as follows:

$$\overrightarrow{AT}_o\left(\widehat{q}, \widehat{k}, \widehat{v}\right) = \Sigma\, \hat{N}_w\, \widehat{v} \quad (15)$$

vi) Fully connected layer

The completely allied dense film is used to convert the profounder geographies from consideration into high-level mawkishness picture to predict sentimentality. Herein, the softmax coating is used to classify the mawkishness. The sentimentality investigation chore can be slow as a second category task, the nose path $\left(\overrightarrow{AT}_o\right)$ from the consideration layer is arranged into the sigmoid meaning, which can take a worth of any 0 or 1 as follows:

$$\overrightarrow{PS} = Sigmoid\left(\overrightarrow{AT}_o\right) \tag{16}$$

$$\tilde{O}_l = \begin{cases} 0, & \overrightarrow{PS} \in (0, 0.5) \\ 1, & otherwise \end{cases} \tag{17}$$

Herein, $\overrightarrow{PS}$ indicates the possibility that the review is a positive or negative, $\tilde{O}_l$ refers the classification result where $\tilde{O}_l = 0$ indicates that the review is positive and $\tilde{O}_l = 1$ indicates a negative review.

4. RESULTS AND DISCUSSION

In this section, the proposed work discusses the experiment design, dataset preparation, evaluation protocols, and results. The proposed work is implemented in the working platform of Python with machine configuration of Window10, Intel (R) Xeon (R) Gold 5218 CPU @ 2.30 GHz processor with a graphics card of GeForce RTX 3090.

4.1 Dataset Descriptions

To cause correct grades, the dataset rummage-sale must be huge and improved. The dataset has been composed from the cell handset and decorations piece operational of the Amazon Appraisals dataset (2018). This is because of the countless user reviews that can be observed. It is easily accessible through https://www.kaggle.com/datasets/rogate16/amazon-reviews-2018-full-dataset. This dataset contains full reviews from Amazon in 2018, consists of 500000+ reviews from 100000+ users. The columns are pretty much self-explanatory, such as username, item name, rating, review text, etc. These collected the dataset product reviews are divided into 70% training, 10% validation, and 20% testing datasets.

4.2 Performance Analysis of Word Embedding

To evaluate the effectiveness of the proposed HRN50-GRUSA model for sentiment analysis of E-commerce product reviews, the proposed system conducts the experiment against the some classical methods, namely, GRU, Persistent Neural Web, Convolutional Neural System, and Support Vector machine (SVM), respectively. In order to evaluate our model, we have used accuracy, precision, recall, and f-measure, and loss metrics. This analysis is shown as follows:

Table 1: Efficiency analysis of the proposed model

Word Embedding	Classifiers	Accuracy (%)	Precision (%)	Recall (%)
TF-IDF	Proposed	93.85	93.92	93.74
	GRU	91.12	91.23	91.08
	RNN	89.65	89.78	89.56
	CNN	86.23	86.36	86.19
	SVM	83.12	83.28	83.04
GloVe	Proposed	95.23	95.36	95.14
	GRU	93.65	93.54	93.74
	RNN	91.12	91.04	91.23
	CNN	88.56	88.48	88.65
	SVM	85.42	85.36	85.56
TF-IDF-GloVe	Proposed	98.89	98.97	98.75
	GRU	96.65	96.71	96.56

	RNN	94.35	94.46	94.26
	CNN	91.12	91.26	91.05
	SVM	88.74	88.69	88.63

Concerning, accuracy, precision together with recall, Table 1 illustrates the techniques' performance analysis for 3 disparate weighting schemes such as TF-IDF, GloVe, and TF-IDF-GloVe. The accuracy of existing GRU, RNN, CNN, and SVM are 96.75%, 94.65%, 91.12%, and 88.74% for the TF-IDF-GloVe scheme, while the proposed one scheme achieves 98.89% of accuracy, which is superior when analogized with the other schemes. Likewise, the highest accuracy values are achieved by the proposed one for TF-IDF and GloVe weighting scheme. Meanwhile consider the precision and recall metrics, the proposed one archives maximum precision and recall of 98.97% and 98.75% when combining the TF-IDF and GloVe weighting schemes the use the weighting scheme alone. Thus, it is evinced that the proposed system utilizing TF-IDF-GloVe weighting scheme proffers the finest precision outcomes. Figure 3 shows the outcomes of the proposed approach with existing methods in terms of loss metric. When using the TF-IDF and GloVe individually, the proposed one has 0.1869% and 0.0256% loss, but we used both methods for embedding the word and it has very less loss value of 0.0186% than the existing methods. Also, the proposed system uses RNet50 and GRU with a self-attention mechanism that extracts high-deeper features for classification. These efficient algorithms boost the performance of the proposed work. Thus the overall experimental results showed that the proposed work sufficiently better than the existing methods.

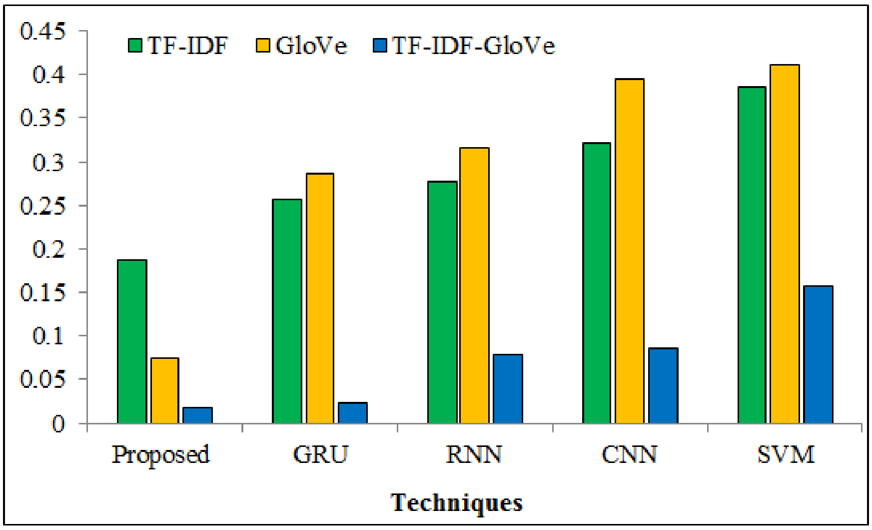

Figure 3: Loss analysis

5. CONCLUSION

In this paper, the wished-for classification proposes a novel DL approach with attention mechanism for sentiment analysis from the E-commerce product reviews. The proposed system mainly comprises '3' phases such as data preprocessing, word embedding, and sentiment classification. The performance of the proposed works is tested with the help of Amazon review 2018 dataset. In experimental analysis section, the outcomes of the proposed HRN50-GRUSA are investigated against the conventional GRU, RNN, CNN, and SVM methods for the weighting scheme of TF-IDF, GloVe, and TF-IDF-GloVe. The outcomes of the proposed work are validated based on accuracy, precision, recall, and loss metrics. Merging both the premium scheme of TF-IDF and Glove, the projected one accomplishes extreme exactness, meticulousness, and recall of 98.89%, 98.97%, and 98.75% with less loss of 0.0186%. Thus the untried fallouts exhibited that our prototypical was reasonable in all the level metrics and it evidences the worth of the organization.

REFERENCES

[1] Iqbal, A., Amin, R., Iqbal, J., Alroobaea, R., Binmahfoudh, A., & Hussain, M. (2022). Sentiment analysis of consumer reviews using deep learning. *Sustainability*, *14*(17), 10844.

[2] Dang, C. N., Moreno-García, M. N., & Prieta, F. D. L. (2021). An approach to integrating sentiment analysis into recommender systems. *Sensors*, *21*(16), 5666.

[3] Mukherjee, P., Badr, Y., Doppalapudi, S., Srinivasan, S. M., Sangwan, R. S., & Sharma, R. (2021). Effect of negation in sentences on sentiment analysis and polarity detection. *Procedia Computer Science*, *185*, 370-379.

[4] Deniz, E., Erbay, H., & Coşar, M. (2022). Multi-label classification of e-commerce customer reviews via machine learning. *Axioms*, *11*(9), 436.

[5] Ozyurt, B., & Akcayol, M. A. (2021). A new topic modeling-based approach for aspect extraction in aspect-based sentiment analysis: SS-LDA. *Expert Systems with Applications*, *168*, 114231.

[6] Kabir, M., Kabir, M. M. J., Xu, S., & Badhon, B. (2021). Empirical research on sentiment analysis using machine learning approaches. *International Journal of Computers and Applications*, *43*(10), 1011-1019.

[7] Marshan, A., Kansouzidou, G., & Ioannou, A. (2021). Sentiment analysis to support marketing decision making process: A hybrid model. In *Proceedings of the Future Technologies Conference (FTC) 2020, Volume 2* (pp. 614-626). Springer International Publishing.

[8] Salmony, M. Y. A., & Faridi, A. R. (2021, April). Supervised Sentiment Analysis on Amazon Product Reviews: A survey. In *2021 2nd International Conference on Intelligent Engineering and Management (ICIEM)* (pp. 132-138). IEEE.

[9] Sindhu, C., Rajkakati, D., & Shelukar, C. (2021). Context-Based Sentiment Analysis on Amazon Product Customer Feedback Data. In *Artificial Intelligence Techniques for Advanced Computing Applications: Proceedings of ICACT 2020* (pp. 515-527). Springer Singapore.

[10] Akter, M. T., Begum, M., & Mustafa, R. (2021, February). Bengali sentiment analysis of e-commerce product reviews using k-nearest neighbors. In *2021 International conference on information and communication technology for sustainable development (ICICT4SD)* (pp. 40-44). IEEE.

[11] Zhao, H., Liu, Z., Yao, X., & Yang, Q. (2021). A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach. *Information Processing & Management*, *58*(5), 102656.

[12] Demircan, M., Seller, A., Abut, F., & Akay, M. F. (2021). Developing Turkish sentiment analysis models using machine learning and e-commerce data. *International Journal of Cognitive Computing in Engineering*, *2*, 202-207.

[13] Geetha, M. P., & Renuka, D. K. (2021). Improving the performance of aspect-based sentiment analysis using fine-tuned Bert Base Uncased model. *International Journal of Intelligent Networks*, *2*, 64-69.

[14] Kaur, G., & Sharma, A. (2023). A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. *Journal of Big Data*, *10*(1), 5.

[15] Gondhi, N. K., Sharma, E., Alharbi, A. H., Verma, R., & Shah, M. A. (2022). Efficient long short-term memory-based sentiment analysis of e-commerce reviews. *Computational intelligence and neuroscience*, *2022*.