International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

REGULARIZED QUADRATIC DISCRIMINANT ANALYSIS BASED ELLIOT SYMMETRIC RECURSIVE DEEP STRUCTURE NEURAL LEARNING CLASSIFIER FOR SENTIMENT CLASSIFICATION

Dr.P.Suresh [1], G.Shumalatha [2]

[1]Associate Professor and HOD, Dept of Computer Science, Salem Sowdeswari College – Govt Aided, Salem, Tamilnadu

[2] Research Scholar, Bharathiar University, Coimbatore, Tamilnadu

Abstract

Sentiment analysis is the process of categorizing the opinions in the text to determine whether the attitude towards a particular product is positive, or negative. Due to a large number of reviews, sentiment analysis faces a several challenges to extract useful information from reviews. In order to improve the sentiment classification accuracy, Regularized quadratic discriminant Analysis based on Elliot Symmetric Recursive Deep Structure Neural Learning classifier (RQDA-ESRDSNLC) technique is introduced for identifying the positive and negative classification with higher accuracy. The RQDA-ESRDSNLC technique comprises four layers, namely one input layer, two hidden layers, and one output layer. In the RQDA-ESRDSNLC technique, the number of customer reviews is taken as an input and sent to the input layer. After that, the tokenization is performed in the hidden layer 1. In hidden layer 2, the stopwords are eliminated using Regularized quadratic discriminant Analysis for improving the classification accuracy in the sentiment analysis process. In the output layer, the Elliot Symmetric activation function is used to classify the customer reviews into positive and negative reviews for providing recommendations to the user for a particular item. This in turn helps to improve the classification accuracy and time complexity. Experimental evaluation is carried out on factors such as classification accuracy, error rate, time complexity, and space complexity with respect to a number of customer reviews. The results and discussion demonstrate that the proposed RQDA-ESRDSNLC technique increases the accuracy and minimizes the error as well as time complexity than the existing techniques.

Keywords: Sentiment analysis, Recursive Deep Structure Neural Learnt Sentiment Classification, Regularized quadratic discriminant Analysis, Elliot Symmetric activation function.

1. Introduction

Sentiment analysis or Opinion Mining refers to extracting and studying the user's emotional states from a given piece of information or text. Due to the large volume of information or reviews on social media platforms, sentiment analysis plays a vital role to find the user's feedback evaluation. Many existing machine learning and deep learning approaches have been developed for sentiment analysis.

A Global and Local Dependency Guided Graph Convolutional Networks (GL-GCN) was developed in [1] for aspect-based sentiment classification. The designed GL-GCN increases the accuracy but the performance of complexity during the sentiment classification was not minimized.

Sentiment Classification Method based on Attention Mechanism and the Bidirectional Long Short-Term Memory Network (SC-ABiLSTM) was developed in [2]. The developed method was more effective and efficient but the accuracy of sentiment classification using large-scale data was not improved.

An enhanced hybrid feature selection approach was introduced in [3] for sentiment classification by means of machine learning approaches. But it failed to apply the larger dataset for improving the efficiency and effectiveness.

The deep learning approach was designed in [4] based on weak tagging information to improve the classification performance. However, it failed to decrease the time complexity of the model while maintaining higher classification performance.

A Filter Gate Network based on Multi-head attention (FGNMH) network was developed in [5] for sentiment classification. However, the designed network failed to improve the performance of the model.

Local Search Improvised Bat Algorithm-based Elman Neural Network (LSIBA-ENN) was developed in [6] for the sentiment analysis of online product reviews. But the deep learning design was not applied for sentiment analysis. Two sentiment classification models were developed in [7] for sentiment classification using the CNN model. But the designed models failed to produce better sentiment classification results.

Organic Simultaneous LSTM and CNN Fit (OSLCFit) was developed in [8] for sentiment mining through classification. But the designed method failed to minimize the error rate of sentiment classification. A novel hybrid deep learning model was introduced in [9] for sentiment classification. But the designed model failed to attain a better classification accuracy rate.

A sentence-to-sentence attention network (S2SAN) was introduced in [10] for sentiment analysis of online reviews. But it failed to continue improving the aspect level sentiment analysis.

1.1 Major contributions

To overcome the issues from the literature review, an RQDA-ESRDSNLC technique is developed with the following novel contributions,

- To improve the sentiment classification accuracy, an RQDA-ESRDSNLC technique is introduced based on three different processes namely Punktword tokenizer, Regularized quadratic discriminant analysis, Elliot Symmetric Recursive Deep Structure Neural Learning classifier.

- To minimize the time as well as space complexity of sentiment classification, Punktword tokenizer, Regularized quadratic discriminant analysis is applied to an RQDA-

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ESRDSNLC to choose the significant words based on the likelihood measure and remove the other words. The word having maximum likelihood is selected for sentiment classification.

- Elliot Symmetric Recursive Deep Structure Neural Learning classifier is applied for sentiment classification at the output layer. The Elliot Symmetric activation function analyzes the extracted words with different observations and finds the positive and negative classification. This helps to provide accurate results by minimizing the error. This helps to improve the accuracy and reduce the error rate involved.

- A comprehensive experiment is conducted to measure the performance of the RQDA-ESRDSNLC technique and state-of-the-art works. The results achieved demonstrate that our proposed, RQDA-ESRDSNLC technique provides better performance in terms of accuracy, time, error rate, as well as space complexity.

1.2 Organization of the paper

The rest of the paper is organized as follows. Section 2 discusses the related works in the field of sentiment classification. In section 3, the RQDA-ESRDSNLC technique is described with a neat diagram. Section 4gives the experimental setup. Section 5 provides a detailed analysis of the experiment results and discussion. Section 6 provides the conclusion of the current work.

2. Related works

The Graph Domain Adversarial Transfer Network (GDATN) was developed in [11] to perform the sentiment analysis. But, the deep model was not considered to perform in-depth analysis. A Deep Neural Network with Multi-Head Attention Mechanism (DNN–MHAT) was introduced in [12] for solving the high dimensionality problems during the sentiment classification. However, it was not efficient to perform sentence-level and aspect-level sentiment analysis.

An attention mechanism and graph convolutional network (ATGCN) was introduced in [13] for aspect-based sentiment classification. But the complexity of sentiment classification was not minimized. A novel Multi-Task Learning Model based on a Multi-Scale Convolutional Neural Network and Long Short Term Memory (MTL-MSCNN-LSTM) was introduced in [14] to solve the multi-tasking sentiment classification problem. However, it was not efficient to further improve the results of sentiment classification for multi-task learning.

An Intelligent Hybrid Feature Selection for Sentiment Analysis (IHFSSA) based on ensemble learning methods was developed in [15]. However, the deep learning methods were not applied for enhancing the performance of sentiment analysis. A new Multi-Grained Attention Representation with ALBERT (MGAR-ALBERT) was introduced in [16] that include the significant information of the sentence. But the performance of error rate during the sentiment analysis was not minimized.

A multi-channel convolutional neural network with a multi-head attention mechanism (MCNN-MA) was introduced in [17] for sentiment analysis. The designed mechanism achieves low training time cost but the performance of the model was not improved. A Deep Selective Memory Network (DSMN) was introduced in [18] for aspect-level sentiment classification. But it failed to predict the sentiment polarities of the extracted aspects.

A novel Fuzzy Deep Learning Classifier (FDLC) was introduced in [19] for data-sentiment classification. But the performance of complexity was not analyzed. Self-supervised Sentiment Analyzer (SSentiA) was developed in [20] for sentiment classification. But the time consumption of sentiment classification was not minimized.

3. Proposal methodology

Sentiment analysis of review aims to extract and investigate knowledge from the individual opinion posted on the internet. Due to its wide range of applications, as well as the increasing growth of social networks, Sentiment analysis has become a hot theme in the field of natural language processing (NLP). Therefore, different techniques have been proposed to recognize the polarity of opinion. Polarity detection is a binary categorization task that plays a significant role in Sentiment analysis applications. The polarity Sentiment analysis is the process of identifying the positive or negative. Most of the previous approaches for Sentiment analysis have been developed for obtaining satisfactory polarity Sentiment analysis. Based on the above-said motivation, a novel RQDA-ESRDSNLC is introduced in this paper for improving the accuracy of Sentiment classification either positive or negative. The different process of the proposed RQDA-ESRDSNLC technique is shown in figure 1.

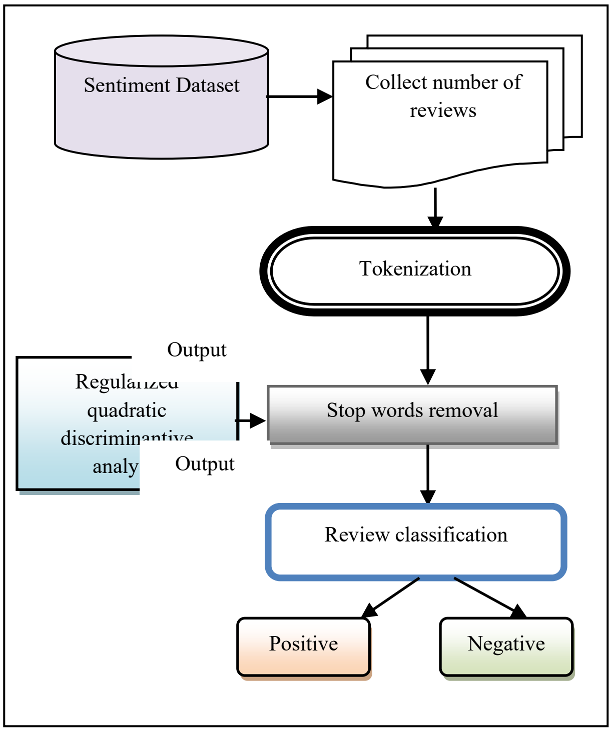

Figure 1 architecture of proposed RQDA-ESRDSNLC technique

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Figure 1 demonstrates the architecture of the proposed RQDA-ESRDSNLC technique to perform the sentiment classification that includes two major processes namely preprocessing and classification. First, the number of customer reviews '$\beta_1, \beta_2, ..\beta_n$ collected from the dataset 'DS'. After collecting the reviews, the proposed RQDA-ESRDSNLC technique includes two different steps in preprocessing such as tokenization and stop word removal and classification. First, the preprocessing step is carried out using Punktword tokenizer and Regularized quadratic discriminant analysis for removing the stop words from the reviews. Secondly, the sentiment classification is performed using the Elliot Symmetric activation function. The different process of the proposed technique is implemented into the Recursive Deep Structure Neural Learnt classifier. The proposed recursive neural network is a type of deep neural network constructed by applying a similar set of weights recursively over a structured input, to generate a structured output.

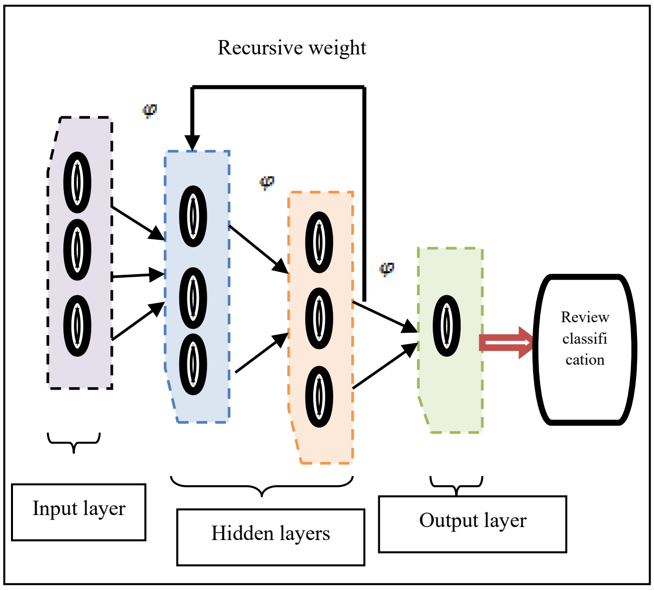

Figure 2 schematic structure Recursive deep neural networks

Figure 2 given above reveals the schematic structure of Recursive Deep Neural Network for sentiment classification. As shown in figure 2, the Recursive Deep Neural Network consists of an input layer, two hidden layers, and an output layer. The customer reviews $\beta_1, \beta_2, ..\beta_n$ are collected from the large database and given to the input layer of deep learning number of customer reviews. The proposed deep learning performs the preprocessing in the first two hidden layers and reviews classification in the output layer. The neuron in one layer is connected in a feed-forward manner to form an entire network. The Recursive Deep Neural Network performs an in-depth analysis of given input.

Let us consider the customer reviews $\beta_1, \beta_2, ..\beta_n$ collected from the dataset. The activity of the neuron is formulated in the input layer is given below,

$$k(t) = c + \sum_{i=1}^{n} \beta_i * \varphi \quad (1)$$

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Where, $k(t)$ denotes an activity of the neuron in the input layer, β_i denotes a customer reviews, φ indicates a weight, c denotes a bias that stores the value of '1' After that, the input transformed into the first hidden layer where the preprocessing is said to be performed.

- **Preprocessing**

The first process of the proposed RQDA-ESRDSNLC technique is the preprocessing of reviews in the first hidden layer. Preprocessing is the process of preparing the text data through the tokenization and stopwords removal from the text. This process of the proposed RQDA-ESRDSNLC technique is to minimize the complexity of sentiment classification.

➢ **Punktword tokenizer**

First, the reviews are partitioned into a number of words using punktword tokenizer. This tokenizer splits the sentences into words by means of punctuation and spaces in the square bracket.

$$S \Rightarrow ['a_1', \ 'a_2', \ 'a_3', \dots 'a_m'] \qquad (2)$$

From (2), the review 'S' is partitioned into a number of words $'a_1', \ 'a_2', \ 'a_3', \dots 'a_m$ using punktword tokenizer.

➢ **Regularized quadratic discriminant analysis based stop word removal**

After tokenizer, the stop words are identified and removed using Regularized quadratic discriminant analysis. The regularized quadratic discriminant analysis is applied for finding the stop words. A Regularized quadratic discriminant analysis is a statistical method used to find the relationship between a dependent variable and one or more independent variables for identifying the stopwords from the customer reviews.

A stop word is identified as a word that has a similar likelihood of occurring in the reviews and list stop words predefined in the library. The Regularized quadratic discriminant analysis is a generative model that follows a Gaussian distribution.

$$\delta\,(S|R_L) = (2\pi V^2)^{-1/2\,n}\, exp\left(-\sum_{i=1}^{m} 0.5 * \frac{(S-R_L)^2}{V^2}\right) \quad (3)$$

Where, $\delta\,(S|R_L)$ denotes a likelihood ratio test between the words 'S' and the list stop words predefined in the library 'R_L', V indicates a deviation between the words. The output of a likelihood ratio test between the words are given below,

$$\delta\,(S|R_L) = \begin{cases} 1\ ; & Stop\ words \\ 0; & not\ stop\ words \end{cases} \quad (4)$$

Where, $\delta\,(S|R_L)$ denotes a likelihood ratio test between the words, $\delta\,(S|R_L)$returns '1' denotes words are identified as stop words,$\delta\,(S|R_L)$returns '0' indicates words are identified as not stop words. The identified stop words are removed and select the other words for sentiment classification. As a result, the time complexity of classification is said to be minimized. The selected words are given to the next hidden layer.

Therefore, the hidden layer output is obtained as follows,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$G\ (t) = [\sum_{i=1}^{n} \beta_i * \varphi] + [\varphi * \ G_{t-1}]$(5)

Where, $G(t)$ indicates an output of a second hidden layer, G_{t-1} indicates output from the previous hidden layer and 'φ'indicates a weight between hidden layers,β_i represents the input. Here the same set of weights is recursively used over a structured input. The hidden layer output is given to the output layer

- **Sentiment classification**

Finally, sentiment classification is performed in the output layer to identify the positive and negative based on the Elliot Symmetric Activation function. The Elliot symmetric activation function is a higher speed function that provides the output ranges from -1 to 1. The classification output is obtained at the output layer,

$Z = \sigma[\varphi * G\ (t)]$ (6)

Where 'Z' indicates an output of the recursive deep neural network,φ indicates a similar weight between hidden and output layer, $G\ (t)$ indicates an output of a hidden layer, σ denotes an Elliot Symmetric Activation function.

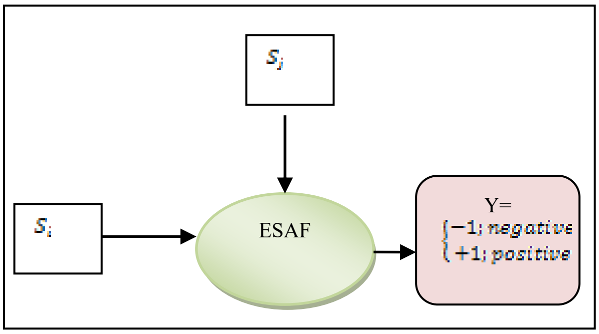

Figure 3 Elliot Symmetric Activation function

Figure 3 illustrates the Elliot Symmetric Activation function which includes an input as two words 'S_i' and'S_j'.Therefore, the output of Elliot Symmetric Activation function is expressed as given below,

$\sigma = \frac{(S_i * S_j)}{(1+|S_i * S_j|)}$ (7)

Where, 'S_i' and 'S_j' denotes the words, 'σ' indicates the output of the Elliot Symmetric Activation function.

$Y = \begin{cases} -1; & negative\ review \\ +1; & positive\ review \end{cases}$ (8)

The output of the coefficient returns a value between −1 and +1. The output of the Activation function varies between '-1' and '+1'. Here, +1 indicates a positive sentiment whereas '-1' indicates the negative sentiment. In this way, the sentiments are correctly identified with higher accuracy. The RQDA-ESRDSNLC algorithmic process is described as given below,

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

// Algorithm 1:Regularized quadratic discriminant Analysis based Elliot Symmetric Recursive Deep Structure Neural Learning classifier
Input: Dataset 'SD', Reviews '$\beta_1, \beta_2, .. \beta_n$', **Output**: Increase classification accuracy
Begin **1. Collect the number of** Reviews '$\beta_1, \beta_2, .. \beta_n$ into **an** input layer 2. Transform the Reviews into the first hidden layer 3. **For** each Review 4. Partition into a number of words' ---[**hidden layer 1]** 5. **If** $\delta\ (S\|R_L) = +1)$ **then--- [hidden layer 2]** **6.** Words are said to stop words 7. Remove the words 8. **else** 9. Words are said to be not stop words 7. Select the words **11. End if** **12. For each selected word**'s_i'---[**hidden layer 3]** **13.** Measure the'Y ' 14. if ($Y = +1$) **then--- [output layer]** 15. Reviews are classified as "positive 16. **else** 17. Reviews are classified as 'negative' 18. **End if** 19. **End for** **End**

Algorithm 1 given above describes the step-by-step process of sentiment classification accuracy using a Regularized quadratic discriminant Analysis based on Elliot Symmetric Recursive Deep Structure Neural Learning classifier. The number of reviews is collected from the dataset. After that, the word tokenization is performed in the first hidden layer to divide the sentence into words. Then the stop words are removed in the second hidden layer by measuring the likelihood between the words using Regularized quadratic discriminant Analysis. Finally, the Elliot Symmetric activation function is applied for identifying the positive or negative. Based on the correlation measure, the reviews are correctly classified as

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

positive or negative in the output layer. This in turn increases the classification accuracy with minimum time.

4. Experimental setup

In this section, experimental evaluation of the proposed RQDA-ESRDSNLC technique and existing GL-GCN [1], SC-ABiLSTM [2] are implemented in Java using Reviews - TripAdvisor (hotels) & Edmunds (cars) dataset.

4.1 Dataset Description:

TripAdvisor (hotels) & Edmunds (cars) dataset gathered from Kaggle [https://www.kaggle.com/enikolov/reviews-tripadvisor-hotels-and-edmunds-cars]. The dataset size is 767 MB. The dataset domain is hotels and car. The dataset type denoted as text. The data set consist of full reviews for cars and hotels gathered from Tripadvisor (~259,000 reviews) and Edmunds (~42,230 reviews). Table 1 and 2 illustrates the dataset description of car reviews and hotel reviews.

4.1.1 Car Reviews:

Table 1 Car Reviews

Dataset	Description
Full reviews of cars for model	Year 2007, 2008 and 2009
Each model year	140-250 cars
Extracted fields	Dates, author name, favorites, full textual review
Total number of reviews	~42,230
Year 2007	18,903 reviews
Year 2008	15,438 reviews
Year 2009	7,947 reviews

Format:

The three diverse folders (2007, 2008, 2009) denotes the three model years. Every file (3 folders) includes all reviews for specific car. The file name indicates the name of the car. Within every car file, set of reviews included in the following format,

<DOC>

<DATE>06/15/2009**</ DATE>**

<AUTHOR>The author**</ AUTHOR>**

<TEXT>the review goes here…</**TEXT>**

<FAVORITE>What are my favorites about this car**</FAVORITE>**

<DOC>

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Every review is enclosed within a <DOC> element and each extracted items are within this element.

4.1.2 Hotel Reviews

Table 2 Hotel Reviews

Dataset	**Description**
Full reviews of hotels in 10 different cities	Dubai, Beijing, London, New York City, New Delhi, San Francisco, Shanghai, Montreal, Las Vegas, Chicago
Each city	80-700 hotels
Extracted fields	Date, review title and full review
Total number of reviews	~2,59,000

Format

The ten dissimilar folders denote 10 cities. Every file (10 folders) includes each reviews connected to specific hotel. The file name signifies name of the hotel. Within each file, set of reviews format is described as given below,

Date1Review title1Full review 1

Date2Review title2Full review 2

....

....

Every line in the file denotes separate review entry. Tabs are employed to separate the dissimilar fields.

Table 1 and 2 reveals that a total of 3,01,230 combined reviews were employed for conducting the simulation. To evaluate performance, number of reviews in the range of 10000 to 100000 was selected from the TripAdvisor (hotels) & Edmunds (cars) dataset.

5. Quantitative Results Analysis

The Quantitative results and discussion of the RQDA-ESRDSNLC technique and existing GL-GCN [1], SC-ABiLSTM [2] are described in this section. The performance results of RQDA-ESRDSNLC are compared to existing methods with various metrics such as Classification accuracy, false-positive rate, computation time, and space complexity. The different graphical results show the performance results of proposed and existing methods.

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Classification accuracy: It is evaluated as the ratio of the number of customer reviews are accurately classified to the total number of reviews. The classification accuracy is formulated as follows,

$$CA = \left(\frac{\beta_{ac}}{k}\right) * 100 \quad (9)$$

Where, CA denotes a classification accuracy, 'β_{ac}' denotes the number of customer reviews accurately classified and 'k' indicates the total number of customer reviews. The accuracy of sentiment classification is determined in terms of percentage (%).

- **Error rate**: It is measured as the number of customer reviews that are incorrectly classified to the total number of customer reviews. This is mathematically formulated as given below.

$$FPR = \left(\frac{\beta_{ic}}{k}\right) * 100 \quad (10)$$

Where 'FPR' denotes a false positive rate, 'β_{ic}' denotes reviews incorrectly classified, k denotes a total number of reviews. It is measured in terms of percentage (%).

- **Time complexity**: It is defined as the amount of time consumed by the algorithm to perform sentiment classification. It is mathematically expressed as given below.

$$TC = [ET] - [ST] \quad (11)$$

From the above mathematical equation (11), 'ST' represents a starting time and 'ET' signifies an ending time of sentiment classification. The time complexity (TC) is determined in terms of milliseconds (ms).

- **Space complexity**: It is defined as the amount of memory consumed by the algorithm to perform sentiment classification. It is measured using the following formula,

$$MEm_{Space} = \sum_{i=1}^{n} \beta_i * Mem\ [SC] \quad (12)$$

Where, MEm_{Space} denotes a Space complexity, 'β_i' denotes the number of reviews considered for simulation, '$Mem\ [SC]$' denotes a memory consumed for sentiment classification. It is measured in terms of Megabytes (MB).

Table 3 Classification accuracy versus the number of reviews

Number of reviews	Classification accuracy (%)		
	RQDA-ESRDSNLC	GL-GCN	SC-ABiLSTM
10000	93.52	89.23	86.5
20000	91.25	87.5	85.5
30000	92.83	88.4	84.83
40000	91.45	86.5	84.12
50000	93.04	88.2	85.2

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

60000	91.25	87.75	85.66
70000	92.25	89.07	87.88
80000	91.75	87.65	85.65
90000	92.44	88.4	86.24
100000	91.35	89.65	87.12

Table 3 provides the experimental outcomes of classification accuracy. The number of reviews is taken as input in range of 10000 to 100000 from TripAdvisor (hotels) & Edmunds (cars) dataset for experimentation. The performance of different classification accuracy using three methods namely RQDA-ESRDSNLC technique and existing GL-GCN [1], SC-ABiLSTM [2] are reported in table 3. The observed table values indicate that the classification accuracy of the RQDA-ESRDSNLC technique is developed than the conventional techniques. The overall value of the comparison results indicates that the classification accuracy of the RQDA-ESRDSNLC technique is said to be improved by 4% when compared to [1] and 7% when compared to [2] respectively.

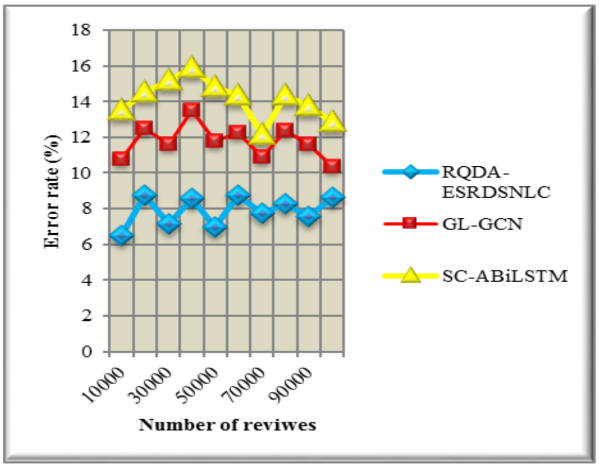

Figure 4 comparison of error rate between different methods

Figure 4 illustrates the performance outcome of the error rate between three different methods. The graph demonstrates that the RQDA-ESRDSNLC technique improves the performance of the model well compared to GL-GCN [1], SC-ABiLSTM [2]. Finally, the average of ten comparison results clearly illustrates that the error rate is found to be significantly decreased by 33% and 44% when compared to existing [1],[2].

Table 4 Time complexity versus the number of reviews

Number of reviews	Time complexity (ms)		
	RQDA-ESRDSNLC	GL-GCN	SC-ABiLSTM

10000	64	69	73
20000	78	85	93
30000	83	96	106
40000	96	110	125
50000	108	117	131
60000	117	129	142
70000	121	138	151
80000	136	152	162
90000	147	165	185
100000	154	173	196

Table 4 summarizes the results of d for different numbers of reviews using our proposed RQDA-ESRDSNLC technique, GL-GCN [1],and SC-ABiLSTM [2]. This final average value indicates that the RQDA-ESRDSNLC technique minimizes the time consumption by 10% compared to [1] and 19% compared to [2] respectively.

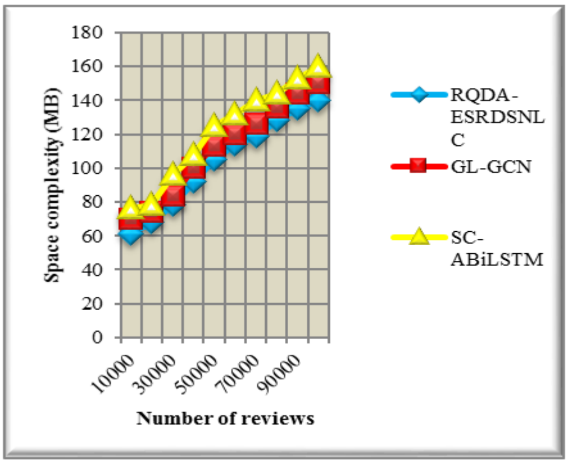

Figure 5 comparison of space complexity between different methods

Figure 5 given above depict the performance of space complexity for a different number of reviews. As shown in the graph, the performance of space complexity using the RQDA-ESRDSNLC technique is found to be minimized when compared to existing [1] [2] respectively. The reason behind the improvement was owing to the application of stop words removal using Regularized quadratic discriminant analysis. This in turn returns the selected words given to the classification process resulting in minimizing the memory consumption. The performance of the RQDA-ESRDSNLC technique is compared to the results of GL-GCN [1] and SC-ABiLSTM [2]. Finally, the average of ten comparison results indicates that the overall results of space complexity using the RQDA-ESRDSNLC technique are minimized by 7% when compared to [1] and 15% when compared to [2] respectively.

International Journal of Applied Mathematics
Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

6. Conclusion

The customer reviews include a huge amount of sentiment information and have considerable value. Sentiment analysis of online reviews plays a vital role. Hence a novel Deep RQDA-ESRDSNLC technique has been designed for accurate Sentiment analysis based on the preprocessing and classification. The recursive deep neural network-based method was designed based on the layer formulation to improve the performance assessment and finally the output layer providing the final classification results. First, tokenization is performed to extract the words from the reviews. Secondly, the stop words are identified by the application of Regularized quadratic discriminant analysis. With the selected words, the classification is done by applying an Elliot Symmetric activation function. The performance of the RQDA-ESRDSNLC technique and existing classification techniques are estimated with different metrics such as Classification accuracy, error rate, time complexity, and space complexity. The observed results reveal that the higher classification accuracy is achieved using the RQDA-ESRDSNLC technique and reduce the time, space complexity as well as error rate when compared to conventional classification methods.

References

[1]Xiaofei Zhu, Ling Zhu, Jiafeng Guo, Shangsong Liang, Stefan Dietze, "GL-GCN: Global and Local Dependency Guided Graph Convolutional Networks for aspect-based sentiment classification", Expert Systems with Applications, Elsevier, Volume 186, 2021, Pages 1-11

[2]Peng Wua, Xiaotong Li, Chen Ling, Shengchun Ding, Si Shen, "Sentiment classification using attention mechanism and bidirectionallong short-term memory network", Applied Soft Computing, Volume 112, 2021, Pages 1-13

[3] Nur Syafiqah Mohd Nafis, Suryanti Awang, "An Enhanced Hybrid Feature Selection Technique Using Term Frequency-Inverse Document Frequency and Support Vector Machine-Recursive Feature Elimination for Sentiment Classification", IEEE Access, Volume 9, 2021, Pages 52177 – 52192

[4]Chuantao Wang; Xuexin Yang; Linkai Ding, "Deep Learning Sentiment Classification Based on Weak Tagging Information", IEEE Access, Volume 9, 2021, Pages 66509 - 66518

[5]Ziyu Zhou, Fang'ai Liu, "Filter gate network based on multi-head attention for aspect-level sentiment classification", Neurocomputing, Elsevier, Volume 441, 2021, Pages 214-225

[6] Huiliang Zhao, Zhenghong Liu, Xuemei Yao, Qin Yang, "A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach", Information Processing and Management, Volume 58, 2021, Pages 1-14

Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[7]Isnaini Nurul Khasanah, "Sentiment Classification Using fastText Embedding and Deep Learning Model", Procedia Computer Science, Elsevier, Volume 189, 2021, Pages 343-350

[8] Kiran R, Pradeep Kumar, Bharat Bhasker, "Oslcfit (organic simultaneous LSTM and CNN Fit): A novel deep learning-based solution for sentiment polarity classification of reviews", Expert Systems with Applications, Elsevier, Volume 157, 2020, Pages 1-12

[9]Mehmet Umut Salur and Ilhan Aydin, "A Novel Hybrid Deep Learning Model for Sentiment Classification", IEEE Access, Volume 8, 2020, Pages 58080 – 58093

[10]Ping Wang, Jiangnan Li, Jingrui Hou, "S2SAN: A sentence-to-sentence attention network for sentiment analysis of online reviews", Decision Support Systems, Elsevier, Volume 149, 2021, Pages 1-12

[11]Hengliang Tang, Yuan Mi, Fei Xue, Yang Cao, "Graph Domain Adversarial Transfer Network for Cross-Domain Sentiment Classification", IEEE Access, Volume 9, 2021, Pages 33051 – 33060

[12]Hashem Saleh Sharaf Al-deen, Zhiwen Zeng, Raeed Al-sabri and Arash Hekmat, "An Improved Model for Analyzing Textual Sentiment Based ona Deep Neural Network Using Multi-HeadAttention Mechanism", Applied System Innovation, Volume 4, Issue 4, 2021, Pages 1-21

[13]Jie Liu, Peiyu Liu, Zhenfang Zhu, Xiaowen Li, and Guangtao Xu, "Graph Convolutional Networks with Bidirectional Attentionfor Aspect-Based Sentiment Classification", Applied Science, Volume 11, 2021, Pages 1-15

[14]Ning Jin, Jiaxian Wu, Xiang Ma, Ke Yan, Yuchang Mo, "Multi-Task Learning Model Based on Multi-Scale CNN and LSTM for Sentiment Classification", IEEE Access,Volume 8, 2020, Pages 77060 – 77072

[15]Jawad Khan, Aftab Alam, Youngmoon Lee, "Intelligent Hybrid Feature Selection for Textual Sentiment Classification", IEEE Access, Volume9, 2021, Pages 140590 – 140608

[16]Yuezhe Chen, Lingyun Kong, Yang Wang, Dezhi Kong, "Multi-Grained Attention Representation with ALBERT for Aspect-Level Sentiment Classification", IEEE Access, Volume 9, 2021, Pages 106703 – 106713

[17]Yue Feng and Yan Cheng, "Short Text Sentiment Analysis Based on Multi-Channel CNN with Multi-Head Attention Mechanism",IEEE Access, Volume 9, 2021, Pages 19854 – 19863

[18]Peiqin Lin, Meng Yang, Jianhuang Lai, "Deep Selective Memory Network with Selective Attention and Inter-Aspect Modeling for Aspect Level Sentiment Classification", IEEE/ACM Transactions on Audio, Speech, and Language Processing, Volume 29, 2021, Pages 1093 – 1106

Received: August 15, 2025

Volume 38 No. 10s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[19]Fatima Es-Sabery, Abdellatif Hair, Junaid Qadir, Beatriz Sainz-De-Abajo,Begoña García-Zapirain, and Isabel De La Torre-Díez, “Sentence-Level Classification Using ParallelFuzzy Deep Learning Classifier”, IEEE Access,Volume 9, 2021, Pages 17943 – 17985

[20]Salim Sazzed and Sampath Jayarathna, “SSentiA: A Self-supervised Sentiment Analyzer for classification fromunlabeled data”,Machine Learning with Applications, Elsevier, Volume 4, 2021, Pages 1-14

Received: August 15, 2025