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LASSO REGRESSIVE PERCENTAGE SIMILARITY BASED EXTREME LEARNING NETWORK FOR SENTIMENT CLASSIFICATION

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Abstract: Sentiment analysis used machine learning to remove the significant data for subjective data analysis by positive, negative or neutral feelings. Different sentiment classification techniques are discussed for performing the opinion mining. However, they failed to enhance the accuracy level and time complexity. To overcome this a novel method called as Lasso Regressive Percentage Similarity based Extreme Learning Network Method (LRPS-ELM) is introduced to perform main objective of efficient sentiment classification with better accuracy and minimum time consumption. Extreme Learning Classification comprises different layers for categorizing the given reviews through performing preprocessing, feature extraction and classification. The number of reviews is initially collected from input dataset as an input. Then, the input reviews are sent to hidden layer 1. In that layer, the review preprocessing is performed through stop words removal and stem words elimination. Then, the pre-processed review is sent to the second hidden layer. In that layer, Lasso Regression is carried out for performing efficient feature extraction from preprocessed reviews. Later, the extracted features are sent to the third hidden layer for classification. In that layer, Percentage Similarity Function is carried out by identifying the user opinion. Finally, accurate sentiment classification is carried out with higher accuracy. Simulation setting is provided with various metrics such as, prediction accuracy, error rate and prediction time with respect to number of reviews. In the proposed LRPS-ELM method results are verified to achieve better accuracy and lesser time complexity when compared to conventional methods.

Index Terms **- Opinion mining, Extreme Learning Classification, Lasso Regression, Percentage Similarity Function, Sentiment Classification.**

I. INTRODUCTION

Sentiment Analysis is a Natural language processing technique used to identify the emotion of a text and to extract the user opinions on products and services from their reviews. Sentiment analysis creates the actionable knowledge for their entity. To improve the business, Sentiment Analysis System can be adopted to take customer feedback about their products and services. Bidirectional LSTM network was designed in [1] for Sentiment Analysis was employed to handle long-term dependencies for efficient prediction. LSTM was employed to categorize the reviews into positive and negative. However, the prediction accuracy was not improved by bidirectional LSTM network. An Assemble+Deft, Edify+Authenticate and Forecast were used to classify the opinion in [2]. But, it failed to enhance the accuracy level.

A novel framework was employed in [3] to remove features from user-related and policy-related social media information. The designed framework forecasted the comment polarity in policy release phase. But, the computational cost was not minimized by designed framework. In [4], an Independent Component

Support Vector Regressive Deep Learnt Sentiment Classification (ICSD) Method was obtained for sentiment classification. Though classification accuracy was improved, the complexity level was not minimized by the method.

The textual data was determined in [5] on passenger reviews. The customer satisfaction was performed with marketing strategy to attract customers and develop their market share. However, it failed to reduce the complexity level with textual data. In [6], a pre-training language model was designed to encode the user features for determining the user interest as well as gathered the text features at various scales. But, prediction time was not minimized by the designed model.

A sentiment knowledge-adaptive pre-training model (ASK-RoBERTa) was introduced in [7]. The sentiment word dictionary was constructed from field sentiment words. But, it did not reduce the space complexity. In [8], proficient Sentiment Analysis (SA) technique was employed with social media reviews to overcome their drawbacks, but the time complexity was not minimized.

Attention-based position-aware Bidirectional Long Short-Term Memory network for aspect-based opinion mining with Sentiment Intensity Lexicon was designed in [9]. The pre-trained vector was adjusted to similar nearest neighbors and dissimilar neighbors. But, the accuracy level was not minimized. The target-level sentiment analysis was carried out in [10] to forecast the sentiment entities throughout the document. A new annotated dataset was employed with named entities and references for sentiment analysis. But, the computational cost was not minimized by designed analysis.

The problems identified from above literature reviews are minimum prediction accuracy, reduced computational cost, minimized computational complexity, better prediction time consumption and improved error rate and so on. To overcome these issues, LRPS-ELM method is proposed.

A. Contribution Remark

The issues reviewed by the above said literature are overcome by introducing a novel LRPS-ELM technique with following contribution -

- To improve accuracy and reduce time consumption. LRPS-ELM Method is introduced for efficient sentiment classification. Extreme Learning Classification includes five different layers for review classification by performing preprocessing, feature extraction and classification.
- The number of reviews is collected from input dataset. Then, the review preprocessing is carried out in LRPS-ELM method through stop words removal and stem words elimination. Lasso Regression is carried out for efficient feature extraction from preprocessed reviews.
- Percentage Similarity Function is carried out in LRPS-ELM method through identifying the user opinion. This in turn, sentiment classification is carried out with higher accuracy.

B. Organization of the paper

The paper is structured into five sections. Section 2 discusses on classification methods for sentiment analysis. Section 3 introduces the LRPS-ELM methodology for efficient sentiment analysis. Section 4 discusses the dataset description with experimental setup. Section 5 provides different results analysis of proposed LRPS-ELM method with table and graphical representation. Finally, section 6 concludes the paper.

II. RELATED WORK

Language Massive Open Online Courses (LMOOCs) learner were examined in [11]. An encapsulated student opinion about LMOOCs and their experiences were identified. But, the complexity level was not minimized. In [12], an Attention Parallel Dual-channel Deep Learning Hybrid Model (ADDHM) was performed into collects the text sentiment features and that words ambiguity is identified. Bidirectional Encoder Representations from Transformers (BERT) extracted the semantic features with text vector representation. But, the error rate was not minimized by designed model.

A deep learning approach was introduced in [13] to identify the fine-tuned Smith algorithm with Adam optimizer (HFS-AO) for opinion mining was utilized into web resources by web scraping algorithm. But, the time complexity was not minimized by designed approach. Cross-Modal Multitask Transformer (CMMT) was introduced in [14] to revise the sentiment aware intra-modal representation. Text-Guided Cross-Modal Interaction Module controlled the contributions of visual information. However, the prediction accuracy was not improved by designed framework.

A new approach was introduced in [15] to predict the user opinions through textual tweets and emojis. The opinions were collected from text to increase the expression of opinion in SNS discussion. However, the prediction accuracy was not enhanced by designed approach. An Enhanced Elman Spike Neural Network based Sentiment Analysis of Online Product recommendation (EESNN-SA-OPR) was introduced in [16]. The Collaborative Filtering was used to forecast the best shops. But, the forecasting time was not minimized by designed analysis.

In [17], a deep learning-based approach was performed for sentiment analysis on drug product review data. However, the space complexity was not minimized by designed approach. The sentiment annotation method was designed with lexicon-based and corpus-based method for unsupervised annotations in [18]. The sentiment analysis impacts on educational process were used to improve the decision-making performance. But, the complexity level was not reduced by designed method.

An opinion mining was carried out in [19] based on app reviews. The textual representation techniques were performed for sentiment analysis. However, the computational complexity was not minimized. In [20], a Hidden Markov Models (HMMs) were examined into renovate the public voice messages into text. The machine learning technique was introduced to recognize the administration department responsible for respective user voice. But, the prediction time was not minimized by HMM.

III. METHODOLOGY

The field of opinion mining is to extract people thoughts. In large development of digital platform likes, blogs and social networks, individuals and organizations are applying public opinion for their decision-making. However, different classification methods attained lesser accuracy due to the deficiency for sentiment analysis. As a result, a novel LRPS-ELM Method is designed to carry out the efficient classification with better accuracy. LRPS-ELM Method technique determined for Extreme Learning Machine using accurate sentiment classification analysis. The architecture diagram of LRPS-ELM Method is described in figure 1.

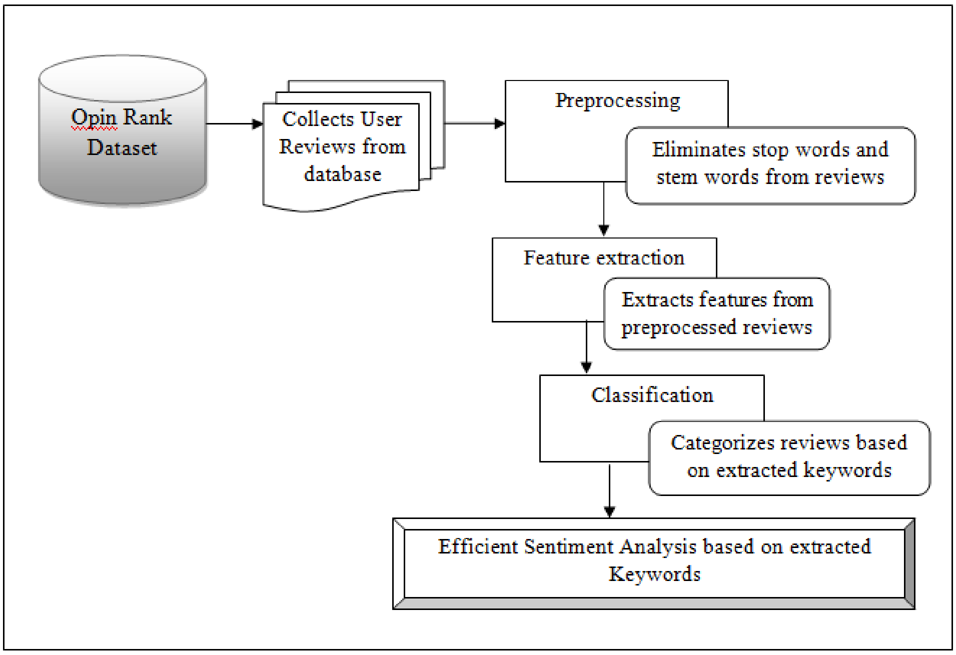

Figure 1 Architecture diagram of LRPS-ELM Method

Figure 1, represents the Architecture diagram of LRPS-ELM Method that performs preprocessing, feature extraction and classification to recognize the positive, negative, or neutral opinion from user reviews. The different layers of LRPS-ELM Method are determined in figure 2.

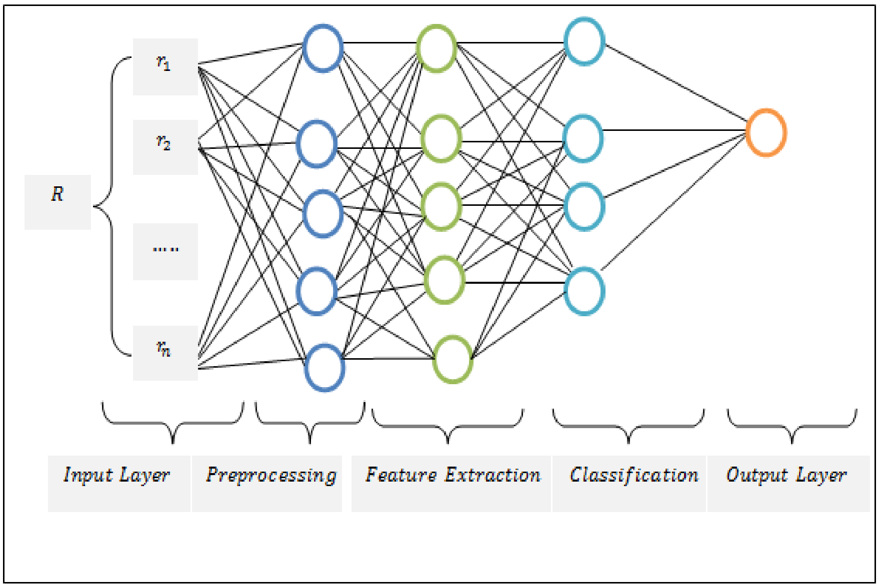

Figure 2 Structural Diagram of Extreme Learning Machine

Figure 2 shows the structural diagram of Extreme Learning Machine. Neural Network is used for classification, regression and clustering with multiple hidden nodes. The parameters of hidden nodes are tuned. The hidden nodes are allocated and not updated. The output weights of hidden nodes are learned in single step. The input layer collects number of user reviews '$r_1, r_2, r_3, \ldots r_n$'. The input layer '$i(t)$' of neural network is given as,

$$i(t) = bias + [\sum_{i=1}^{n} r_i * we_i] \text{ ------ (1)}$$

From equation (1), '$r_i(t)$' symbolizes the review. 'we_i' symbolizes the initial weight at input layer. Then, input data is sent to the first hidden layer for review preprocessing.

- **Preprocessing**

Preprocessing is carried out for organizing the text to perform efficient classification. The online reviews comprised number of words in text. In reviews, the irrelevant word minimizes the dimensionality for performing classification. The proposed LRPS-ELM Method performed the pre-processing with stop words removal and stem word removal process.

- **Stopword Removal**

Stopword is a word used for connecting the high discriminating words for forming the sentence. Stop words have no meaning. Stop-words are considered as the language-specific functional words. Stop words are frequent words that not carry any information (i.e., pronouns, prepositions, conjunctions). In English language, 400 - 500 stop words are present. The stop words include 'the', 'of', 'and', 'to', etc. The first step during preprocessing is to eliminate the stop words. Stopword is a word used for linking the high discriminating power words while forming the sentence. LRPS-ELM Method uses the stopword exclusion process to improve the review classification performance.

- **Porter Stemmer**

Stemming techniques are used to identify the root/stem of word. Stemming converts the words to their stems with language-dependent linguistic knowledge. The hypothesis is the words with same stem or word root that describe close concepts in text and words are conflated by using stems. For instance, the words such as user, users, used and using are stemmed to the word 'USE'. Porter stemmer is a progression for removing the commoner morphological and inflexional endings from words in English.

- **Lasso Regressive Feature Extraction**

Feature extraction is process of selecting the relevant features in sentiment analysis to choose the relevant features for classification. Feature extraction minimizes the time complexity. LRPS-ELM Method uses the lasso regression models where relevant features (i.e. words) are chosen depending on certain threshold in the second hidden layer. Lasso regression is regularization term for accurate prediction with shrinkage operator. Shrinkage is collection of data values in which shrunk towards central point. The lasso process promoted the sparse model with parameters. The regression is performed with higher multi-collinearity problems to achieve the model selection like variable selection/parameter elimination. Lasso Regression used L1 regularization for feature selection. LASSO model formed similar to linear and ridge regression model. The coefficients are instructed by lesser the regularized by penalty MSE objective function. Lasso regression function is calculated as,

$$L_f = \beta_{0j} + x_1\beta_{0j} + \cdots . + x_p\beta_{pj} \quad \text{----------} \quad (2)$$

In above equation (2), 'x_i' denotes the independent variables. 'y_j' represent the dependent coefficients. To recognize the minimal distance between features are utilized to threshold function by Lasso regression function (L_f). Consequently, the relevant features are computed as,

$$y_j = \begin{cases} L_f > t\,; irrelevant\ features \\ L_f < t\,; relevant\ features \end{cases} \quad \text{-------} \quad (3)$$

From equation (3), 'Z' represents the output function, 'D' denotes the distance, 't' denotes the threshold. The LRPS-ELM Method identifies the relevant features (i.e. words). Other features are extracted and the extracted relevant features are specified to third hidden layer.

- **Percentage Similarity Function**

In third layer, percentage similarity function is utilized in LRPS-ELM Method for sentiment classification of opinion words with extracted features. Percentage similarity index is used to compute the similarity between sentiment words. The percentage similarity is formulated as,

$$PSI = \frac{\sum \min(r_i, r_j)}{\sum (r_i + r_j)} \quad \text{------------} \quad (4)$$

From equation (4), 'PSI' is a percentage similarity coefficient. The percentage similarity coefficient achieves the output value between '0' and '1'.

$$\varphi = \begin{cases} PSI > 0.5\ ; & Positive\ Opinion \\ PSI = 0.5\,; & Neutral\ Opinion \\ PSI < 0.5\,; & Negative\ Opinion \end{cases} \quad \text{-------} \quad (5)$$

In equation (5), 'φ' specifies the percentage similarity index. When 'PSI' is '0.5', then review is classified as neutral opinion. When the 'PSI' is greater than '0.5' the review is classified as positive opinion. When the 'PSI' is lesser than '0.5', the review is classified as negative opinion. Depending on the similarity measure, the sentiments are exactly categorized. The hidden layer results are obtained as,

$$Hd(t) = \sum_{k=1}^{n} r_k * we_l + [we_{ih} * Hd(t-1)] \quad \text{-----} \ (6)$$

In above equation (6), '$Hd(t)$' denotes the hidden layer output, 'w_{ih}' describe the weight with input and hidden layer. '$Hd(t-1)$' denotes the previous hidden layer. Finally, hidden layer result is transmitting to output layer. The output layer of LRPS-ELM Method is given as,

$$Ot(t) = we_{oh} * Hd(t) \quad \text{---------} \quad (7)$$

In above equation (7), the output layer result specified to '$Ot(t)$'. 'we_{oh}' is weight between hidden layer and output layer. This in turn, efficient sentiment classification is carried out in efficient manner. The algorithmic process of proposed LRPS-ELM method is described in algorithm 1.

// Algorithm 1: Lasso Regressive Percentage Similarity based Extreme Learning Network

Input: Dataset, Number of reviews
Output: Increases Classification accuracy

Begin
Number of reviews '$r_1, r_2, r_3, \dots r_n$' is considered as an input
For each review 'r_i'
    Compute review pre-processing
    Perform stopword removal
    Apply porter stemmer to remove the stem words
end for
Perform Lasso regression
if ($L_f < t$) **then**
    Extract relevant features
else
    Remove irrelevant features
End if
For each feature with extracted features
    Compute similarity '*PSI*'
    If (*PSI* > 0.5) **then**
        Review is positive opinion
    else if (*PSI* $= 0.5$) **then**
        Review is neutral opinion
    else if (*PSI* < 0.5) **then**
        Review is negative opinion
    end if
Obtain classification results at the output layer
end for
End

Algorithm 1 represents the sentiment classification that yields better accuracy with minimal time consumption. The preprocessing is performed to remove stop words perform and stemming to minimize the time consumption. Feature extraction is performed using Lasso Regression and the classification task is carried out using the percentage of similarity coefficient for identifying the positive, negative and neutral opinions. When similarity coefficient is greater than '0.5', reviews are classified as the positive opinion. When similarity is lesser than '0.5', reviews are classified as negative opinions. When the similarity is equal to '0.5', reviews are classified as neutral. Finally, the classification results are obtained by output layer with improved prediction accuracy.

IV. EXPERIMENTAL ANALYSIS

The experimental evaluation of proposed LRPS-ELM Method and existing Bidirectional LSTM network [1] and Assemble+Deft, Edify+Authenticate and Forecast [2] are implemented in Java using OpinRank Review Dataset Data Set taken from UCI Machine Learning Repository https://archive.ics.uci.edu/ml/datasets/opinrank+review+dataset . The data set comprises user reviews of cars and hotels gathered from Tripadvisor (~259,000 reviews) as well as Edmunds (~42,230 reviews). Full reviews of 140-250 cars are collected for the years 2007, 2008, and 2009. The Total numbers of reviews about the reviews are 42,230. Full reviews of hotels are collected from 10 different cities (Dubai, Beijing, London, New York City, New Delhi, San Francisco, Shanghai, Montreal, Las Vegas, Chicago). The total numbers of reviews are 259,000. From the reviews, 10000-100000 reviews are considered for conducting the experiment.

V. RESULT AND DISCUSSION

The result analysis of proposed LRPS-ELM Method and existing Bidirectional LSTM network [1] and Assemble+Deft, Edify+Authenticate and Forecast framework [2] are discussed based on certain parameters such as accuracy, error rate and prediction time with respect to a number of reviews. The efficiency of proposed and existing techniques is discussed with help of tables and graphical representation in bellowed section.

5.1 Impact of Prediction Accuracy Level

It is measured as ratio of number of reviews accurately classified from total number of reviews. The prediction accuracy level is calculated as,

$$Acc_{Pre} = \left[\frac{Number\ of\ reviews\ correctly\ classified}{Total\ number\ of\ reviews}\right] * 100 \text{ - (8)}$$

In above equation (8), 'Acc_{Pre}' denotes the prediction accuracy level. The prediction accuracy is measured in terms of percentage (%).

Table 1 Tabulation for Prediction Accuracy

Number of reviews	Prediction Accuracy (%)		
	Proposed LRPS-ELM Method	Bidirectional LSTM network [1]	Assemble+Deft, Edify+Authenticate and Forecast framework [2]
10000	98.75	96.42	92.79
20000	92.36	88.26	78.96
30000	93.16	84.95	81.99
40000	92.18	88.75	86.50
50000	91.56	89.78	87.58
60000	94.64	90.99	87.80
70000	89.27	88.28	86.05
80000	92.31	91.23	89.57
90000	91.66	91.09	89.29
100000	93.576	90.896	89.37

Table 1 describes the results of prediction accuracy with various numbers of reviews varying from 10000 to 100000 from input dataset. The prediction accuracy results using LRPS-ELM Method are compared with two existing prediction techniques [1] and [2]. The proposed LRPS-ELM Method attains higher prediction accuracy than different existing classification techniques. In first iteration, assume the number of reviews as 10000 for experimental consideration. By applying LRPS-ELM Method, the attained prediction accuracy is 98.75% whereas prediction accuracy of the Bidirectional LSTM network [1] and Assemble+Deft, Edify+Authenticate and Forecast framework [2] are 96.42% and 92.79% correspondingly. Subsequently, prediction accuracy results are attained for every method. The proposed LRPS-ELM Method is computed with two existing methods. Figure 3 describes the prediction accuracy results of proposed method and existing techniques.

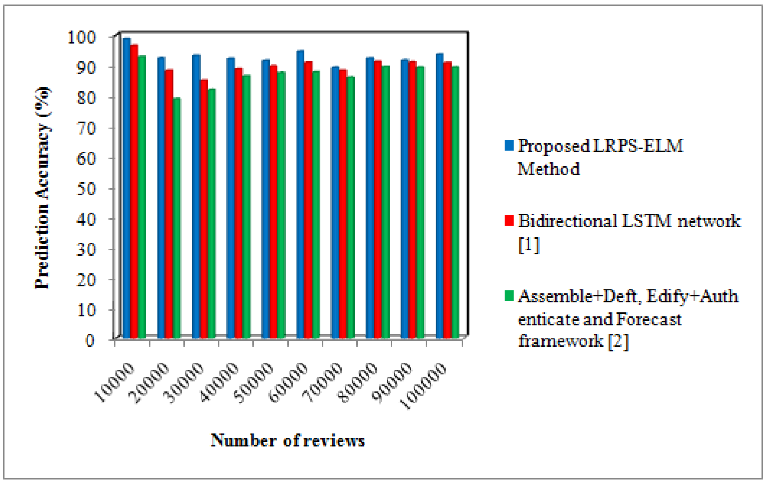

Figure 3 Measurement of Prediction Accuracy

Figure 3 describes the performance analysis of prediction accuracy for different number of reviews ranges from 10000 to 100000. The reviews are considered in horizontal direction and the prediction accuracy is attained in the vertical axis. The blue color cylinder represents the prediction accuracy of proposed LRPS-ELM Method. The red color and green color cylinder represents the prediction accuracy of Bidirectional LSTM network [1] and Assemble+Deft, Edify+Authenticate and Forecast framework [2] respectively. As discussed in graph, the prediction accuracy of the proposed LRPS-ELM Method is higher than existing methods. This is due to the application of extreme learning classification for categorizing the reviews through preprocessing, feature extraction, and classification. The review preprocessing performs stop word removal and stem word elimination. Lasso Regression is used for efficient feature extraction from the preprocessed reviews. Percentage Similarity Function is used for identifying the user opinion. Depending on similarity values, the reviews are correctly classified into positive, negative, and neutral with higher prediction accuracy. As a result, the average prediction accuracy using proposed LRPS-ELM Method is improved by 3% and 7% when compared to [1] and [2].

5.2 Impact of Error Rate

Error Rate is measured as ratio of number of reviews wrongly classified into total number of reviews. The error rate is mathematically formulated as,

$$\mathrm{Err}_{\mathrm{Rate}} = \frac{Number\ of\ reviews\ incorrectly\ classified}{Total\ number\ of\ reviews} * 100 \quad \text{------ (9)}$$

From equation (9), 'Err_{Rate}' symbolizes the error rate. The error rate is computed in terms of percentage (%).

Table 2 Tabulation for Error Rate

Number of reviews	Error Rate (%)		
	Proposed LRPS-ELM Method	Bidirectional LSTM network [1]	Assemble+Deft, Edify+Authenticate and Forecast framework [2]
10000	1.25	3.58	7.21
20000	7.64	11.74	21.04
30000	6.84	15.05	18.01
40000	7.82	11.25	13.5
50000	8.44	10.22	12.42
60000	5.36	9.01	12.2
70000	10.73	11.72	13.95
80000	7.69	8.77	10.43
90000	8.34	8.91	10.71
100000	6.42	9.1	10.63

Table 2 represents the results of error rate with different number of reviews ranging from 10000 to 100000 from input dataset. The error rate results using LRPS-ELM Method are evaluated with two existing prediction techniques [1] and [2]. The proposed LRPS-ELM Method attains lesser error rate than different existing classification techniques. Let us consider that number of reviews as 80000 for experimental consideration. By applying LRPS-ELM Method, the attained error rate is 7.69% whereas error rate of the [1] and [2] are 8.77% and 10.43% correspondingly. Then, error rate results are achieved for proposed LRPS-ELM Method and two existing methods. Figure 4 illustrates the error rate results of proposed method and existing techniques.

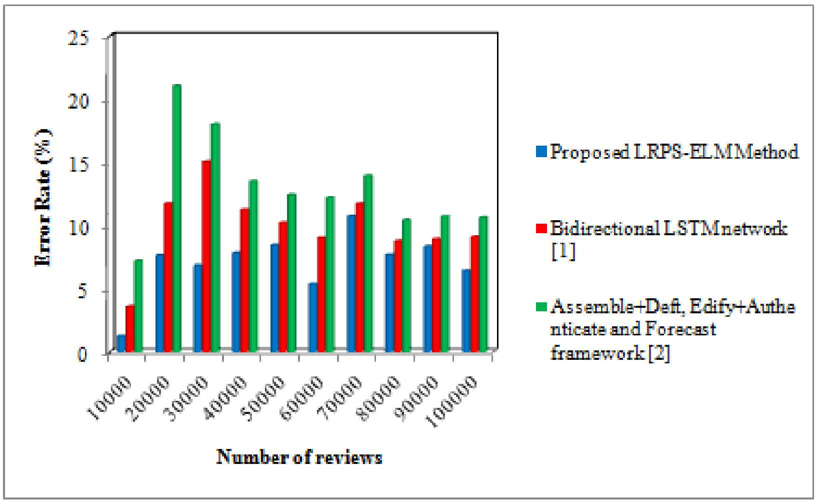

Figure 4 Measurement of Error Rate

Figure 4 examines the performance analysis of error rate for different number of reviews varies from 10000 to 100000. The number of reviews is taken in the horizontal direction and the error rate is achieved in vertical axis. The blue color cylinder symbolizes the error rate of proposed LRPS-ELM Method. The red color and green color cylinder represents the error rate of existing [1] and [2] respectively. As shown in graph, the error rate of proposed LRPS-ELM Method is lesser than conventional techniques. This is because of using extreme learning classification with preprocessing, feature extraction, and classification process. The review preprocessing performed the stop word removal and stem word elimination. Lasso Regression extracts the feature from the preprocessed reviews. Then, Percentage Similarity Function is used in LRPS-ELM Method for classifying the user opinion. Depending on the similarity values, reviews are categorized into positive, negative, and neutral with lesser error rate. As a result, the average error rate using proposed LRPS-ELM Method is minimized by 30% when compared to [1] and 45% when compared to [2].

5.5 Impact of Prediction Time

Prediction time is product of time consumed by one online review classification and number of reviews. It is formulated as,

$$Pre_{Time} = N * \text{time consumed to performed one review classification} \quad \text{-------} \ (10)$$

In equation (10), 'Pre_{Time}' is prediction time. 'N' is a number of reviews. The time is measured in terms of milliseconds (ms).

Table 3 Tabulation for Prediction Time

Number of reviews	Prediction Time (ms)		
	Proposed LRPS-ELM Method	Bidirectional LSTM network [1]	Assemble+Deft, Edify+Authenticate and Forecast framework [2]
10000	21	33	41
20000	23	35	44
30000	27	38	47
40000	29	41	50
50000	32	45	53
60000	33	48	56
70000	35	52	59
80000	38	55	62
90000	40	58	65
100000	43	60	68

Table 3 shows the results of prediction time of review classification using three methods, namely LRPS-ELM Method, Bidirectional LSTM network [1] and Assemble+Deft, Edify+Authenticate and Forecast framework [2]. Among three different methods, the proposed LRPS-ELM Method consumed lesser prediction time than conventional methods. Let us consider that number of reviews as 40000 for classification, the proposed LRPS-ELM Method consumes 29*ms* of prediction time whereas prediction time consumption of existing [1] [2] is 41ms and 80ms respectively.

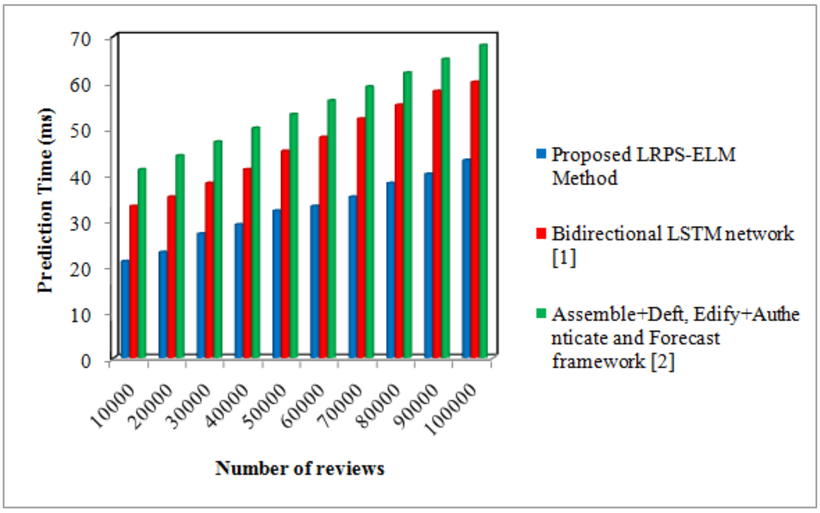

Figure 5 Measurement of Prediction Time

Figure 5 illustrate the analysis of prediction time for different number of reviews varies from 10000 to 100000. The number of reviews is considered in horizontal direction and the prediction time is obtained in the vertical axis. The blue color cylinder symbolizes the prediction time of proposed LRPS-ELM Method. The red color and green color cylinder represents the existing [1] and [2] respectively. The prediction time of proposed LRPS-ELM Method is minimized than conventional techniques. This is due to the application of extreme learning classification. The preprocessing task performed stop word removal and stem word elimination. In LRPS-ELM Method, Lasso Regression extracts the relevant feature from the preprocessed reviews. Subsequently, Percentage Similarity Function in LRPS-ELM Method categorizes the user opinion. With similarity values, reviews are classified into positive, negative, and neutral with lesser time complexity. As a result, the average prediction time of proposed LRPS-ELM Method are reduced by 31% and 42% when compared to [1] and [2].

VI. CONCLUSION

The proposed LRPS-ELM Method performs sentiment classification with better accuracy and consumes less time. Extreme Learning Classification categorizes reviews through preprocessing, feature extraction and classification. The review preprocessing performs stop words removal and stem words elimination. Then, Lasso Regression in LRPS-ELM Method extracts the relevant features from preprocessed reviews. Next, the extracted features are utilized for classification. Percentage Similarity Function in LRPS-ELM Method identifies the user opinion, namely positive opinion, neutral and negative opinion. In this manner, accurate sentiment classification is obtained with improved prediction accuracy and lesser time consumption. A simulation setting is provided with several metrics such as prediction accuracy, error rate and prediction time with respect to a number of reviews. LRPS-ELM Method improves the prediction accuracy and minimizes prediction time and error rate when compared to conventional methods .

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