Asian Journal of Research in Computer Science

Volume 16, Issue 4, Page 125-132, 2023; Article no.AJRCOS.107390
ISSN: 2581-8260

Analyzing Election Sentiments in Tweets with Gated Recurrent Units (GRU)

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/AJRCOS/2023/v16i4376

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/107390

Original Research Article

Received: 01/08/2023
Accepted: 07/10/2023
Published: 12/10/2023

ABSTRACT

Sentiment analysis, a key task in natural language processing, is important for detecting the emotional tone portrayed in text. In this study, we focus on implementing a Gated Recurrent Unit (GRU) model to analyze attitudes within the 2020 Donald Trump Election tweets dataset. By setting the GRU model with carefully selected parameters, the aim of the study is to unveil the inherent sentiment patterns in the dataset. To develop the sentiment analysis model, the study devised a three phase methodology which that include data preprocessing, feature selection using correlation matrix, and lastly the implementation of GRU. Futhermore, we provided the outcomes of our experiment, evaluating the model's performance through important measures such as accuracy, precision, and recall. Notably, our data exhibit an exceptional accuracy rate of 93%, verifying the model's power to appropriately categorize attitudes. Additionally, both recall and precision receive outstanding ratings of 94% and 96%, indicating the model's skill in distinguishing both positive and negative attitudes. This inquiry emphases the

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effective usage of the GRU model in sentiment analysis, shedding light on the emotional nuances within the 2020 Donald Trump dataset and enriching our understanding of sentiments during the election period.

Keywords: Sentiment analysis; natural language processing; tweets; Gated Recurrent Unit (GRU); machine learning and deep learning.

1. INTRODUCTION

The pervasive expression of sentiment due to the widespread use of digital communication and social media has had significant impacts on consumer behaviour, political outcomes, and brand perceptions [1]. It has become paramount for enterprises, governmental entities, and individuals to perceive and measure this sentiment's influence. Specifically, the ability to analyze public opinion during election campaigns is crucial for aspirants, allowing them to understand voters' opinions and preferences in the lead-up to and during an election [2]. Nonetheless, the task of analyzing sentiment during election campaigns can be daunting. Fortunately, advances in artificial intelligence, machine learning, and deep learning techniques have revolutionized the field of sentiment analysis in response to the growing demand for a systematic approach to analyzing and extracting vital insights from the vast volume of sentiment-rich textual data generated on the internet [3].

Sentiment analysis is an essential topic within the realm of Natural Language Processing (NLP) and thus focuses on an automated extraction and interpretation of sentiments and emotions expressed in written text [4,5]. The rise of digital material, namely on social media platforms, blogs, and review websites, has led to the importance of sentiment analysis as a valuable tool for understanding public attitudes, consumer feelings, and social trends [6]. The growing fascination with sentiment analysis has resulted in a plethora of scholarly investigations focused on the advancement of more intricate models that possess the ability to distinguish subtle emotions from a wide range of textual materials.

A significant development in the field of sentiment analysis involves the application of Recurrent Neural Networks (RNNs), which are a type of deep learning models that are well-known for their capacity to grasp sequential relationships in data [7,8]. The Gated Recurrent Unit (GRU) has garnered significant interest within the realm of RNNs due to its computational efficiency and efficacy in capturing the patterns inherent in sequential data [9]. This discourse explores the justification for employing the Gated Recurrent Unit (GRU) in the context of sentiment analysis, drawing upon pertinent literature in the domain.

The utilization of recurrent neural networks, specifically the Long Short-Term Memory (LSTM) and GRU architectures, has initiated a paradigm shift in the field of sentiment analysis [10]. These models have excellent proficiency in capturing contextual information, rendering them very suitable for the analysis of text sequences. Long Short-Term Memory (LSTM) and GRU have been widely utilized in addressing the difficulties presented by sentiment analysis, ranging from the identification of sentiment in individual sentences to the understanding of the sentiment progression throughout complete documents [11].

The advancement in the recurrent neural network to the development of the GRU algorithm and also the contribution made by several authors in the realm of sentiment analysis have prompted this study to examine the efficacy of the GRU algorithm in analyzing sentiments from 2020 Donald Trump and Joe Biden election dataset sourced from the Kaggle machine learning repository. The utilization of the GRU in sentiment analysis is driven by several considerations as the GRU algorithm has a more streamlined structure in comparison to LSTM networks, leading to a reduction in the number of parameters [12]. Consequently, this facilitates accelerated training and decreased computational requirements, rendering GRUs well-suited for extensive sentiment analysis tasks. Moreover, GRUs demonstrate exceptional proficiency in capturing extensive dependencies in sequential data, which is essential for accurately identifying subtle emotional nuances in textual content.

1.1 Problem Statement

In the current era characterized by the widespread use of social media and digital communication, examining sentiment expressed in tweets has become increasingly significant for understanding prevailing public opinion and attitudes. However, a significant challenge arises from the presence of chaotic and genuine behaviours in sentiment analysis, which can lead to errors in classifying tweets as positive or negative in terms of sentiment polarity. Unethical behaviours involve the use of caustic or sarcastic language, which can convey emotions that are in opposition to the literal interpretation of the words used. Certain behaviours have the potential to provide genuine indications of sentiment that may differ from the established standards of sentiment analysis. The behaviours outlined above pose a notable difficulty in precisely determining the authentic emotion conveyed in tweets, which is a vital factor for various applications such as brand monitoring, political sentiment analysis, and market research. Therefore, it is crucial to address the issue of disruptive and authentic behaviours in sentiment tweets to improve the reliability and precision of sentiment analysis models.

2. RELATED WORKS

Tyagi et al. [13] introduced a hybrid model that combined a convolutional neural network (CNN) and bidirectional long short-term memory (BiLSTM) for sentiment analysis on the Sentiment140 dataset, comprising 1.6 million Tweets labelled as positive or negative. The dataset underwent preprocessing, including case folding, stemming, and removing stop words, numerals, URLs, Twitter usernames, and punctuation. Their hybrid model included layers such as GloVe pre-trained embeddings, a one-dimensional convolutional layer, BiLSTM layers, fully connected layers, dropout layers, and a classification layer. The results showed a precision rate of 81.20% when evaluated on Sentiment140.

Harjule et al. [14] conducted a comparative study of machine learning and deep learning techniques for sentiment analysis, employing two datasets: Sentiment140 and Twitter US Airline Sentiment. Preprocessing steps included tokenization, case folding, and the removal of stop words, URLs, hashtags, and punctuation. Evaluated methods encompassed multinomial naive Bayes, logistic regression, support vector machine, long short-term memory (LSTM), and an ensemble approach combining multinomial naive Bayes, logistic regression, and support vector machine with majority voting. LSTM achieved an 82% accuracy rate on the Sentiment140 dataset, surpassing the support vector machine's 68.9% accuracy on the Twitter US Airline Sentiment dataset.

Chaudhry et al., [15] developed a sentiment classifier for the U.S. 2020 Presidential election via Twitter tweets. Additionally, the authors made comparisons between the 2016 and 2020 elections, both involving Donald J. Trump, to discern sentiment trends. The data preprocessing technique employed by the authors includes the use of Term Frequency-Inverse Document Frequency (TF-IDF) for feature extraction and utilizes the Naive Bayes Classifier to assess public sentiments. The results demonstrated that the Naive Bayes classifier sentiment classifier demonstrates a high accuracy of 94.58% and precision of 93.19%.

Hananto et al. [16] conducted sentiment analysis on Twitter data related to the 2024 Indonesia presidential election. They compared three classification algorithms, namely support vector machine (SVM), K-Nearest Neighbor (K-NN), and Naïve Bayes (NB), using a dataset comprising 9,966 tweets about presidential candidates collected during the second week of September 2022. The findings revealed that the SVM algorithm outperformed K-NN and Naïve Bayes, achieving an accuracy rate of 79.57%. This study identified SVM as the most effective algorithm for classifying positive and negative comments related to the 2024 presidential candidates' trends.

Chandra and Saini [17] applied a deep learning approach for the analysis of the US 2020 presidential election sentiments via Twitter tweets. The algorithm includes the long short-term memory (LSTM) and also the Bidirectional Encoder Representations Transformers (BERT). Experimental results revealed that the LSTM outperformed the BERT result with an accuracy of 88.10%.

3. METHODOLOGY

The employment of a methodology that facilitates the efficient development of the intended system is of utmost importance within the realm of standardized engineering and computer science practices [18,19]. Hence, the conceptual framework delineates the planned methodological approach for the accomplishment of the proposed sentiment analysis model. Essentially, the methodology for this study encompassed the consideration of three essential phases. The initial phase involved extracting null values from the dataset and subsequently eliminating them through the use of a filtering mechanism. Subsequently, the text stream underwent tokenization and lemmatization processes to isolate individual words. These words were then transformed into vectors by vectorization or normalization techniques. Furthermore, a correlation matrix was employed to choose features based on their influence within the dataset. Upon the completion of the sub-stages in the preceding phase, the dataset was partitioned into predetermined proportions for machine learning training and testing. The third methodology involved implementing the GRU network models. Subsequently, the performance of these models was assessed. The phases of the approach employed are depicted in Fig. 1.

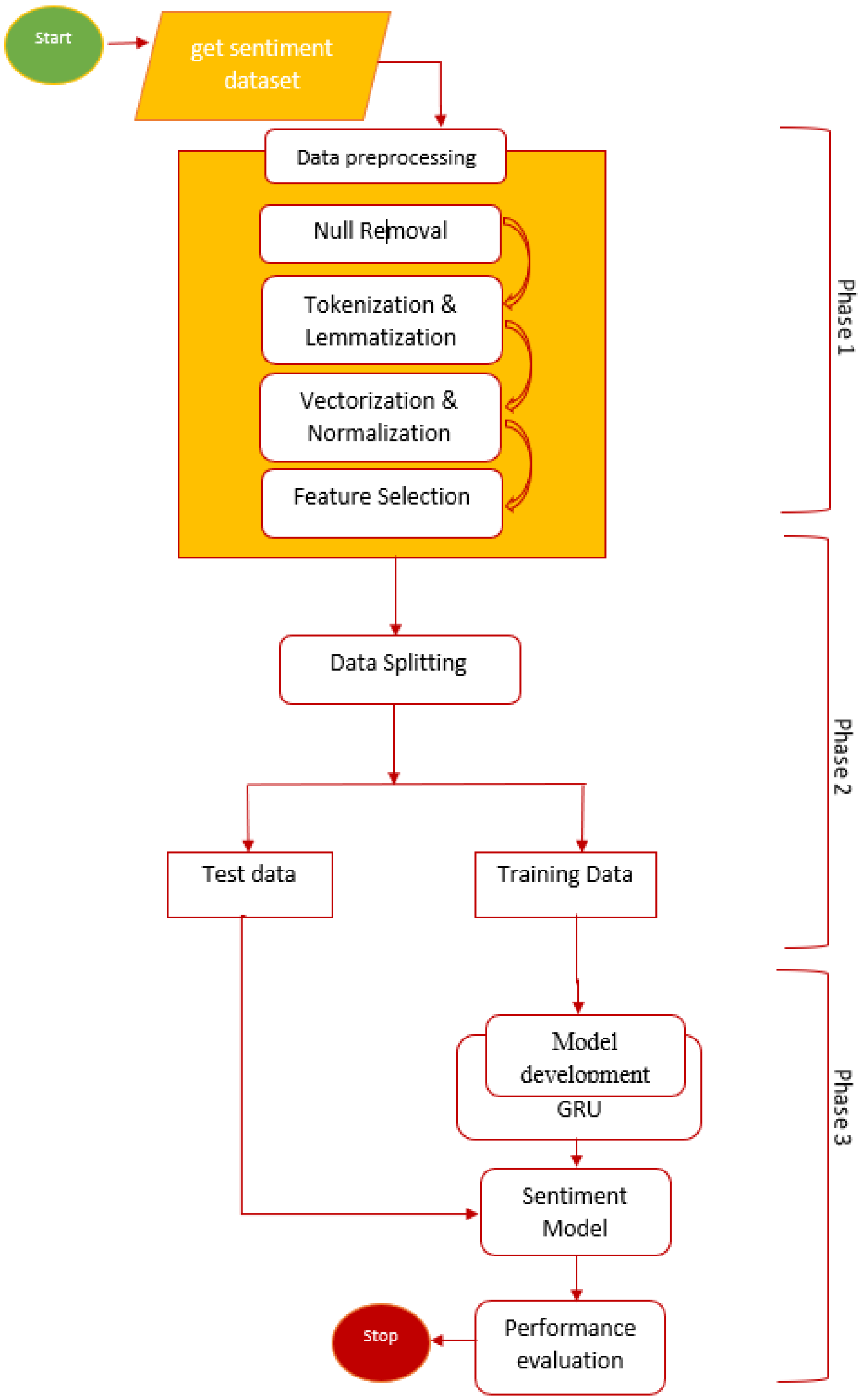

Fig. 1. Research methodology framework

3.1 Dataset Description

The dataset proposed by this study is a Twitter Sentiment Analysis dataset obtained from the Kaggle dataset repository. The Twitter record captures tweet reviews from the 2020 United States American election between Donald Trump and Joe Biden dated 3rd November 2020. The dataset contains over 970,919 tweets, but in this experiment, 50,000 of the records were utilized. The dataset contains the following attributes:

1. created_at: date and time of tweet creation
2. tweet_id: unique id of the tweet.
3. tweet: full tweet text.
4. likes: number of likes.
5. retweet_count: number of retweets
6. sources: utility used to post a tweet
7. user_id: user id of tweet creator.
8. user_name: username of tweet creator.
9. user_screen_name: screen name of tweet creator.
10. user_description: description of self by tweet creator.
11. user_join_date: join date of tweet creator.
12. User_followers_count: follower count on tweet creator.
13. user_location: location given on tweet creator's profile.
14. lat: latitude parsed from user_location.
15. long: longitude parsed from user_location.
16. city: city parsed from user_location.
17. country: country parsed from user_location.
18. state: state parsed from user_location.
19. state_code: state code parsed from user_location.
20. collected_at: date and time data were mined from Twitter.

3.2 Gated Recurrent Unit

A Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) architecture designed for sequential data processing tasks. It was introduced as a simpler alternative to the more complex Long Short-Term Memory (LSTM) networks, which were originally developed to address the vanishing gradient problem in traditional RNNs [20]. GRU was proposed by Cho, Kyunghyun; van Merrienboer, Bart; Bahdanau, DZmitry; Bougares, Fethi; Schwenk, Holger; and Bengio, Yoshua as a way to maintain similar modelling capabilities to LSTMs while simplifying the architecture and are known for their efficiency and practicality [21,22]. In the context of understanding GRUs, it's important to highlight key differentiators from LSTMs, including the reduction in the number of parameters, simplified training processes, and the role of specific gates like the update gate z_t, and the reset gate r_t. These aspects contribute to the unique characteristics and advantages of GRUs in sequence modelling tasks.

Considering the GRU architecture on Fig. 2, the update gate controls the amount of information to be retained by the state of the current time point h_t From the state of the last time point h_{t-1}, as well as the amount of new information received from the candidate state h_t , the reset gate controls the amount of information to be retained from the state of the last time h_{t-1} point by the candidate state of the current time point h_t. The methods for the calculation of the two gates are shown in equations (1) and (2). $W_*(*=z,r,h)$ and $U_*\,(*=z,r,h)$ stand for the weight matrix from the cell to the gate, and $b_*(*=z,r,h)$ denotes the vector of each gate.

$$z_t = \sigma(U_z h_{t-1} + w_z x_t + b_z) \qquad \ldots\ldots\ldots\ldots 1$$

$$r_t = \sigma(U_r h_{t-1} + w_r x_t + b_r) \qquad \ldots\ldots\ldots 2$$

The methods for updating the states are shown in equations (3) and (4):

$$\overrightarrow{h_t} = \tanh(U_t(r_t * h_{t-1}) + W_h x_t + b_h) \qquad \ldots\ldots 3$$

$$h_t = z_t * h_{t-1} + (1 - z_t) * \overrightarrow{h_t} \qquad \ldots\ldots 4$$

In the case where $z_t = 0$, and $r_t = 1$ The GRU network degenerates into a simple RNN.

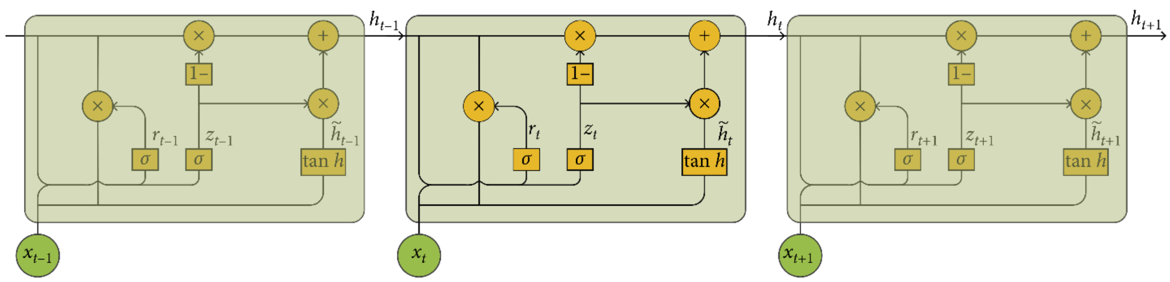

Fig. 2. GRU Architecture

3.3 Evaluation Parameters

To evaluate the performance of the Gated Recurrent Unit (GRU) model on the adopted Twitter dataset. This study optimized the viability of different performance evaluation parameters which are precision, recall, and accuracy which were calculated.

Precision: is defined as the ratio of correctly classified positive samples to the total number of samples predicted as positive:

$$precision = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Were,

True Positive (TP): The number of positive reviews that have been correctly classified.
False Positive (FP): Number of incorrectly classified positive reviews.

Recall: measures the classifier's completeness. It is the percentage of correctly predicted positive reviews to the actual number of positive reviews on the corpus. Therefore, recall indicates the number of related reviews identified:

$$Recall = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

False Negative (FN): Number of incorrectly classified negative reviews.

Accuracy: One of the most crucial performance evaluation criteria is accuracy. Essentially, accuracy is the ratio of correct classification to total predictions done by the model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \ldots\ldots (7)$$

True Negative (TN): The number of negative reviews correctly classified as negative.

4. EXPERIMENTAL SETUP

To experiment and analyze the sentiment as of positive or negative influence, this study utilized a 64-bit Windows Operating System, with an Intel(R) Corel (TradeMark-TM) i5-2560QM CPU @2.40GHZ with 4.00 GB of RAM (Random Access Memory). The programming environment utilized for implementing the program code was the Anaconda environment using the Python 3.8 software development kit. The application programming interface utilized was Kera's TensorFlow API, and Natural Language Toolkit such as Word-Cloud, and Word-Net. Some other Python dependencies utilized include NumPy for vector operations, pandas for reading files, and the Seaborn library for data visualization.

4.1 Parameter Setting

The GRU model is configured with parameters that include a minimum batch size. This batch size divides the dataset into smaller batches, with each batch containing 200 instances. The training process of the model was conducted for a maximum of 50 epochs. An epoch denotes a single iteration across the entirety of the dataset during the training process. The starting learning rate was established at 0.001. The rate in question is responsible for determining the magnitude of the step performed during the gradient descent process, which is used to update the parameters of the model. The Adam optimizer was utilized. The Adam optimization technique is designed to dynamically adjust the learning rate for individual parameters by utilizing information from the first and second moments of the gradients. The Binary Cross Entropy loss function was selected to measure the loss rate. The utilization of Binary Cross Entropy is prevalent in binary classification jobs when the objective is to categorize instances into one of two classes. A dropout rate of 0.4 was implemented. The regularization technique known as dropout involves the random deactivation of a portion of input units during each parameter update of the model. The reduction of reliance on specific traits during training aids in the prevention of overfitting. The parameters of the GRU model are presented in Table 1.

Table 1. Parameter setting

Parameter	Value
Min-Batch Size	200
Max epochs	50
Initial learn rate	0.001
Optimizer	Adam
Loss	Binary Cross Entropy
Dropout	0.4

4.2 Result Presentation

Table 2. Gated recurrent unit result for the 2020 Donald trump dataset

Metrics	Scores
Accuracy	93
Precision	96
Recall	94

Table 2 displays the GRU model's performance on the 2020 Donald Trump dataset. The model achieved a 93% accuracy rate, indicating its proficiency in correctly classifying sentiments. It also demonstrated a noteworthy precision of 96%, emphasizing its precision in sentiment predictions. Moreover, with a recall score of 94%, the model effectively identified positive and negative sentiments within the dataset, avoiding significant sentiment patterns' omission. Overall, these results highlight the GRU's robust performance in sentiment analysis, making it a valuable tool for extracting insights from sentiment-rich textual data.

4.3 Result Comparison

Table 3. Result comparison of the Donald trump dataset

Metrics	Algorithm	Accuracy
Chandra and Saini [17]	LSTM	88.10%
Current study	GRU	93

Table 3 presents a comparison of results for the Donald Trump dataset, specifically evaluating the performance of two different algorithms, LSTM and GRU, based on their accuracy scores. In the study conducted by Chandra and Saini in [17], they employed an LSTM-based model to analyze the dataset. Their reported accuracy score was 88.10%. This indicates that their LSTM model achieved an 88.10% accuracy rate in correctly classifying or predicting outcomes on the given data. In contrast, the current study employed a different algorithm, GRU, to experiment with the same dataset. The reported accuracy for the GRU algorithm was 93%. This suggests that the GRU-based model in the current study performed even better, with a higher accuracy rate of 93%.

Comparing these results, it appears that the GRU-based model used in the current study outperformed the LSTM model employed by Chandra and Saini in 2021 in terms of accuracy. A 4.9% increase in accuracy may be considered significant, indicating that the GRU model may be a more effective choice for this particular dataset or task.

5. CONCLUSION

In summary, the body of research examining Gated Recurrent Unit (GRU) models for sentiment analysis, as documented in a range of deep learning studies within the academic literature, underscores their efficacy in discerning and comprehending sentiments within diverse domains. The experimental endeavours showcased in these investigations have illuminated the GRU model's remarkable ability to effectively process sequential inputs, particularly textual data, and discern significant underlying patterns. Consequently, the model's performance in sentiment classification tasks has been notably enhanced. Repeatedly, the GRU model has exhibited promising results in sentiment analysis, marked by its exceptional accuracy, precision, and recall scores.

As exemplified by an application involving sentiment classification related to the 2020 US election and the discourse surrounding Donald Trump, the GRU model excelled in capturing nuanced emotional fluctuations within textual data. In this specific evaluation, the GRU model achieved an impressive accuracy rate of 93%, a precision rate of 96%, and a recall rate of 94%. These results underscore the substantial advantages of employing Gated Recurrent Units (GRUs) in the realm of sentiment analysis, particularly when dealing with intricate emotional dynamics embedded within textual data. This is largely attributable to the model's inherent capacity to capture and model long-range dependencies within sequential data, thus facilitating nuanced sentiment interpretation.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/107390