An Efficient Sentiment Classification Model Using Fusion of BERT and Deep Learning RNN Variants

Raja Rao PBV[1(✉)], M. Prasad[1], Kiran Sree Pokkuluri[1], P. Srikanth[1], Srinivasa Rao Dangeti[1], and B. Venkateswara Rao[2]

[1] Shri Vishnu Engineering College for Women(A), Bhimavaram, A.P, India
rajaraopbv@gmail.com
[2] B V Raju Institute of Technology, Narsapur, Medak District, T.S, India

Abstract. This paper explores the fusion of BERT with various recurrent neural network (RNN) architectures, including simple RNN, LSTM, and GRU, for Twitter sentiment classification. For experimentation, we used a Kaggle Sentiment 140 dataset with positive and negative sentiments. Initially, three DL models (RNN, LSTM, and GRU) were applied for sentiment analysis and achieved accuracies of 86%, 91%, and 90%, respectively. By integrating BERT with these RNN variants, the proposed method enhanced the performance of sentiment analysis on Twitter data. The methodology involves tokenizing and encoding Twitter messages using the BERT tokenizer to obtain contextual embeddings. These embeddings are then fed into RNN-based classifiers, including Simple RNN, LSTM, and GRU, to capture sequential dependencies within the text. Later, a hybrid model with BERT and RNN variants was applied. The hybrid model combining BERT with LSTM achieves the highest accuracy at 93.5%, followed by BERT + GRU with 91% and BERT + RNN with 90%. These findings underscore the effectiveness of leveraging BERT in conjunction with LSTM and GRU architectures for Twitter sentiment classification, offering promising avenues for further research and real-world applications.

Keywords: Twitter Sentiment · Kaggle · BERT · RNN · LSTM · GRU

1 Introduction

Social media platforms such as Twitter have emerged as vibrant hubs where individuals from all walks of life converge to share their thoughts, feelings, and reactions on a plethora of topics. Within this bustling virtual landscape, sentiment analysis has emerged as a crucial tool for deciphering the collective mood, opinions, and sentiments of users. Twitter, with its extensive user base and real-time nature, stands as a veritable goldmine of data for sentiment analysis endeavors. The ability to automatically categorize tweets into positive, negative, or neutral sentiments holds immense significance across various domains, including business, governance, and academia. For businesses,

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understanding customer sentiment on Twitter can inform marketing strategies, product development decisions, and brand management efforts. Governments can gauge public opinion on policies, social issues, and public services to inform policy-making processes and improve citizen engagement. Researchers can leverage Twitter data to gain insights into societal trends, cultural shifts, and public discourse on a global scale.

However, sentiment analysis on Twitter presents a unique set of challenges owing to the platform's distinctive characteristics. Tweets are often characterized by brevity, with users constrained by a limited number of characters to express their thoughts. This brevity necessitates the use of shorthand, informal language, and abbreviations, making sentiment analysis more challenging compared to longer-form textual data. Moreover, the pervasive use of emojis, hashtags, and other linguistic elements adds layers of complexity to the task of sentiment classification [1]. Furthermore, the dynamic nature of Twitter, with its ever-evolving trends and topics, poses additional challenges for sentiment analysis. The rapid dissemination of information and the ephemeral nature of tweets require sentiment analysis models to adapt and respond swiftly to shifting contexts and emerging sentiments. Traditional approaches to sentiment analysis, which rely on lexicon-based methods or simple statistical models, often fall short in effectively capturing the nuanced and context-dependent nature of sentiment expressed in tweets. As a result, there is a growing interest in leveraging advanced machine learning and deep learning techniques [2] to tackle these challenges and extract meaningful insights from Twitter data.

This work investigates the integration of BERT with RNN architectures, namely RNN, LSTM, and GRU, for Twitter sentiment classification. RNNs are well-suited for modeling sequential data, like text, due to their ability to capture temporal dependencies. By combining the strengths of BERT's contextual embeddings with the sequential modeling capabilities of LSTM and GRU, we aim to enhance performance of sentiment analysis on Twitter data.

2 Literature Review

Parveen et al. [3] utilized Sentiment 140 to test the GARN architecture. After preprocessing the dataset, the LTF-MICF model extracted features, and the HHMWSO selected them. The GARN architecture, which merged RNN with attention, recognized positive, negative, and neutral emotions. These findings demonstrate GARN's sentiment classification effectiveness, adding to the field. Masoud AminiMotlagh et al. [4] analyzed Twitter sentiment using four prominent data mining classifiers: KNN, DT, SVM, and NB. Ensemble methods [5] were used to analyze two- and three-class datasets to improve dependability. Improved accuracy of 3.53% and 7.41% on two-class and three-class datasets showed SVM superiority. Group techniques were more trustworthy, while individual classifiers were more accurate. Tenfold cross-validation performed better, and training using 50% of the dataset produced results equivalent to 70%, proving the model's endurance. Yili Wang et al. [6] conducted an exhaustive analysis of recent advancements in the field, examining a variety of newly proposed methodologies and applications. An exhaustive classification is applied to every published work in accordance with its level of pertinence to specific TSA processes. The primary objective of the study was to provide a succinct yet comprehensive overview of TSA procedures and related topics. Notable novelties encompass an exhaustive categorization of numerous ongoing studies and an overview of the current state of TSA research. A compilation of airline tweets was generated utilizing natural language processing (NLP) techniques, encompassing positive, neutral, and negative sentiments [7]. Sentiment analysis was conducted utilizing the subsequent techniques: RNN, LSTM, stacked LSTM, bidirectional LSTM, and GRU. In terms of accuracy, the model exhibited the following comparisons in tweets: 90% for positive and negative sentiment, 84.5% for neutral to positive sentiment, and 83.8% for neutral to negative sentiment.

The proposed RNN model classified airline tweet sentiment effectively in [8]. Transformer-based architectures, RNN, and SVC were used for sentiment analysis with ML and DL methods. Practical applications of fine-grained sentiment analysis in public opinion research, social media, and customer-focused enterprises were highlighted. Sentiment analysis has made it possible to understand human emotions, enabling informed decision-making in many scenarios. To find the optimum [9] sentiment analysis approach, Harjasdeep Singh et al. constructed an ML model [10]. Several ML classifiers were evaluated using movie reviews, accuracy, and F1 metrics. Fusion sentiment analysis was introduced by Huaqian He et al. [11] to mine online product experiences. It combines machine learning and text analysis. LDA models extracted sentiment themes, SVM algorithms detected sentiment polarity, and sensitive sentiment dictionaries extracted sentiment characteristics. To overcome the lack of emotional data, semantic similarity was used to expand vocabulary and account for word sentiment in assessments.

As observed by S. K. Satti [12], sentiment classification within natural language processing stands as a crucial field, demanding sophisticated methodologies to ensure precise and effective classification of textual data. Recent strides in deep learning and language models have played a pivotal role in augmenting sentiment analysis systems. This literature survey takes inspiration from the successful integration of multiple neural network architectures for diverse tasks, particularly evident in the domain of image caption generation. Proposing the amalgamation of BERT, a potent pre-trained language model, with various deep learning Recurrent Neural Network (RNN) variants, our approach aims to forge an innovative sentiment classification model. Following the paradigm of utilizing pre-trained models for feature extraction, analogous to the ResNet-50 Convolutional Neural Network (CNN) in image captioning, our model endeavors to leverage BERT's contextual understanding alongside the expressive capabilities of RNNs. This integration seeks to capture subtle linguistic nuances and contextual dependencies, thereby pushing the boundaries of sentiment classification performance. The subsequent chapters will present the empirical evaluation of our proposed model against existing methods, substantiating its potential to surpass current benchmarks and make significant contributions to the field of sentiment analysis.

Using the RoBERT based WangChanBERTa pre-trained Thai language model, [13] developed a features. These features combined with Word2Vec, TF-IDF [14], and BOW vectors to construct a hybrid representation. The model was trained and meta-learners generated using seven complex MLP models like RF, ET, LGBM, MLP, PLS, and LR. After benchmarking four datasets, including a subject matter expert-annotated sentiment corpus, our stacking ensemble technique proved better. CNN, attention-based BiGRU, and sentiment lexicon comprise Li Yang et al., SLCABG sentiment analysis model [15]. It corrected product review analysis issues with DL and sentiment lexicons. Lexicons improved sentiment characteristics; CNN and BiGRU extracted critical features; and an attention mechanism weighted data before classification. Several feature sets and classifiers were tested for sentiment measurement in [16]. Modern feature-set-based DL algorithms, ensemble-based techniques, and classic machine learning methods were examined using empirical performance analysis. The findings showed that feature settings affected sentiment quantification classifier performance. Results showed that DLethods outperformed traditional ML algorithms. An enlarged sentiment lexicon comprising basic, industry-specific, and polysemic terminology was proposed in [17] to address sentiment analysis difficulties. Using a naïve Bayesian classifier enhanced accuracy by contextualizing polysemic terms.

Most of the previous works focused on traditional ML or DL approaches. But conventional algorithms may not perform well in all cases. In this paper, a novel fusion of pretrained BERT and DL techniques was applied and achieved good results.

3 Proposed Methodology

The proposed method is shown in Fig. 1. The proposed method endeavored to advance the field of sentiment analysis on Twitter data by integrating two powerful deep learning [18, 19] models: BERT (Bidirectional Encoder Representations from Transformers) and RNN variants, namely Simple RNN, LSTM, and GRU. Twitter, with its vast user base and real-time nature, presented a rich source of data for sentiment analysis, providing insights into public opinions, reactions, and sentiments on diverse topics. However, the brevity of tweets, informal language, and the dynamic nature of trending topics posed unique challenges for sentiment analysis.

To address these challenges, a comprehensive methodology was devised. Initially, a Kaggle dataset with Twitter sentiments was collected. This dataset underwent rigorous preprocessing, involving the removal of noise such as special characters, URLs, mentions, and irrelevant information while preserving sentiment-relevant elements such as emojis and hashtags. Standardizing text formatting ensured consistency in tokenization, a crucial step in subsequent processing. Tokenization, a fundamental task in NLP, was performed using the BERT tokenizer, renowned for its ability to handle complex linguistic structures and context. This step ensured that the text data was appropriately segmented into individual tokens, ready for input into the BERT. It is a pre-trained model, was leveraged to generate contextual embeddings for each tokenized input sequence. By capturing rich semantic information and contextual relationships within the text, BERT embeddings provided a powerful representation of the input data. In the next phase, integration of BERT with RNN [20] variants will be done. The integration of BERT and RNN models marked a significant advancement in the methodology. Three RNN types, namely simple RNN, LSTM, and GRU, were applied. The RNN variant architectures were carefully defined, with parameters such as the suitable number of units and activation functions tailored to the task of sentiment analysis.

BERT embeddings were fed into the RNN/LSTM/GRU layer to capture sequential dependencies within the text, augmenting the contextual understanding provided

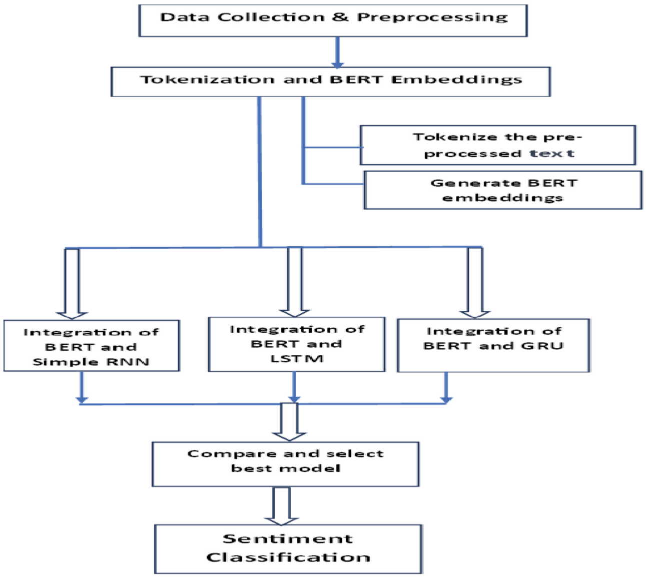

Fig. 1. Proposed Methodology

by BERT with the ability to model temporal dynamics. Concatenating BERT embeddings with the output of the RNN/LSTM/GRU layer facilitated the fusion of contextual information with sequential modeling, enhancing the model's ability.

The integrated BERT + RNN, BERT + LSTM, and BERT + GRU models underwent rigorous analysis with the dataset split into training and testing sets to assess their accuracy and recall for sentiment classification. Comparative analysis against baseline models, including standalone BERT or LSTM models, provided valuable insights.

4 Experimentation and Results

All experiments was conducted using python language in google collaborator environment.

4.1 Data Collection and Preprocessing

A Kaggle dataset [21] of Twitter messages covering various topics with positive and negative sentiments was collected. The dataset contains 1,600,000 tweets. Out of which, half of the tweets are positive, and the remaining half are negative sentiments. To reduce model complexity, only 50,000 samples of positive and negative sentiments are used in experimentation. The text data was preprocessed to remove noise and standardize formatting. Special characters, URLs, mentions, and other irrelevant information were removed. Text formatting was standardized to ensure consistency in tokenization. Emojis, hashtags, and other non-textual elements relevant to sentiment analysis were retained. The dataset is divided into training and testing parts with a 75% and 25% split ratio, respectively.

4.2 Applying DL Models RNN, LSTM and GRU

Initially, basic DL algorithms, namely Simple RNN, LSTM, and GRU, were applied. The architecture used for the RNN model contains 3 hidden layers with 180, 100, and 80 neurons, respectively. The LSTM and GRU models used only two hidden layers with 180 and 90 neurons in each layer. The loss function used in three models is "binary_cross entropy." The "Adam" optimzer is utilized in all three models. The number of epoches used in the models is 30. The results of the three models are shown in Table 1. From Table 1, it is observed that RNN has 86% accuracy and 84% recall. The accuracy and recall achieved with LSTM are 91% and 90%, respectively. GRU gave 90% and 87.8% accuracy and recall values, respectively. Among the three, LSTM performed well.

Table 1. DL Model Results

Model	*Recall*	*Accuracy*
RNN	84%	86%
LSTM	90%	91%
GRU	87.8%	90%

4.3 Tokenization and BERT Embeddings

Following the successful tokenization process, the focus shifted to the generation of BERT embeddings for the tokenized input sequences. In this step, we harnessed the capabilities of a pre-trained BERT model, utilizing its contextual understanding to produce embeddings that encapsulate the nuanced semantic information within the text. In the subsequent phase, we delved into the extraction of BERT embeddings from the last hidden state of the BERT model. This step was instrumental in obtaining a comprehensive representation of contextualized information for each token. The embeddings derived from the last hidden state provided a detailed snapshot of the semantic nuances present in the text.

4.4 Integration of BERT and RNN

In this step, the fusion of BERT and Simple RNN implemented. This process involves various steps.

4.4.1 Define RNN Architecture

In this step, the RNN architecture is specified. The number of RNN units is set to 256, and an input layer is created to accommodate the shape of BERT tokenized input sequences. The RNN layer is configured to return sequences to capture sequential dependencies within the text. A GlobalMaxPooling1D layer is added to further extract essential features from the RNN output.

4.4.2 Process BERT Embeddings Using the LSTM Layer

In this step, the BERT embeddings obtained from the last hidden state are inputted into the RNN layer. This step allows the model to capture sequential patterns and dependencies within the text.

4.4.3 Concatenate BERT Embeddings with LSTM Output

The BERT embeddings and the output from the LSTM layer are concatenated. This step aims to fuse contextual information from BERT with sequential modeling from the LSTM, creating a hybrid representation.

4.4.4 Design the Neural Network Architecture

In this step, additional dense layers are introduced for sentiment classification. A dense layer with ReLU activation, followed by a dropout layer for regularization, and a final dense layer with a sigmoid activation for binary classification are added.

4.4.5 Compilation, Training and Evaluation of the Model

The model is then compiled using cross-entropy loss and the Adam optimizer. The model is trained using tokenized and split data, with 5 epochs and a batch size of 64. The trained model is evaluated on the test set, and the test loss and accuracy are printed. The trained model is evaluated on the test set, and recall and accuracy are calculated. The accuracy and recall achieved with this integration are 90% and 88%, respectively.

4.5 Integration of BERT and LSTM

In this step, the fusion of BERT and LSTM is implemented. This process involves various steps. Initially, an LSTM architecture is specified. The number of LSTM units is set to 128, and an input layer is created to accommodate the shape of BERT tokenized input sequences. The RNN layer is configured to return sequences to capture sequential dependencies within the text. A GlobalMaxPooling1D layer is added to further extract essential features from the LSTM output. Next, the BERT embeddings obtained from the last hidden state are input into the LSTM layer. This step allows the model to capture sequential patterns and dependencies within the text. Later, the BERT embeddings and the output from the LSTM layer are concatenated. This step aims to fuse contextual information from BERT with sequential modeling from the LSTM, creating a hybrid representation. Additional dense layers are introduced for sentiment classification. The model is then compiled using binary cross-entropy loss and the Adam optimizer. The model is trained using tokenized and split data, with 5 epochs and a batch size of 64. The accuracy and recall achieved with this integration are 93% and 92.5%, respectively.

4.6 Integration of BERT and GRU

In this step, the fusion of BERT and GRU is implemented. This process involves various steps. Initially,a GRU architecture is specified. The number of GRU units is set to 128, and an input layer is created to accommodate the shape of BERT tokenized input sequences. The GRU layer is configured to return sequences to capture sequential dependencies within the text. A GlobalMaxPooling1D layer is added to further extract essential features from the GRU output. Next, the BERT embeddings obtained from the last hidden state are input into the GRU layer. This step allows the model to capture sequential patterns and dependencies within the text. Later, the BERT embeddings and the output from the GRU layer are concatenated. This step aims to fuse contextual information from BERT with sequential modeling from the GRU, creating a hybrid representation. A dense layer with ReLU activation, followed by a dropout layer, and a dense layer with output function are added. The model is then compiled using cross-entropy loss and the Adam optimizer. The model is trained using tokenized and split data, with 5 epochs and a batch size of 64. The accuracy and recall achieved with this integration are 93.5% and 91%, respectively.

4.7 Comparison of Results

After integrating BERT with three DL models, a comparison of these three models was performed to identify the best model for sentiment analysis. The results of the comparison are shown in Table 2 and Fig. 2. From Fig. 2, it is identified that the integration of the BERT and DL models performed well when compared to the conventional DL models.

Table 2. Comparison of Models

Model	*Recall*	*Accuracy*
RNN	84%	86%
LSTM	90%	91%
GRU	87.8%	90%
BERT + RNN	88%	90%
BERT + LSTM	91%	93.5%
BERT + GRU	92.5%	91%

The accuracy [22] and recall have increased for all three proposed models. The accuracy of BERT + RNN compared to RNN improved from 84% to 90%, and recall increased from 84% to 90%. The accuracy of BERT + LSTM compared to LSTM improved from 91% to 93.5%, and recall [23] increased from 90% to 91%. The accuracy of BERT + GRU compared to GRU improved from 90% to 91%, and recall improved from 90% to 91%.

Table 3 shows a comparison of the BERT + LSTM with previous models. Our proposed method outperforms previous models in terms of accuracy [24]. While LSTM achieved an accuracy of 91% and the Stacking Ensemble method attained 84%, our approach utilizing the fusion of BERT with LSTM achieved an accuracy of 93.5%.

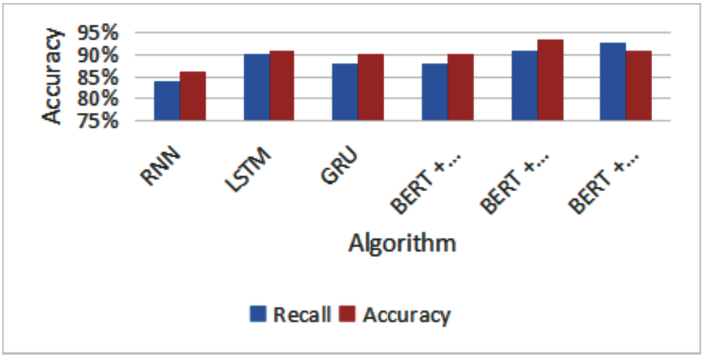

Fig. 2. Performance Comparison of Models

Table 3. Comparison of Models

Model	*Accuracy*
LSTM	91%
Stacking Ensemble	84%
Proposed Method	93.5%

5 Conclusion

This paper proposes the integration of BERT with different RNN architectures, specifically Simple RNN, LSTM, and GRU, for the task of Twitter sentiment classification. The experimentation was conducted on the Kaggle Sentiment140 dataset, which encompasses both positive and negative sentiments. Initially, three deep learning models, namely RNN, LSTM, and GRU, were employed for sentiment analysis, yielding respectable accuracies of 86%, 91%, and 90%, respectively. Building upon these results, the paper proposes a novel approach by fusing BERT embeddings with the aforementioned RNN variants to enhance sentiment analysis accuracy on Twitter data. The methodology involved the tokenization and encoding of Twitter messages using the BERT tokenizer, generating contextual embeddings. These embeddings were subsequently fed into RNN-based classifiers, including Simple RNN, LSTM, and GRU, to capture sequential dependencies within the text. A pivotal aspect of the study involved the introduction of a hybrid model, combining BERT with each RNN variant. The results showcased significant improvements in accuracy compared to the standalone RNN models. Notably, the hybrid model incorporating BERT with LSTM achieved the highest accuracy at 93.5%, followed closely by BERT + GRU with 91% and BERT + RNN with 90%. These outcomes underscore the efficacy of leveraging BERT in conjunction with LSTM and GRU architectures for Twitter sentiment classification. The successful integration of BERT with LSTM and GRU models demonstrates the potential for more accurate and context-aware sentiment analysis in social media data. For future work, the methodology could be extended to other social media platforms, exploring multi-class sentiment classification tasks. Additionally, experimenting with different pre-trained language models and fine-tuning strategies could enhance adaptability. Integrating techniques to handle noisy data in social media could further improve the robustness of sentiment analysis systems.

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