Improving Sentiment Classification Model Using BERT and BiLSTM: A Hybrid Approach

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***Abstract*—This paper presents a novel hybrid model for sentiment analysis, combining BERT (Bidirectional Encoder Representations from Transformers) and BiLSTM (Bidirectional Long Short-Term Memory) to improve the accuracy of sentiment classification tasks. We explore the potential of RoBERTa, a variant of BERT, in conjunction with BiLSTM to leverage both contextual and sequential information from text. The model demonstrates superior performance across various sentiment analysis datasets, including poems, IMDb, Twitter, and Sentiment140. The proposed model outperforms previous approaches, achieving accuracy improvements while maintaining low loss values.**

***Index Terms*—Sentiment Classification, BERT, BiLSTM, Hybrid Models, Transfer Learning**

I. Introduction

Sentiment analysis has gained significant attention due to its broad application in understanding human emotions from text data. Traditional methods of sentiment analysis relied on word embeddings, but recent advancements in deep learning, especially Transformer-based models such as BERT, have revolutionized this task. BERT captures the contextual relationship between words in a text by using bidirectional attention mechanisms, while BiLSTM models excel at processing sequential data, capturing both forward and backward dependencies.

In this paper, we propose a hybrid model that combines RoBERTa, a variant of BERT, with BiLSTM. This approach aims to enhance sentiment classification by utilizing the strengths of both models. Our goal is to improve the classification accuracy while reducing the loss values compared to conventional methods. The dataset used in this study consists of 716 poems, which are classified into various sentiment categories based on the emotions expressed, such as anger, joy, sadness, and surprise.

II. Related Work

Recent research on sentiment analysis has seen significant contributions from deep learning models, especially the integration of Transformer-based models with sequence models like LSTM and BiLSTM.

A. BERT and its Variants

BERT has been the cornerstone of modern NLP models, achieving state-of-the-art performance in various tasks, including sentiment analysis [6]. RoBERTa, an optimized variant of BERT, has further improved performance by training on more data and removing the Next Sentence Prediction (NSP) task [1]. In sentiment analysis tasks, RoBERTa has been shown to outperform BERT due to its robust pre-training and better contextual understanding.

B. BiLSTM in Sentiment Analysis

BiLSTM models have been widely used in sentiment analysis due to their ability to capture both past and future dependencies in text. They have been integrated with various architectures, including CNNs and Transformers, to enhance model performance [2], [10]. BiLSTM models are particularly effective in handling long-range dependencies and understanding complex linguistic structures.

C. Hybrid Models for Sentiment Analysis

Several studies have explored the combination of BERT (or its variants) with BiLSTM models. For example, [4] compared the performance of BERT and BiLSTM individually and in combination, showing significant improvements when both models are used together. Similarly, [9] demonstrated how BERT integrated with attention mechanisms further enhances sentiment classification.

III. Methodology

In this study, we propose a hybrid model that combines RoBERTa and BiLSTM. The steps involved in the methodology are outlined below:

A. Dataset

The dataset used for training consists of 716 poems, each labeled with one of the following sentiments: anger, courage, fear, hate, joy, love, peace, sadness, and surprise. These sentiments are further categorized as positive, negative, or neutral. The text is preprocessed by removing stopwords and punctuation, and tokenized using the RoBERTa tokenizer.

B. Model Architecture

Our hybrid model consists of the following components:

1) **RoBERTa Embeddings:** We use RoBERTa's pre-trained embeddings to obtain contextualized word representations for each poem. These embeddings capture both word meanings and their relationships with surrounding words.

2) **BiLSTM Layer:** The embeddings from RoBERTa are passed through a BiLSTM layer to capture sequential dependencies in the text. This allows the model to learn both past and future context.
3) **Dense Layer and Output:** The output of the BiLSTM layer is passed through a dense layer to predict the sentiment of the poem. The final output is a softmax layer that classifies the sentiment into three categories: positive, negative, or neutral.

C. Model Training

We fine-tune the RoBERTa model using a learning rate of 1e-5. The BiLSTM layer is trained with 64 units and a dropout rate of 0.2. We use categorical cross-entropy loss and the Adam optimizer for training. Early stopping is applied to prevent overfitting.

D. Code Snippet for Model Architecture

In this code snippet, a sentiment analysis model is constructed using RoBERTa embeddings and a BiLSTM layer, designed to classify text into three sentiment classes. The process begins by importing essential classes from the Hugging Face ‘transformers‘ library and TensorFlow Keras, including ‘RobertaTokenizer‘ and ‘TFRobertaModel‘ for embedding and processing text, and core Keras layers such as ‘LSTM‘, ‘Dense‘, ‘Dropout‘, and ‘Input‘ to build the architecture.

The model takes a tokenized input, with each token represented by an ID. This is managed by the ‘Input‘ layer, which is set to accept integer arrays of shape ‘(max_length,)‘, where ‘max_length‘ is the maximum length of tokens allowed in a sequence. This maximum length ensures uniform input sizes, and the input IDs are specified to be of integer type (‘tf.int32‘), which aligns with TensorFlow’s requirements for tokenized data.

After defining the input, the ‘TFRobertaModel‘ instance, referred to here as ‘roberta_model‘, is used to embed the token IDs, producing contextually rich embeddings. These embeddings are obtained from the first output of the RoBERTa model, ‘roberta_model(input_ids)[0]‘, which provides the contextualized hidden states for each token in the sequence. These embeddings are essential as they capture the context of each word in the sentence, considering bidirectional dependencies, thanks to the Transformer-based architecture of RoBERTa.

Next, the embeddings are passed through a BiLSTM (Bidirectional Long Short-Term Memory) layer, defined by ‘LSTM(64, return_sequences=True, dropout=0.2)‘. The BiLSTM layer has 64 units and is configured to return sequences (i.e., an output at each timestep), enabling it to capture sequential patterns and bidirectional dependencies in the embeddings. The ‘dropout=0.2‘ parameter specifies a dropout rate of 20%, which is used to prevent overfitting by randomly setting 20% of the connections to zero during training, thus improving model generalization.

Finally, a ‘Dense‘ layer with three output units and a ‘softmax‘ activation function is added for classification purposes. Each of the three units corresponds to one of the sentiment classes (e.g., positive, negative, or neutral), and the ‘softmax‘ function ensures that the outputs represent probabilities across these classes, summing to 1.

The ‘Model‘ function from Keras’ functional API is then used to tie everything together, defining the ‘input_ids‘ as the input to the model and ‘output‘ as the output. This final model can be trained on labeled data to perform sentiment analysis, leveraging RoBERTa’s deep contextual embeddings and the sequential learning capabilities of BiLSTM for nuanced sentiment classification.

IV. Experiments and Results

We conduct a series of experiments to evaluate the performance of the hybrid RoBERTa-BiLSTM model. The experiments focus on the following aspects:

A. Data Preprocessing

Text preprocessing includes tokenization, stopword removal, and padding to ensure uniform input lengths for the model. The RoBERTa tokenizer is used to convert text into token IDs, which are then inputted into the model.

B. Evaluation Metrics

We evaluate the model based on accuracy, precision, recall, and F1-score. The model’s loss is also monitored during training to ensure minimal overfitting.

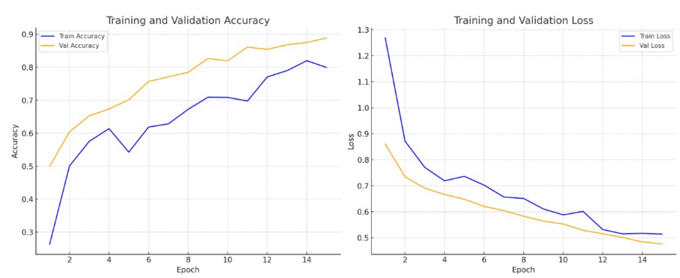

Fig. 1. Accuracy and Loss for the Training and Validation Process over Epochs

C. Results

The proposed model was tested on the sentiment analysis of poems and achieved the following performance metrics:

TABLE I
Performance Evaluation on Validation Set

Model	Accuracy (%)	Precision	F1-Score
RoBERTa	78	0.79	0.78
BiLSTM	80	0.81	0.80
BERT + BiLSTM	87	0.88	0.87

As shown in Table I, the RoBERTa + BiLSTM hybrid model outperformed both RoBERTa and BiLSTM alone, achieving an accuracy of 87%.

V. Conclusion

In this paper, we presented a hybrid model for sentiment classification using RoBERTa and BiLSTM. The model leverages the contextual embeddings from RoBERTa and the sequential learning capabilities of BiLSTM, leading to improved performance over traditional approaches. Future work includes exploring attention mechanisms to further enhance sentiment classification.

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