

Sentimen based-emotion classification using bidirectional long short term-memory (Bi-LSTM)

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ABSTRACT

Social media is now an important platform for sharing information, expressing opinions, and daily feelings or emotions. The expression of emotions such as anger, sadness, fear, happiness, disappointment, and so on social networks can be further analyzed either for business purposes or just analyzing the habits of a community or someone's posts. However, analyzing manually will be a time-consuming process, and the use of conventional methods can affect the results of less accurate accuracy. This research aims to improve the accuracy of recognizing emotions in text by using the Bidirectional Long Short Term Memory (Bi-LSTM) method, which is a subset of RNNs that tend to be more stable during training and show better performance on various NLP and other processing tasks. The method used includes several stages, namely preprocessing, tokenization, sequence padding, and modeling. The results of this study show that the Bi-LSTM model is capable of predicting emotions in text with an accuracy of 94.45% because it excels in handling the temporal context and can avoid vanishing gradients.

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1. INTRODUCTION

Social media is currently a large platform that connects many people around the world. Social media now plays a role in sharing content, information, expressing emotions, community-based collaboration and other [1]. The expression of emotions such as anger, sadness, fear, happiness, disappointment, and so on social media can be further analyzed either for business purposes or just analyzing the habits of a community or someone's posts. However, analyzing manually will be a time-consuming process. In its current development, analysis can be done with NLP (Natural Language Processing), which helps identify analysis through text mining, one of which is sentiment analysis [2]. Sentiment analysis is a technique to determine how people think and feel about things. Sentiment analysis is a cognitive technique for determining the emotional tone [3]. Sentiment analysis includes emotion detection, which can predict different emotions rather than simply indicating positive, negative, or neutral emotions [4]. Emotions are an integral part of how communication happens [5], [6]. Text communication has become an important part of daily life with the rapid development of online social networks [7]. Due to its important role in human communication, emotion recognition has

become an increasingly interested research subject [8]. Emotion recognition is the technique to recognize people's feelings through behavior, facial expressions, or even written words [9]. In natural language processing (NLP) and artificial intelligence (AI), emotion recognition in text has become an important component, especially in terms of sentiment analysis and human-computer interaction [4].

Emotion recognition in text using Recurrent Neural Networks (RNN) has gained significant attention in recent years due to its many applications in natural language processing and artificial intelligence [10]. The ability to understand emotions is very important, given the amount of human interaction with AI systems. Many studies have been conducted to analyze the role of emotions through the sentiments expressed by a person. As in the research conducted by Santosh Kumar Bharti et al [11] proposed text-based emotion recognition with a combination of deep learning and machine learning using ISEAR, WASSA, and Emotion-Stimulus datasets. SVM, a ML technique, yields an accuracy of 78.97%. The CNN model had the highest F1 score of 80.76% in the DL approach, while the Bi-GRU model had the highest accuracy at 79.46%. The hybrid model that was employed produced results including 82.39 precision, 80.40 recall, 81.27 F1-score, and 80.11% accuracy. With its ability to operate on multitext phrases, teets, dialogs, easily identifiable keywords, and emotion lexicons, the suggested model offers numerous benefits. Electroencephalogram (EEG)-based emotion recognition in the brain computer interface (BCI) was proposed by M. Kalpana Chowdary et al. [10]. This study uses three architectures: a gated recurrent unit (GRU), a long-short-term memory network (LSTM), and a recurrent neural network (RNN) to identify emotions using EEG signals. For the emotion recognition task, it obtained an average accuracy of 95% for RNN, 97% for LSTM, and 96% for GRU using the EEG brain wave data set. Sadil Chamishka et al. [12] suggested an RNN-based emotion detection model to predict categorical emotions in real time while capturing the conversational context and state of each party. Using the IEMOCAP dataset, the suggested method demonstrated 60.87% weighted accuracy and 60.97% unweighted accuracy for six fundamental emotions. An artificial intelligence method to automatically identifying human emotions was presented by Kristina Machova et al. [13], allowing machines (chatbots) to correctly determine human emotional states and tailor their interactions accordingly. To create an emotion recognition model in a text, this study employed lexicon-based techniques and machine learning techniques appropriate for text processing, such as naive bayes, support vector machines, and deep learning utilizing neural networks. Six different emotions from the text data were multiclassified and the neural network detection model performed well. It received an $F1 = 0.95$ for sadness. Seunghyun Yoon et al. [14] proposed a deep dual iterative encoder model to recognize emotions from speech, using audio and text data simultaneously. Through extensive experiments, we examined the effectiveness and characteristics of the proposed model. The results show that our model outperforms previous approaches by 68.8% to 71.8% on the IEMOCAP dataset. Error analysis demonstrates the model's ability to identify emotion classes, with a reduction in neutral class misclassification bias that often occurs in previous models that focus on audio features.

In this research, a recurrent neural network (RNN) method is used to identify emotions in text. This is done by utilizing the advantages of RNN in processing sequential data, such as text, as RNN can consider context and word order. Therefore, this research focuses on the use of RNN to identify emotion patterns in text. However, traditional RNNs suffer from limitations such as an exploding and vanishing gradient. The LSTM architecture is a variant of RNN that can overcome the weaknesses of traditional RNN [15]. For more optimal information absorption, a Bi-LSTM (Bidirectional LSTM) layer is used because it is capable of processing input data forward and backward [16], [17]. This can be a new contribution to the development of text-based emotion recognition methods.

2. METHOD

The research proposes the bidirectional long- and short-term memory (Bi-LSTM) method as part of RNN for the detection in text. There are several stages in this research, namely the data pre-processing, tokenization, pad sequences, and modeling stages described in Figure 1.

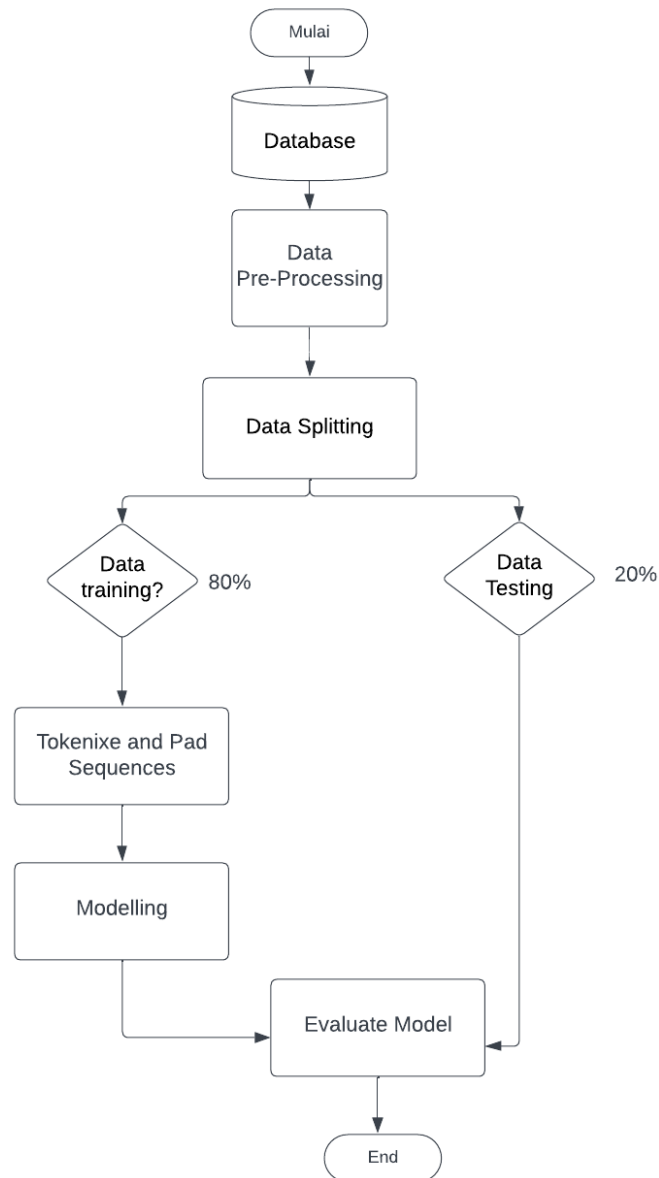


Figure 1. Flowchart research model

Dataset

The data set used in this research comes from Kaggle, namely Emotions Analysis in csv format, which can be accessed at <https://www.kaggle.com/code/abdmental01/emotions-analysis-gru-94/notebook>. This dataset contains text labels and emotions on Twitter. There are six categories of emotional expressions, namely sad, happy, love, anger, fear, and surprise. for sad expressions emotion label 0 with 141,067 data. The Happy Expression Emotion Label is 1 with the number of data 121,187. Expression of love emotion is labeled 2 with a data count of 57,317. Expression of anger emotion label 3 with a data count of 47,712. Fear expression emotion label 4 with a data count of 34,554. Then the expression surprised emotion label is 5 with the number of data 14,972. This dataset can be used in the social media domain to understand and analyze various emotions expressed in short texts.

Data Pre-processing

The next step is text preprocessing, which aims to clean and prepare the raw text for use in machine learning models. Some of the preprocessing steps performed in this model are rename columns by changing column names for text and labels to make them easier to read, drop unnamed column by removing columns that are not needed for analysis or for the model. Next Stopword Removal by removing words that appear frequently but are not needed to improve model accuracy, simplify data, and reduce noise. The next step is to remove URL, punctuation, and Number Removal by removing links or URLs, removing punctuation, and

removing numbers to simplify the text and focus more on words. The last step is lowercase and lemmatization. In lowercase to avoid word differences based on capital letters by changing all letters to lowercase letters in the text, and in lemmatization, it is used by returning words to their basic form to facilitate model analysis.

Tokenize Text Data and Pad Sequences

After the data are processed, the next step is to divide the data into 2 sets, namely, the training set and the test set. divide the data using `train_test_split` with 80% training set and 20% test set. The training set is used to train the model so that it can “learn” from the data. The test set is used to evaluate the performance of the model after training.

The next stage is text data tokenization and pad sequencing. In the text data tokenization stage, all words in the training set are learned and indexed for each word so that each word in the text has a unique token. The text is converted into a sequence of tokens using a tokenizer. This makes it easier for the model to understand and identify the words in the text. At the pad sequences stage, all input text is equalized in length so that it can be processed easily by the model. This research uses the Bi-LSTM model which requires input or input with a fixed size, so it requires tokenize and pad sequences.

Modelling

The model uses a sequential architecture and is built by creating an embedding layer by converting text tokens into a 100-dimensional vector, as well as 2 Bi-LSTM layers to capture text context from both directions. Next, dropout layers are performed to prevent overfitting and dense layers are performed to make the final prediction using ReLU activation and the last activation function with softmax which is used at the output for multiclass classification. Once completed, the model is compiled using Adam’s optimizer and loss function for multiclass classification. The stages of each layer used in this Bi-LSTM model are detailed in Figure 2.

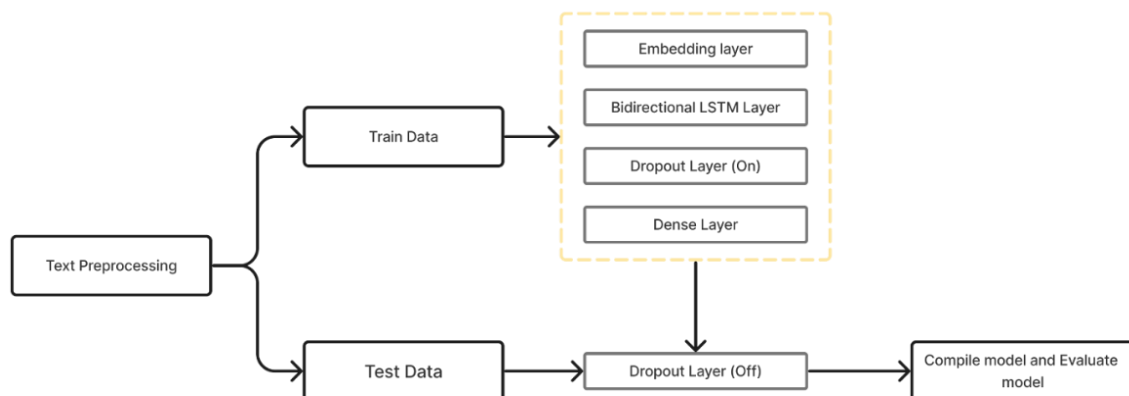


Figure 2. Bi-LSTM model layer stages

Bi-LSTM is a type of neural network that processes data sequences in two directions: forward and backward. This allows the model to capture contextual information from both directions. Bi-LSTM is very useful for tasks such as entity recognition and sentiment analysis because it can consider both past and future context [18].

The dense layer is a neural network component that connects every neuron in one layer to every neuron in the next layer. serves to reduce and combine information from previous layers to make better decisions or predictions. Dense layers are very important in the classification and regression process, converting input from various features into the desired output [19].

Evaluating Model

Evaluate the performance of the model on test data to assess model performance. In the program, the evaluation is done with `model.evaluate(X_test_padded, y_test)` to calculate the loss and accuracy on the test data. Accuracy to measure the percentage of correct predictions and loss to measure the difference between

model predictions and actual labels. Based on actual data, the confusion matrix shows how many predictions are correct and incorrect [20]. The loss is calculated using the `sparse_categorical_crossentropy` function, and the formula used is shown in formula 1.

$$Loss = -\frac{1}{N} \sum_{i=1}^N \log(p_{model}(y_i|x_i)) \quad (1)$$

where N is the number of samples, y_i is the actual label, and $p_{model}(y_i|x_i)$ is the probability predicted by the model for label y_i on input x_i . while for accuracy is shown in formula 2.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Where TP (True Positive) is the number of cases of correct prediction of positive classes, TN (True Negative) is the number of cases of correct prediction of negative classes. for FP (False Positive) is the number of cases of wrong prediction of positive classes (the actual class is negative), and FN (False Negative) is the number of cases of wrong prediction of negative classes (the actual class is positive). To generate probabilities for each class, is done with the `model.predict(X_test_padded)` function. Then these probabilities are converted into classes using `np.argmax(y_pred, axis=1)`, which means selecting the class for each input with the highest probability as shown in formula 3.

$$y_{pred} = \underset{c}{arg\ max} p_{model}(c|x_i) \quad (3)$$

where $p_{model}(c|x_i)$ is the probability predicted by the model for class c on input x_i . Next, a confusion matrix is created to further analyze the model's prediction results by using actual and predicted labels, which show the number of correct and incorrect predictions for each class. This provides a more in-depth view of how the model handles each class. The program uses `confusion_matrix(y_test, y_pred)` to create the confusion matrix. The confusion matrix table can be seen in Table 1.

Table 1. Confusion Matrix Representations

Predict class	Actual Class	
	Positive	Negative
Positive	True Positive	False Positive
Negative	False Negative	True Negative

The confusion matrix is then visualized using Seaborn's heatmap, to provide a visual representation of the number of correct and incorrect predictions and displayed in numerical format within the heatmap boxes.

3. RESULTS AND DISCUSSIONS

The dataset used in this research comes from kaggle, namely Emotions Analysis in csv format. This dataset consists of Twitter message text segments and labels that indicate emotions. Emotions are classified into six categories, namely sadness, joy, love, anger, fear, and surprise.

The architecture of the neural network model used in this research provides a description of the types of layers used in the model, including embedding layers, bidirectionally processed LSTM layers (Bi-LSTM) and dense layers to process learned information and produce emotion classification output. Each layer has trainable parameters, which indicate the complexity and ability of the model to learn patterns in the data. The layers of the neural network used in text emotion detection are shown in Table 2.

Table 2. Neural network layers used

Layer (type)	Output Shape	Param #
Embedding (Embedding)	(None, 100, 100)	6089400
Bidirectional (Bidirectional)	(None, 100, 256)	234496
Bidirectional_1 (Bidirectional)	(None, 128)	164352
Dropout (Dropout)	(None, 128)	0
Dense (Dense)	(None, 64)	8256
Dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2080
dense_2 (Dense)	(None, 6)	198
Total params: 6498782		
Trainable params: 6498782		
Non-trainable params:0		

Next, the preprocessing process removes irrelevant elements such as URLs, punctuation marks, numbers, and common words that do not help in detecting emotions (stopwords). The words are then converted to their base form using a lemmatization technique. This allows the model to focus more on emotion-related words, thus improving the accuracy of the model. After preprocessing was completed, the average text length was significantly reduced from X words to Y words, indicating that the process successfully filtered out unimportant elements.

Model training was carried out, where the results showed that the training accuracy increased sharply and then stabilized around 94.45%, while the validation accuracy followed a similar pattern, stabilizing around 94.45% after the initial increase. The loss graph shows a sharp drop in training loss initially, which then stabilizes around 0.08, while validation loss remains relatively stable around 0.1 after the initial drop. The accuracy and loss results of the RNN model are shown in Figure 3.

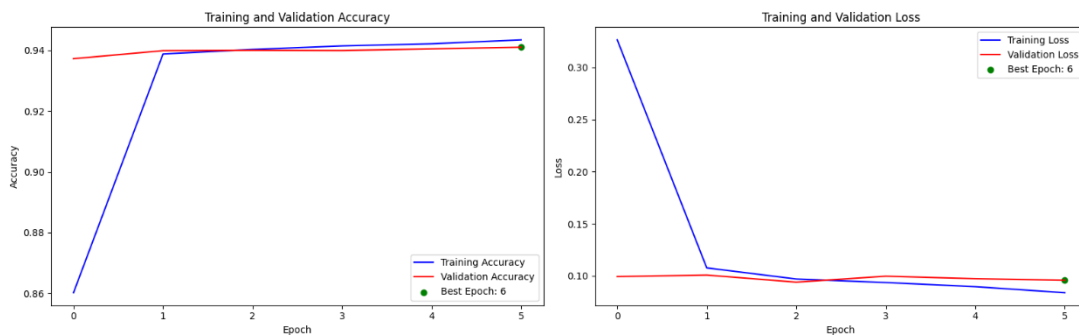


Figure 3. Model performance

Then, the performance of the model on the test data was evaluated using the confusion matrix. The results show that the value of the loss function on the test data is 0.094, while the accuracy of the model on the test data is 0.94. Figure 4 shows the visualization of the confusion matrix.

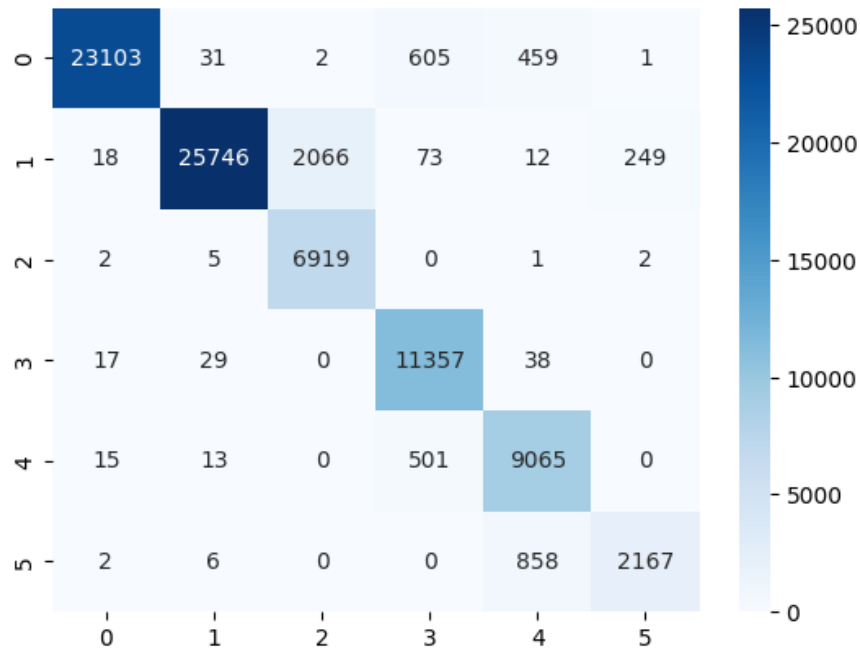


Figure 4. Confusion matrix

The results of previous research are shown in Table 3, where the accuracy results will be a reference to measure the performance of the Bi-LSTM model in this study. Therefore, this research can be developed and provide better results than previous research.

Table 3. Results of previous research

Methods	Accuracy
Deep learning dan machine learning [4]	80.11%
RNN [12]	60.97%
Deep dual recurrent encoder [14]	71.8%
Voting Classifier (LR-SGD) [21]	79%
LSTM-Word2Vec, LSTM-GloVe, LSTM-Fast Text [22]	73.15%, 60.10%, 73.15%
Bi-LSTM-Fast Text [23]	70.83%
Naïve Bayes-Unigram, Naïve Bayes-UnigramPOS [24]	67.5%, 72.25%
Multinomial Naïve Bayes [25]	64.08%
CNN-Bi-LSTM [26]	82.3%
BERT [27]	92% & 90%
Proposed Method	94.45%

The results of this study show that the developed Bi-LSTM model successfully achieved an accuracy of 94.45%. Thus, the research results make a positive contribution to the development and performance improvement of models for emotion detection in text.

4. CONCLUSION

This research focuses on the problem of low accuracy in the detection of emotions in text using conventional methods. To overcome this problem, the research applies the bidirectional long-short-term memory (Bi-LSTM) method, which is famous for its ability to handle temporal context in text. This research consists of several stages such as text data preprocessing, which includes stopwords and lemmatization, then

text tokenization, sequence padding, model training, and model evaluation using test data. The results show that Bidirectional Long Short-Term Memory (Bi-LSTM) in this study is very effective in improving emotion identification in text, with an accuracy rate of 94.45% and a loss rate 0,086%. This increase in accuracy shows that the bidirectional long- and short-term memory method has an excellent ability to capture and understand the temporal context in text data, which is important for emotion recognition tasks and provides better results than some previous studies using other methods. The advantage of Bi-LSTM is that it is capable of handling long-term dependency and avoids the vanishing gradient problem, making it reliable for text-based sentiment analysis. The implementation of the Bi-LSTM method in emotion recognition has the potential to make a significant contribution to the development of more sophisticated and effective sentiment analysis methods.

However, this research has limitations on the size of the dataset used. Future research is expected to use larger and more diverse datasets, as well as try other more complex methods to improve performance in emotion detection in text. Therefore, this research paves the way for further research to improve and refine text-based emotion recognition techniques.

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