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Toward nuanced sentiment analysis through multi-sense emoji embedding

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ABSTRACT

This research investigates the role of emojis in sentiment analysis using a more comprehensive multi-sense skip-gram approach. Emojis, which can convey facial expressions, body movements, and intonations often challenging to express in text, enhance digital communication by enriching the meaning of messages. Previous studies have shown that emojis improve sentiment analysis, yet most focused solely on their positive and negative connotations. This study broadens the scope by incorporating positive, negative, and neutral sentiment contexts. In the experiments, emojis were embedded in text and converted into vector representations for further analysis. The classification of sentiment texts was performed using a bidirectional long short-term memory (Bi-LSTM) method enhanced with an attention layer. The experiments resulted in accuracy of 0.83, recall of 0.83, precision of 0.82, and F1-score of 0.82. Statistical tests confirmed the significance of these findings, indicating that the approach improves the accuracy of sentiment analysis involving emojis. Overall, the study demonstrates that the integration of text and emojis leads to a more nuanced and precise understanding of sentiment in sentences, confirming the effectiveness of this method.

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1. INTRODUCTION

Twitter users often use emojis to convey emotions, ideas, or objects that are difficult to express with text alone [1], [2]. Emojis also help express body movements, facial expressions and intonations that usually appear in spoken conversations [3]. Research shows that the use of emojis can improve the performance of sentiment analysis models, by providing additional context that enriches the understanding of sentiment in text. Emoji embedding allows grouping similar emojis in vector space, thus strengthening the accuracy of sentiment classification. The use of emojis in sentiment analysis enriches context and provides additional insights that cannot be gained from text alone [4]. Someone might use the angry face emoji (😠) to express anger or the laughing face emoji (😀) to express joy. Emojis in sentiment analysis can improve model performance, making text more representative of the emotions you want to convey [5]-[7].

Previous research generally only considered two meanings (bi-sense) of emoji, namely positive and negative [8]. However, this approach is not enough to capture the complexity of sentiment. Therefore, a multi-sense approach that identifies positive, negative, and neutral meanings is necessary for more accurate representation. Multi-sense is a concept in translating natural language that allows a word to have more than one meaning or nuance, depending on the context in which it is used. In sentiment analysis, words often have meanings that depend on their context.

Multi-sense word embedding models such as probabilistic fast text and multi-sense skip-gram have shown promising results in dealing with words with multiple meanings. In this research, researchers will compare multi-sense with bi-sense approaches using the bidirectional long short-term memory (Bi-LSTM) model equipped with an attention layer to improve understanding of text and emoji in sentiment analysis [9].

This research aims to develop a multi-sense emoji model to develop effective embedding in understanding the meaning of emoji in text and improve the performance of sentiment analysis [9]. The dataset used is Twitter data from Kaggle which has been labeled, consisting of text and emoji. With this model, it is hoped that a deeper understanding of the meaning of emoji use and the actual meaning contained in the text can be achieved, and the performance of sentiment classification can be improved. This research is also expected to make a significant contribution to the field of sentiment analysis, especially in understanding the role of emojis in digital communication.

2. METHOD

To guide this research, we first formulated research questions (RQ) to achieve the objectives discussed in the previous section. After that, we collect the data that will be used in the experiment and adjust it to the RQ. The data will be analyzed and processed to produce accuracy, then the results will be concluded.

2.1. Research question

There are three RQs that we want to answer through experiment.

- RQ1: how to build a multi-sense emoji embedding model with multi-sense skip grams in sentiment analysis? We are interested in developing an effective multi-sense emoji embedding model for sentiment analysis that allows a deep understanding of the application of emoji usage as well as the actual meaning contained in a text by considering the concept of multi-sense emoji embedding.
- RQ2: what is the performance of the attention based Bi-LSTM with multi-sense skip gram model? In this research, we want to see the performance of the Bi-LSTM model with a multi-sense skip-gram that adds an attention layer and uses a dataset that contains emojis and does not use emojis.
- RQ3: how does the use of emoji affect the representation of text sentiment? This question was created because we wanted to see how much influence the use of emojis has on the sentiment in a text.

2.2. Data collection method

We use four different tweet data taken from Kaggle, namely sentiment and emotions labeled tweets, leveraging sentiment analysis on Twitter data, Twitter airline sentiment, and Fifa World Cup. These four data have different contexts, but all datasets contain the same sentiment, namely positive, negative and neutral. The data collected is tweet sentiment data in the form of English text that uses emojis and contains these three sentiments [10].

2.3. Data preprocessing

In this research, four stages were carried out, namely data selection, data integration, data cleaning, and data imbalance. At the data selection stage, we only used tweets consisting of English text and emojis. After that, at the selection stage, select features that are suitable for research purposes, namely only requiring text and sentiment attributes from each data. Then the data will be combined (integrated), but first the inappropriate attribute names will be renamed to "tweet" and "sentiment". After the data is combined, there are 12,330 rows and 2 columns. Because after checking the integration data it was not balanced, balancing was carried out using the oversampling technique. With this technique, the number of samples in the minority class is increased [11].

2.4. Text preprocessing

This stage focuses on text attributes and the processes carried out, namely remove URL, remove username, case folding, remove number, remove punctuation, remove stop word, tokenizing, and lemmatization. In remove URL, all URLs contained in the text will be deleted because they do not represent sentiment, so they are deemed unnecessary. Then, all words referring to the user's username, typically marked with the @ symbol and followed by the username, will be removed because such elements do not contribute meaningful semantic information and may negatively affect the performance of sentiment analysis models [12]. If the text contains capital letters, they will be converted into lower case to maintain consistency during processing [13]. Numbers contained in text are still recognized as characters and will be processed by the model, therefore numbers will be deleted because they are not needed. Remove punctuation needs to be done so that punctuation or unnecessary characters do not interfere with the dictionary and the calculation process in implementing the algorithm. Then, in the dataset used for this research, several words need to be removed because they do not contribute to the semantic interpretation of the sentence and may interfere with the sentiment analysis process [12]. After passing these stages, the text is separated into tokens such as words, phrases, symbols and punctuation to help make it easier to filter out unwanted words in further text processing. After being separated, the words contained in the data will be converted into basic words and stored in one token or one word during word processing [14]-[16].

2.5. Emoji preprocessing

Emoji embedding will use the word embedding method that will be used on text but will convert the emoji into Unicode emoji. Emojis are converted to Unicode using the emoji library in python. Unicode in the emoji library is a character coding standard used to describe emoji, where each emoji has a specific Unicode code that represents the character of each emoji, implementations of the emoji library generally utilize the Unicode standard to represent emoji [15], [17].

2.6. Bi-LSTM

In this research, Bi-LSTM was chosen as the algorithm because the dataset used is text and has two layers in opposite directions. Bi-LSTM is also proven to be more accurate than LSTM in comparing sentence meanings and Bi-LSTM is not prone to overfitting, this was proven in Habelnart's research. Researchers use Bi-LSTM to classify sentiments to avoid bias. In the context of sentiment classification, Bi-LSTM can learn patterns and relationships between words in sentences to determine positive, negative, or neutral sentiment. By using Bi LSTM, researchers hope that the model can capture the meaning of emojis in the text used. With this, this research can also provide insight into the ability of the Bi LSTM model to handle classification of sentiment and meaning of emojis in text. Bi-LSTM has a very complex architecture so that when using the Bi-LSTM algorithm the computational load becomes high. However, this algorithm has advantages compared to other neural network algorithms. In building the Bi-LSTM model, the Keras library was used which added several layers, such as the embedding layer, bidirectional layer (LSTM), dropout, and dense [18]. Figure 1 is the Bi-LSTM architecture.

Dropout is responsible for reducing overfitting in the model. Dropout will randomly disable some units in the previous layer, making the model more resistant to overfitting. Dense layer is the output layer in the model and it is used to produce output in the form of certain class or category labels from the given text data [19]. The Bi-LSTM layer concurrently processes the input sequence forward and backward. This bidirectional processing enables the model to accurately capture long-term relationships in input sequences [20]. The Bi-LSTM layer's output can be utilized for a variety of applications, depending on the tasks at hand. The Bi-LSTM architecture can be expanded or changed to meet the exact needs of the job [21], [22].

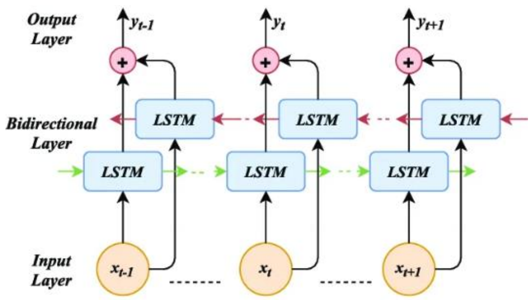

Figure 1. Bi-LSTM architecture

2.7. Attention based Bi-LSTM

The implementation of Bi-LSTM is carried out using the Keras library, where layers such as embedding, attention, Bi-LSTM, and activation are used sequentially for weighting text and emoji in sentiment sentences. The process begins with an embedding layer that converts text and emoji data to a numerical representation, followed by the creation of a Bi-LSTM model that processes the input sequentially [23]. An attention layer is added to select the most relevant input parts from the Bi-LSTM output, giving weights to the LSTM encoder to measure the influence of text and emoji in sentiment sentences, while the activation layer activates the output of both layers [24].

2.8. Experiment

The process begins with collecting a tweet dataset which then goes through the data preprocessing and text preprocessing stages to clean and prepare the data for further analysis. After preprocessing, the data was divided into four different experiments. Figure 2 is the experiment design in this research.

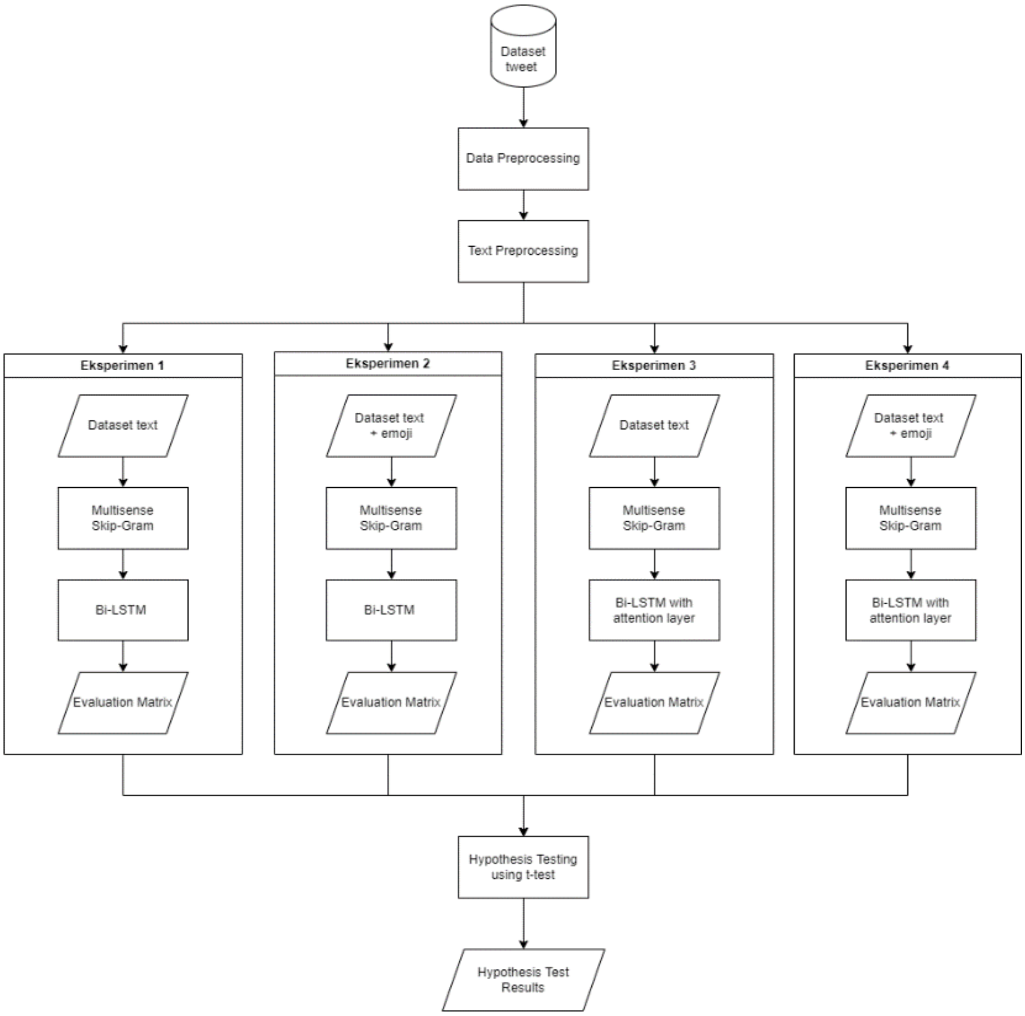

Figure 2. Experiment design

The first experiment uses a dataset containing emojis and processes it with the multisense skip gram method, followed by the Bi-LSTM model, and the results are evaluated using evaluation metrics. The second experiment uses a dataset without emojis, goes through the same process as multisense skip gram and Bi-LSTM, followed by evaluation. The third experiment also uses a dataset with emojis but with a more complex model, namely Bi-LSTM with an attention layer before evaluation. The fourth experiment uses a dataset without emoji, through multisense skip gram and Bi-LSTM processing with an attention layer, followed by evaluation. After all experiments were completed, the results were analyzed through hypothesis testing using the t-test to determine the significance of the differences between the methods used. The results of this hypothesis test then provide conclusions from the entire experiment.

3. RESULTS AND DISCUSSION

Based on this research, a multi-sense emoji embedding model was built by dividing the dataset according to labels, namely positive, negative and neutral, then converting the emojis into Unicode form. The Unicode will be converted into a vector with word embedding, namely skip-gram. Each of these labels has a different vector, which means one emoji can have three vectors. The three vectors of resulting labels will be combined with the concat function before becoming input for the classification model. The classification model in this study uses Bi-LSTM and Bi-LSTM with attention layer. There were four experiments carried out, namely classification using the Bi-LSTM model and the Bi-LSTM model with an attention layer. Classification is carried out with two different datasets, namely a text only dataset and a text dataset with emojis.

3.1. Experiment I: Bi-LSTM multi-sense skip-gram with text dataset

The results obtained in terms of accuracy, precision, recall, and F1-score for each fold have different values but tend to increase. In fold 1 the accuracy result is only 0.50 while in fold 10 the accuracy increases to 0.75. Likewise, other evaluation metrics increase at fold 10. The result of experiment I is in Table 1.

Table 1. Result of experiment I

Fold	Accuracy	Precision	Recall	F1-score
Fold 1	0.50	0.47	0.44	0.44
Fold 2	0.58	0.54	0.47	0.47
Fold 3	0.51	0.48	0.46	0.47
Fold 4	0.57	0.56	0.51	0.52
Fold 5	0.57	0.54	0.54	0.54
Fold 6	0.59	0.57	0.54	0.55
Fold 7	0.69	0.68	0.66	0.67
Fold 8	0.69	0.67	0.67	0.67
Fold 9	0.72	0.71	0.67	0.69
Fold 10	0.75	0.73	0.71	0.72

3.2. Experiment II: Bi-LSTM multi-sense skip-gram with text and emoji dataset

The results obtained in terms of accuracy, precision, recall, and F1-score for each fold have different values but tend to increase. In fold 1 the accuracy result is only 0.50 while in fold 10 the accuracy increases to 0.75. Likewise, other evaluation metrics increase at fold 10. The result of experiment II is in Table 2.

Table 2. Result of experiment II

Fold	Accuracy	Precision	Recall	F1-score
Fold 1	0.66	0.63	0.62	0.62
Fold 2	0.65	0.63	0.65	0.64
Fold 3	0.57	0.55	0.56	0.55
Fold 4	0.70	0.68	0.69	0.68
Fold 5	0.82	0.80	0.79	0.80
Fold 6	0.63	0.61	0.63	0.61
Fold 7	0.77	0.75	0.77	0.76
Fold 8	0.89	0.87	0.88	0.88
Fold 9	0.72	0.70	0.71	0.70
Fold 10	0.75	0.74	0.75	0.73

3.3. Experiment III: attention based Bi-LSTM multi-sense skip-gram with text dataset

The values of these metrics vary across each fold, reflecting the model's performance on different subsets of the data. For example, on Fold 1, accuracy is 0.54, precision is 0.50, recall is 0.48, and F1-score is 0.48. These values increase on the next folds, with the highest value on Fold 10 where accuracy reaches 0.83, precision 0.82, recall 0.81, and F1-score 0.81. The result of experiment III is in Table 3.

Table 3. Result of experiment III

Fold	Accuracy	Precision	Recall	F1-score
Fold 1	0.54	0.50	0.48	0.48
Fold 2	0.56	0.53	0.51	0.51
Fold 3	0.61	0.60	0.56	0.57
Fold 4	0.72	0.70	0.68	0.69
Fold 5	0.72	0.72	0.68	0.69
Fold 6	0.77	0.77	0.75	0.75
Fold 7	0.76	0.76	0.72	0.74
Fold 8	0.78	0.76	0.76	0.76
Fold 9	0.81	0.80	0.78	0.79
Fold 10	0.83	0.82	0.81	0.81

3.4. Experiment IV: attention based Bi-LSTM multi-sense skip-gram with text and emoji dataset

Overall, these k-fold cross-validation results show that the model performance increases consistently from Fold 1 to Fold 10, indicating that the model has good generalization ability on different data, with high performance stability in the final folds. The result of experiment IV is in Table 4.

Table 4. Result of experiment IV

Fold	Accuracy	Precision	Recall	F1-score
Fold 1	0.68	0.66	0.65	0.65
Fold 2	0.73	0.72	0.72	0.72
Fold 3	0.79	0.77	0.77	0.77
Fold 4	0.85	0.84	0.84	0.84
Fold 5	0.86	0.85	0.85	0.85
Fold 6	0.87	0.86	0.87	0.87
Fold 7	0.89	0.88	0.88	0.88
Fold 8	0.89	0.88	0.89	0.89
Fold 9	0.90	0.89	0.90	0.90
Fold 10	0.92	0.91	0.92	0.91

3.5. Comparison of each experiment result

The Bi-LSTM multi-sense skip-gram model with an attention layer shows better performance compared to the Bi-LSTM multi-sense skip-gram without attention on all evaluation matrices for both types of datasets. However, the most significant improvement was seen in the text dataset with emojis where accuracy reached 0.838 with the attention layer compared to 0.716 on Bi-LSTM multi-sense skip-gram without attention. Adding attention layer in any LSTM or Bi-LSTM can improve the performance of the model and also helps in making prediction an accurate sequence [25]. Likewise for precision, recall, and F1-score which show a significant increase when using the attention layer. If we compare the text-only dataset and the text dataset with emojis, both models perform better on the dataset containing emojis. This is because emojis can convey meaning and strengthen the meaning of a sentiment sentence by adding a vector representation of the text. The addition of an attention layer to the Bi-LSTM model also has a significant impact on running the sentiment classification model. The comparison of each experiment result is in Table 5.

Table 5. Comparison of each experiment result

Metrix evaluation	Bi-LSTM		Bi-LSTM with attention layer	
	Text	Text + emoji	Text	Text + emoji
Accuracy	0.61	0.71	0.71	0.83
Precision	0.59	0.69	0.69	0.82
Recall	0.56	0.70	0.67	0.83
F1-score	0.57	0.69	0.67	0.82

Attention based Bi-LSTM model with multi-sense skip gram produces good performance in sentiment analysis. Apart from accuracy, this model also shows other metric values well. This model is able to classify the correct sentiment with a small error tolerance limit. The attention layer in this model gives more attention to input elements that are more relevant or important in the sentiment sentence so that the classification results are better. Each performance matrix is based on the value of the confusion metric, namely true positive, false positive, true negative, and false negative. True positive is the number of cases that are truly positive, neutral, and negative and successfully identified correctly by the model. False positive is the number of cases that are actually positive, neutral, negative but incorrectly identified by the model. True negative is the number of cases that are truly positive, neutral, negative, and successfully identified correctly by the model. False negative is the number of cases that are actually positive but incorrectly identified as negative by the model.

These findings emphasize the importance of emojis in sentiment analysis. Utilizing a multi-sense skip-gram methodology for inserting emojis enabled us to more effectively discern nuanced variations in sentiment expressions. This is especially important considering the increasing prevalence of emojis in social media communication, where meaning is frequently subtle and multimodal. Our findings corroborate and expand upon previous research, including [8], which presented bi-sense emoji embeddings. In contrast to other research that generally restrict sentiment to positive or negative classifications, our multi-sense technique include a neutral category, resulting in a more nuanced and adaptable sentiment analysis.

The significant performance improvements exhibited by the attention-based Bi-LSTM model indicate that attention mechanisms effectively emphasize essential sentiment indicators from both textual and emoji inputs. This corresponds with previous research demonstrating the efficacy of attention layers in sequential modeling. Future study may investigate the application of this approach to multilingual datasets or its use in real-time sentiment monitoring systems. Moreover, subsequent research could integrate additional multimodal elements, such as photos or GIFs, frequently utilized in conjunction with emojis in digital dialogues. Essential experiments may encompass transfer learning methodologies or assessing cross-domain generalization.

4. CONCLUSION

This research aims to analyze the influence of emoji on sentiment analysis with a focus on developing a multi-sense emoji embedding model using the multi-sense skip-gram method. The Unicode will be transformed to a vector containing word embedding, known as skip-gram. Each of these labels has a unique vector, therefore a single emoji can have three vectors. The three vectors of resultant labels will be concatenated with the concat function before being sent into the classification model. The classification model in this work employs Bi-LSTM and Bi-LSTM with attention layer. Attention based Bi-LSTM model with multi-sense skip gram produces good performance in sentiment analysis. Based on research results, this model succeeded in achieving the highest accuracy on text and emoji datasets, namely around 92% and an average of 83%. The attention layer in this model gives more attention to input elements that are more relevant or important in the sentiment sentence so that the classification results are better. These results highlight the necessity of considering emojis not just as accessories to text, but as semantic carriers that contribute meaningfully to sentiment context.

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AUTHOR CONTRIBUTIONS STATEMENT

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Hanna Dhea Christi Sihombing		✓	✓	✓	✓		✓	✓	✓		✓			
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets analyzed during the current study are publicly available on Kaggle. Specifically, the datasets used include data sentiment and emotions, data leveraging sentiment analysis, Twitter airline sentiment, and FIFA World Cup Data. These datasets can be accessed from the Kaggle platform (https://www.kaggle.com) under their respective titles. The processed data and codes used for analysis are available from the corresponding author upon reasonable request.

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