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Sentiment Analysis of 2024 Election Reviews in Twitter using BERT with Emoticon Feature Extraction

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ABSTRACT

National elections are critical components of a functioning democracy, as they empower individuals to influence their nation's trajectory through active participation. In the contemporary digital landscape, social media platforms such as Twitter have emerged as pivotal forums for political discourse, enabling the expeditious dissemination of public sentiments. Nevertheless, assessing sentiment on Twitter poses various difficulties, primarily due to the casual nature of the language, the prevalent use of slang, sarcasm, and emoticons that often convey implicit emotional undertones. The present study puts forth a sentiment analysis framework that utilizes the Bidirectional Encoder Representations from Transformers (BERT) model, particularly IndoBERT, augmented with insights derived from emoticons. Emoticons are classified into three sentiment categories: positive, negative, and neutral. The dataset under consideration is composed of Indonesian tweets that have been pre-labeled and that pertain to the 2024 national election. Two configurations of the model were evaluated: a foundational IndoBERT model that relies solely on text, and an enhanced model that includes binary emoticon features. The experimental findings reveal that the emoticon-inclusive model attained a higher accuracy (78.5%) as opposed to the baseline model (77.7%) and demonstrated enhanced sensitivity in distinguishing neutral and negative sentiments. This finding suggests that emoticons offer valuable contextual information, thereby enhancing the accuracy of sentiment classification. The strategic integration of emoticons and BERT for Indonesian political sentiment analysis has received scant attention, rendering this method a novel addition to the field. The findings underscore the potential benefits of integrating text-based deep learning systems with emoticon characteristics to more effectively capture intricate emotional expressions in social media, particularly during political campaigns.

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1. INTRODUCTION

General elections play a critical role in democratic systems, allowing individuals to directly shape the direction of their country. As digital technology evolves, social media has become central to political discussion, expression of public opinion, and immediate response to political events. Among these social platforms, Twitter is notable for its accessible, instant communication style, making it an excellent resource for examining public opinion related to electoral matters.

The technique of sentiment analysis has become essential for evaluating how people feel about political figures and topics within campaigns. In Indonesia, a range of approaches has been examined for this purpose, including simpler statistical methods like Naive Bayes and SVM, as well as more sophisticated neural network techniques. However, studies conducted in the local context demonstrate the remarkable superiority of transformer-based frameworks, particularly IndoBERT, in processing Indonesian language information when compared to conventional techniques. For instance, Prasetyo and colleagues (2024) examined Multinomial Naive Bayes, SVM, and IndoBERT in their study of tweets concerning Garuda Indonesia, finding that IndoBERT delivered the best results with an accuracy of 75.6% [1]. In a related effort, Tanaja and team (2024) attained an accuracy of 84.7% by employing IndoBERT for sentiment analysis of tweets associated with the upcoming Indonesian presidential election in 2024 [2].

Despite the advancements witnessed, a notable shortcoming in the realm of sentiment analysis in Indonesia pertains to the underutilization of non-textual indicators of sentiment, particularly emoticons, which are extensively employed in informal interactions on Twitter. Emoticons such as ":)", "<3", or ">:(" have been shown to facilitate more effective communication of sentiment in social media posts, particularly in cases where the content is concise or ambiguous. Research conducted in various settings has indicated that the incorporation of emoticons can enhance the effectiveness of models. For instance, there have been improvements of as much as 7.3% in identifying hate speech [3], yet only a few studies within Indonesia have specifically and systematically incorporated emoticon elements into the representation of transformer models, particularly within the [CLS] token embedding utilized for classification purposes.

In a similar vein, the incorporation of emoticon features into the sarcasm detection model on Twitter led to an enhancement in model accuracy by 5.8% relative to the version without emoticons [4]. Furthermore, Mubaraq and Maharani (2022) employed the

IndoBERT model to evaluate public sentiment concerning climate change in Indonesia, leveraging Twitter data for this analysis. The model, trained exclusively on textual data, attained an F1-score of 95.6%, thereby substantiating IndoBERT's proficiency in discerning sentiment in the absence of non-verbal cues, such as emoticons [5].

In a similar vein, Arifin et al. (2024) examined Indonesian public perceptions of Rohingya refugees by leveraging the IndoBERT model on social media and news content. Despite the comprehensive text preprocessing implemented in the study, emoticon features were not incorporated. Nevertheless, the model demonstrated commendable performance, attaining an F1-score of 84% [6]. These findings underscore the efficacy of IndoBERT in sentiment analysis tasks that rely solely on textual information. However, they also indicate potential avenues for enhancement, particularly in the realm of capturing nuanced emotional expressions that might be more effectively conveyed through non-verbal cues such as emoticons.

To address this discrepancy, the current research proposes a mixed-method approach that integrates IndoBERT with binary emoticon characteristics classified as positive, negative, or neutral. These emoticon signals are integrated with the [CLS] token to augment the sentiment representation obtained by the model. The objective of this study is to ascertain whether the incorporation of emoticons can improve the precision of sentiment analysis in political tweets originating from Indonesia, with a particular focus on the impending 2024 general election. This study makes a pioneering contribution to the field by methodically examining emoticon-enhanced IndoBERT models using actual political data. This aspect has not been sufficiently investigated in the realm of Indonesian NLP studies.

2. RESEARCH METHOD

This research proposes a sentiment classification method for Indonesian political tweets during the 2024 general election using a combination of BERT and emoticon-based features. This research methodology consists of five main stages: dataset, preprocessing, emoticon feature extraction, feature integration, and classification.

2.1 Related Work

The assessment of public sentiment on social media channels, particularly Twitter, has been the subject of extensive research due to its immediate and expansive characteristics, rendering it well-suited for tracking public sentiment during political events. A considerable body of research has been dedicated to the exploration of transformer-based architectures, such as BERT, for this purpose.

Roihan et al. (2024) conducted a sentiment analysis of Indonesian tweets related to the 2024 presidential election, employing the BERT framework as a methodological foundation. The investigation focused on data preprocessing, categorizing sentiment among three groups (positive, negative, and neutral), and assessing the model's capacity to decode shifting political narratives. The results emphasized BERT's efficacy in comprehending intricate tweet patterns and contexts, yielding substantial classification outcomes [7].

In a similar vein, Putra and Sibaroni (2024) performed sentiment classification on tweets centered on the Indonesian presidential election of 2024. A juxtaposition of the performance of BERT and CNN was conducted, revealing that BERT attained an impressive accuracy rate of 90.02%, thereby underscoring its superiority in processing contextual textual data in the domain of Indonesian political dialogue [8]. Furthermore, Devlin et al. (2019) were the pioneers in presenting BERT, showcasing its proficiency in a range of natural language processing applications. Subsequent studies, including those by Nguyen et al. (2020), have employed BERT for sentiment analysis in various linguistic contexts, thereby demonstrating its versatility across diverse languages and fields [9].

Despite these advances, most of the research continues to concentrate on textual data and frequently disregards non-verbal indicators such as emoticons, which are commonly employed on social media platforms to convey sentiment. For instance, Kumar et al. (2021) underscored the significance of incorporating multimodal features, encompassing emojis, to enhance sentiment analysis in settings characterized by noise and informality, such as social media environments [10]. In a related study, Li et al. (2023) explored emoji-based sentiment enhancement in BERT for multilingual tweets. Their experiments demonstrated that incorporating emoji features alongside text enhanced F1 scores across various datasets, thereby underscoring the potential of integrating emotive symbols with language models [11].

However, in the Indonesian context, a substantial research gap remains. To date, only a limited number of studies have explicitly integrated vector emoticon features with the [CLS] token representation of IndoBERT. The incorporation of emoticons as binary emotional indicators (positive, negative, or neutral) into the classification pipeline presents a promising avenue for research, particularly in the context of detecting nuanced public reactions during significant national events, such as elections.

The following Table 1 offers a concise overview of pertinent literature and a determination of the originality of the present research.

Table 1. Summary of Related Studies

Study	Model Used	Data Domain	Emoticon Used	Accuracy (%)
Roihan et al. (2024)	BERT	Tweets on Election 2024	No	Not specified
Putra & Sibaroni (2024)	BERT vs CNN	Indonesian Politics	No	90.02%
Nguyen et al. (2020)	Multilingual BERT	Multilingual tweets	No	>80%
Kumar et al. (2021)	BERT with Multimodal	Twitter	Yes	+3% gain
Li et al. (2023)	Emoji-enchanced BERT	Multilingual tweets	Yes	+F1-score

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This study makes a significant contribution to existing literature by explicitly integrating emoticon features with the vector representation of the IndoBERT model. This integration addresses a critical research gap in the domain of Indonesian sentiment analysis.

2.2 Dataset and Labeling

The dataset consists of Indonesian tweets related to political issues ahead of the 2024 elections, collected using keywords associated with candidates, parties, policies, and campaigns. Each tweet includes text and emoticons (e.g., :), :(, :D), which were manually labeled with sentiment classes (positive, negative, neutral) based on their contextual meaning. To ensure data integrity, a validation process was conducted to remove duplicates, verify format consistency, and check class balance.

The dataset was split into training (70%), validation (15%), and testing (15%) sets. Despite being pre-labeled, the data underwent further manual validation to ensure annotation quality. Pre-processing involved several key steps:

1) **Data Cleaning** is the process that entails the removal of superfluous components such as URLs, mentions, hashtags, numeric values, and punctuation marks.
2) **Stop Words**, the objective of this procedure is to eliminate words from tweets that offer no substantial contribution to sentiment classification. Such words include conjunctions, pronouns, and other common words that are merely functional. In this study, the removal of stop words was carried out by utilizing the Indonesian stopword dictionary from the Sastrawi library, which has been commonly used in natural language processing for Indonesian. The dictionary under review includes hundreds of words that usually do not have strong semantic meaning in text analysis. As illustrated in Table II, the following list contains examples of stop words as they appear in a tweet.
3) **Stemming**, the process of simplifying a word by removing affixes, which can be prefixes, infixes, or suffixes, and converting it into its fundamental form, is referred to as affix removal. This process can be applied to both affixes that are contained within the word and affixes that are external to the word. In this study, the stemming algorithm from the Sastrawi library is employed to execute the stemming process, which is specifically designed for the Indonesian language. Sastrawi has formulated a set of linguistic principles capable of recognizing morphological structures in the Indonesian language. A notable example of this is the transformation of the word "menyampaikan" to "sampai" and "perubahan" to "ubah". This process is critical for enabling the BERT model to manage words in a more consistent basic form, thereby enhancing the effectiveness and accuracy of text representation for sentiment classification purposes
4) **Case Folding**, this is the process of changing the uppercase letters of the input data to lowercase letters.

5) **Tokenization**, this is the process of breaking the text into small pieces (words or phrases) using the BERT tokenizer. The BERT tokenizer was employed to segment sentences into tokens, with a maximum sequence length of 128.

2.3 BERT

Bidirectional Encoder Representations from Transformers (BERT) is a model for understanding the context of words in a sentence by simultaneously looking at the surrounding words from both the left and the right. BERT's structure consists of several layers of transformers that allow the model to capture complex relationships between words in text, as shown in Figure 1.

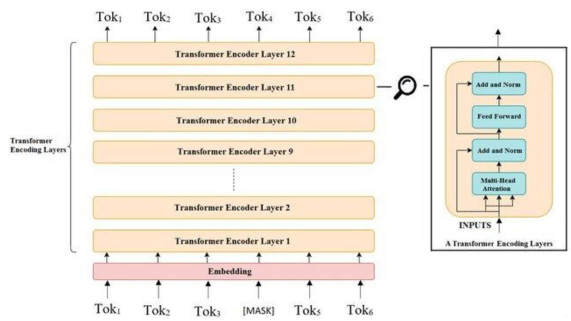

Figure 1. BERT's Structure [12]

During the fine-tuning stage, modifications were made to the IndoBERT model to ensure its compatibility with the dataset employed in this study. The dataset under consideration contained 3,000 tweets from Indonesian users that pertained to the 2024 general elections. Each tweet was subjected to a series of preprocessing steps, including tokenization with the IndoBERT tokenizer. The resulting tokenized tweets and their corresponding sentiment labels were incorporated into PyTorch's DataLoader to enable efficient mini-batch training.

This configuration ensures an equilibrium between efficiency and performance capabilities. The adjustment process entailed modifying the model's parameters to align more closely with the distinctive framework and sentiment distribution within the dataset of tweets pertinent to elections. The output from the [CLS] token in BERT served as the ultimate pool representation for classification tasks. In the subsequent phase, the output was augmented with additional emoticon features to enhance sentiment analysis, particularly for nuanced or implied emotional signals frequently observed in social media discussions.

This integrated approach, incorporating both BERT and emoticon elements, aims to enhance sentiment classification effectiveness by leveraging the written context and non-verbal indicators, particularly in the context of assessing political opinions during a national electoral event.

2.4 Emoticon Feature Extraction

In sentiment analysis, emoticons can provide additional insight into sentiment grouping, as they often convey clearer meanings than words [13]. Emoticons such as :), :(, and :D are often used to quickly convey emotions, especially in short formats such as tweets. Therefore, the use of emoticons serves to strengthen the recognition of the polarity of emotions, especially in the context of people's views on political issues.

This capstone research applies a direct labeling approach to emoticons into three sentiment classifications, namely positive, negative, and neutral. Emoticons such as :), :D, and ^-^ are labeled as positive, emoticons such as :(, :'(, and >:(are labeled as negative, and emoticons such as :| or -_- are labeled as neutral. These additional features are then represented in binary form according to the following formula is given by Equation 1:

$$E_{sentiment} = \begin{cases} [1,0,0], if\ tweet\ x\ contains\ positive\ emoticons \\ [0,1,0], if\ tweet\ contains\ negative\ emoticons \\ [0,0,1], if\ tweet\ x\ contains\ a\ neutral\ or\ none \end{cases} \quad (1)$$

After being represented as a binary vector, these emoticon features are combined with the text representation results from the BERT model, specifically the [CLS] token, which is the final representation for the classification stage as shown in Equation 2:

$$h_{final} = [h_{BERT}\ ;\ E_{sentiment}(x)] \quad (2)$$

The probabilities for each sentiment class are then calculated using the softmax activation function as shown in Equation 3:

$$P\ (y \mid x) = softmax\ (W\ \cdot\ h_{final} + b) \quad (3)$$

This approach has been successful in improving the accuracy of sentiment classification, as highlighted in a study by Sri Muspani et al. (2025). In this study, the BERT model combined with expressive character processing such as emoticons was able to achieve an accuracy of 93.6% and an F1 score of 93.61% in the analysis of Indonesian language social media sentiment [14].

2.5 Pre-training and Fine-tuning

Pre-training is the first step where the BERT model is trained on a large unlabeled dataset to understand the general language structure and context before being used in a specific task such as sentiment analysis. This process involves two main tasks, namely Masked Language Model (MLM), where some words in the sentence are removed and the model must guess the words, and the second task, namely Next Sentence Prediction (NSP), where the model learns to understand the connections between sentences [15].

Fine-tuning is the step where the pre-trained BERT model is adapted to a specific dataset for a specific task, such as sentiment analysis. In this step, the labeled dataset is used to retrain the model to classify sentiment more accurately according to the context of the given data. Fine-tuning is typically done by changing some training parameters and adapting the model architecture to the needs of the analysis task [16][17].

During pre-training, the model is taught with various pre-training tasks on unlabeled data. The model is then fine-tuned using pre-training parameters. The previous parameters are retrained (fine-tuned) with labeled data from downstream tasks, as shown in Figure 2 below.

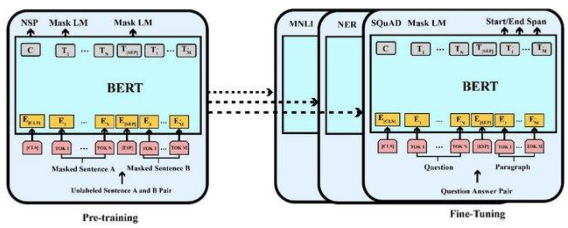

Figure 2. Pre-training and Fine-tuning in BERT

2.6 Evaluation of Sentiment Classification Model

Accuracy measures the proportion of correct predictions out of all predictions as shown in Equation 4:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

However, accuracy alone is not sufficient for unbalanced data. Therefore, precision and recall are used to assess the accuracy and completeness of predictions for the positive class as shown in Equation 5 and Equation 6:

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

The utilization of these four metrics furnishes a more comprehensive depiction of model performance, particularly in scenarios characterized by imbalanced data, such as public sentiment related to the election. A similar strategy was employed by Jayadianti et al. (2022), who utilized a combination of IndoBERT and a Recurrent Convolutional Neural Network (RCNN) to classify sentiment in Indonesian product reviews. The absence of emoticon features in the approach yielded thereby demonstrate that attaining high accuracy

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and balanced prediction results remains a possibility through architecture-level enhancements and the implementation of appropriate evaluation metrics [18].

3. RESULTS AND DISCUSSION

After implementing and evaluating two sentiment classification models using BERT, namely a text-only model and a text-based model with added emoticon features, various results were obtained that became the basis for the analysis in this chapter. The purpose of this test is to determine whether the addition of emoticons can improve the performance of the model in classifying sentiment from tweet data related to the Indonesian election.

3.1 WordCloud Analysis

The initial phase in comprehending the dataset entails an examination of the distribution of words and emoticons through WordCloud visualizations. This technique offers a swift and intuitive glimpse into the most seen terms within the tweet collection. In the model that focuses exclusively on text, the WordCloud highlighted key terms such as election, prabowo, ganjar, and vote. These terms indicate the primary subjects of the tweets and affirm that the dataset is pertinent to the political sentiments expressed during the election season.

In contrast, the model that combines text with emoticons utilizes WordCloud to display the same keywords and frequently used emoticons, such as <3, :), and :D. This finding suggests that emoticons play a significant role in conveying emotions within the tweet narratives and can function as emotional markers that enhance sentiment analysis. The incorporation of these visual elements serves as a manifestation of user sentiment, particularly in instances where textual clarity is compromised. Therefore, the incorporation of emoticons into the analysis could enhance the recognition of emotional subtleties that plain text might fail to convey, as illustrated in Figure 3, which presents the WordCloud result showing the distribution of frequent terms and emoticons used in the tweets.

Figure 3. Result from WordCloud

3.2. Model Training Process

Both configurations, BERT utilizing solely text and BERT incorporating emoticon enhancements, were trained with identical hyperparameters to facilitate fair evaluation. The training process was executed with a batch size of 16, a learning rate of 5e-5, and a total of 4 epochs. For the loss function, CrossEntropyLoss was selected due to the multi-class nature of the classification (positive, negative, and neutral), and the AdamW optimizer was utilized owing to its proven success in training transformer models.

As illustrated in Table 2, the training loss exhibited a consistent decline throughout the iterations, particularly evident between steps 200 and 1000. This observation indicates that the model effectively identified the fundamental patterns present in the dataset. After the completion of step 1000, the decline in loss began to decelerate, thereby suggesting that the model was nearing convergence. It is noteworthy that there were no indications of overfitting, as the validation loss remained relatively stable and did not exhibit a substantial increase.

Table 2. Training Process

Step	Training Loss	Validation Loss	Accuracy
200	0.601	0.594	0.758
400	0.565	0.581	0.763
600	0.547	0.582	0.761
800	0.491	0.575	0.777
1000	0.486	0.564	0.784
1200	0.413	0.597	0.778
1400	0.434	0.603	0.771

Figure 4 and Figure 5 below illustrate the trend of training loss and validation loss, thereby confirming the consistency of model improvement throughout the training phase.

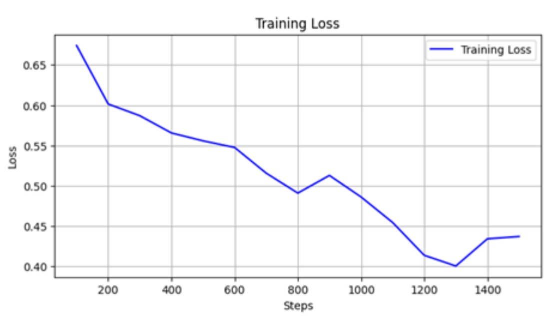

Figure 4. Training Loss

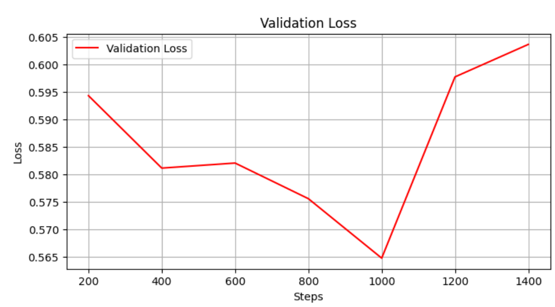

Figure 5. Validation Loss

3.3. Models Evaluation Results

To assess performance, three evaluation metrics were used: accuracy, precision, and recall. Table 3 summarizes the results for both models.

Table 3. BERT Model Performance

Metric	BERT (text only)	BERT (text + emoticon)
Accuracy	77.7%	78.5%
Precision	75.3%	76.1%
Recall	63.2%	64.7%

Despite the modest enhancement in performance, the incorporation of emoticon functionalities has augmented the model's capacity to discern sentiment with greater precision across a range of metrics. This enhancement is of particular significance due to the intricacies involved in categorizing vague or emotionally nuanced social media content.

A comprehensive evaluation of the models' performance was conducted by employing confusion matrices, as depicted in Figure 6 and Figure 7, to assess the efficacy of each model in categorizing the three distinct sentiment categories. The confusion matrix for the model that processed only text in Figure 6 displays a pronounced inclination toward the positive category, with numerous neutral and negative tweets misidentified as positive. In contrast, the matrix for the BERT + emoticon model in Figure 7 demonstrates a more equitable classification distribution.

Notwithstanding this advancement, errors are predominantly identified in the neutral and negative classifications. For instance, a substantial proportion of neutral tweets were erroneously classified as positive, indicating that the model exhibits challenges in recognizing tweets devoid of emotionally charged terminology or those that rely on contextual information for interpretation. Conversely, a few tweets that exhibited subtle forms of mockery or critique were erroneously classified as neutral or even positive. These results underscore the challenges associated with interpreting ambiguous sentiment signals, particularly in circumstances where sarcasm or courteousness serve to mask underlying discontent.

Therefore, although emoticons provide significant indications, further refinements, such as the incorporation of sarcasm detection or additional linguistic characteristics, may be essential to enhance precision within these underrepresented categories.

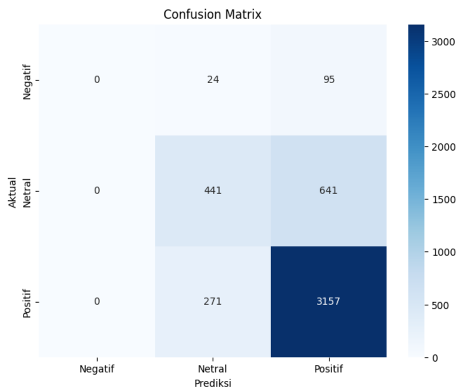

Figure 6. BERT Confusion Matrix (text only)

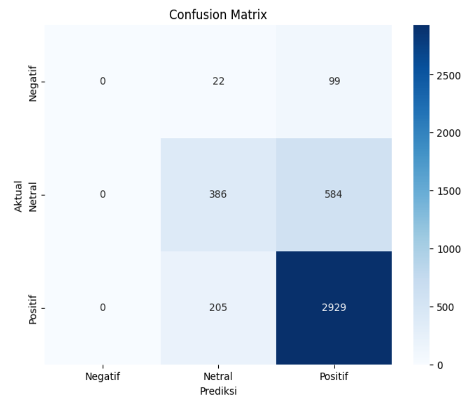

Figure 7. BERT Confusion Matrix (text+emoticon)

4. CONCLUSION

From the assessment findings, one can infer that incorporating emoticon functionalities into the BERT architecture significantly enhances the effectiveness of sentiment classification. Emoticons present in tweets have demonstrated their ability to assist the model in more accurately identifying user feelings. Icons like <3, frequently found in affirmative tweets, and >:(in negative ones, offer extra context that mere text fails to convey, enabling the model to categorize information with greater precision.

However, this research identified notable issues related to data imbalance, with a far larger quantity of data classified as having positive sentiment compared to the negative and neutral sentiments. Consequently, the model often leans towards predicting mostly the positive category. Nevertheless, incorporating emoticons improved the model's responsiveness to neutral and negative data, albeit still not at an ideal standard.

In continuation of this research, enhancing the distribution of data is suggested, either by augmenting the volume of negative and neutral sentiment examples or by utilizing data balancing methods like oversampling or undersampling. By implementing these strategies, the aim is for the model to attain more consistent and equitable classification outcomes throughout all sentiment types.

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