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Analysis of Public Sentiment about Sea Games eSport on Twitter using the Adaboost Algorithm

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Abstract

This research aims to analyze public sentiment towards the Sea Games eSports as reflected in conversations on the Twitter platform. The two main issues in focus are how the public sentiment towards the Sea Games eSports event and whether their responses tend to be positive or negative towards the event. The research method used is the Adaboost Algorithm, a technique in data mining that aims to improve classification accuracy. Adaboost was used to analyze sentiment from Twitter conversation data by using feature selection to select weak classification functions, then combining them into a new classification function. The results showed that the highest evaluation was achieved in the 2nd test with the use of training data by 90% and testing by 10%, which resulted in an accuracy of 98%. Sentiment analysis of the Sea Games eSports showed that the majority of Twitter users expressed 111 (95.7%) positive sentiments, while only 5 (4.3%) negative sentiments. This indicates that people tend to give positive responses to the Sea Games eSports event. This research illustrates that sentiment analysis using the Adaboost Algorithm is able to provide accurate results in mapping public responses to the Sea Games eSports event on Twitter. The implication is that the strong support from the community towards this event can be an important basis for further development and promotion of Sea Games eSports.

Keywords: Sentiment; eSports; Adaboost; Classification

1. INTRODUCING

In the ever-evolving digital age, social media has become a significant source of information in everyday life. One of the popular social media platforms is Twitter, where users can share their opinions, thoughts and experiences on various topics. The information contained in tweets on Twitter can reflect people's sentiments and perceptions of a particular event, occasion or phenomenon [1] [2].

As the gaming and electronic sports (eSports) industry continues to grow, major events such as Sea Games eSports have come under the international spotlight [3] [4]. Sea Games eSports is one of the largest competitive events in the Southeast Asian region featuring competitive gaming matches with participants from various countries. The event showcased the huge potential of eSports in creating a strong community and sparking enthusiasm [5].

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An analysis of public sentiment towards Sea Games eSports on Twitter can provide valuable insights in understanding the public's response to the event [6]. Through sentiment analysis, we can identify whether people's responses tend to be positive or negative towards Sea Games eSports, as well as understand the reasons behind those responses. This information can be used by organizers, sponsors, and other stakeholders to measure the impact of the event, correct shortcomings, and improve the participant and audience experience [7] [8] [9].

Several previous studies have applied sentiment analysis to sports and eSports-related discussions on social media. Research conducted by Rifa et al. analyzed public sentiment regarding the SEA Games 2023 football final using the Support Vector Machine (SVM) method, while Setiawan et al. focused on sentiment and topic analysis of the Piala Presiden eSports event [3] [6]. Other studies have utilized Naïve Bayes, Decision Tree, and various machine learning approaches for sentiment classification on Twitter data [1] [12] [18]. Although these studies demonstrated promising performance, most of them focused on specific sporting events, game reviews, or general social media topics. Furthermore, limited studies have specifically investigated public sentiment toward SEA Games eSports using the AdaBoost ensemble learning algorithm on Twitter data, creating a research gap that warrants further investigation.

In addition, previous studies generally emphasized classification accuracy without extensively exploring the capability of boosting-based methods in improving sentiment classification performance. Several conventional algorithms such as Naïve Bayes and Decision Tree are relatively simple and computationally efficient; however, their performance can decrease when handling complex textual features and highly diverse public opinions [1] [11] [18]. Therefore, a more robust classification approach is required to improve prediction performance and reduce classification errors.

AdaBoost was selected in this study because Twitter sentiment data often contain noisy, diverse, and highly dynamic textual information. Through its boosting mechanism, AdaBoost can iteratively focus on misclassified instances and improve classification performance by combining multiple weak learners into a stronger predictive model [7] [12] [17].Through an iterative weighting mechanism, AdaBoost can focus on previously misclassified instances, thereby improving overall classification performance. Compared with single-classifier approaches, AdaBoost has demonstrated competitive results in various text classification and sentiment analysis studies [8] [12] [16].

The scientific urgency of this research is driven by the rapid growth of eSports as an officially recognized competitive sporting event in international tournaments, including the SEA Games [3] [4] [5]. Understanding public sentiment toward SEA Games eSports is important for evaluating public acceptance, identifying audience perceptions, and providing strategic insights for event organizers, sponsors, and policymakers in developing future eSports competitions.

Based on the identified research gap, this study contributes by applying the AdaBoost algorithm to classify public sentiment toward SEA Games eSports using Twitter data and evaluating its performance under several training-testing data compositions. The novelty of this study lies in the application of the AdaBoost ensemble learning algorithm to classify public sentiment toward SEA Games eSports based on Twitter data, combined with an evaluation of different training-testing data compositions to identify the most effective classification performance.

2. METHODOLOGY

2.1 Research Stage

The research stages in this study can be seen in Fig. 1

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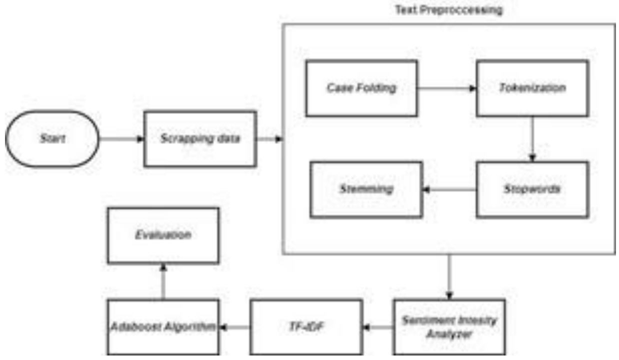

Figure 1. The Research Stage

The following is an explanation of the research stages :

1. Data collection (Scrapping data): This research has collected data as many as 1153 records using the Twitter API (Application Programming Interface), which comes from the developer.twiiter.com website [10]. To access it requires a key that comes from Twitter by registering to the Twitter developer portal which serves to confirm to Twitter in giving permission to explore data related to Twitter[2]. After the data collection process, a dataset filtering stage was conducted to ensure the quality and relevance of the collected tweets. The filtering process involved removing duplicate tweets, tweets containing only URLs, tweets unrelated to SEA Games eSports, and records with incomplete textual information. This filtering stage was necessary to reduce noise in the dataset and improve the quality of sentiment classification results.
2. Dataset Text Preprocessing: Text preprocessing is a series of steps or processes performed on raw text (input) before further analysis or processing [11][12]. The main purpose of text preprocessing is to clean, change the format, and organize text to make it easier to understand and process by certain algorithms or models. In the research, the stages of text preprocessing are case folding, tokenization, stop words, and stemming [13].
3. The Sentiment labeling was performed automatically using the VADER Sentiment Intensity Analyzer. Tweets with a compound score greater than 0 were categorized as positive sentiment, tweets with a compound score less than 0 were categorized as negative sentiment, and tweets with a compound score equal to 0 were categorized as neutral sentiment. To observe the impact of preprocessing on the dataset, the distribution of sentiment labels was examined before and after preprocessing. The preprocessing procedures were applied only to clean and normalize textual data without modifying the original sentiment labels.
4. Sentiment Sentiment Intensity Analyzer (SIA) is a tool used to measure the strength of sentiment in text. It works by scoring the text and providing a numerical score that indicates the polarity (positive, negative, or neutral) and intensity of emotion in the text [14]. One popular implementation of SIA is VADER (Valence Aware Dictionary and Sentiment Reasoner), which is often used in sentiment analysis due to its accuracy and simplicity [15][16]. Sentiment labeling was performed automatically using the VADER Sentiment Intensity Analyzer. Tweets with a compound score greater than 0 were categorized as positive sentiment, tweets with a compound score less than 0 were categorized as negative sentiment, and tweets with a compound score equal to 0 were categorized as neutral sentiment. To observe the impact of preprocessing on the dataset, the distribution of sentiment labels was examined before and after preprocessing. The preprocessing procedures, including case folding, tokenization, stopword removal, and stemming, were

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applied only to clean and normalize textual data without modifying the original sentiment labels.

5. TF-IDF: At this stage, text processing and information retrieval are performed to assess the importance of a word or phrase in a text document or document collection (corpus). This method is used to measure how often a particular word or phrase appears in a particular document (Text Frequency or TF) while considering how common the word or phrase is in the entire document collection (inverse document frequency or IDF)[7] [12].
6. Adaboost algorithm: is one of the algorithms in machine learning that is used to improve model performance by combining several weak learner models into a stronger model [17].
7. Evaluation: Furthermore, conclusions will be made from the data that has been processed from the beginning of the research flow to the end of the research process [12].

2.2 Data Analysis

After getting the value of TF-IDF, the results of TF-IDF D1, D2, and D3 will be processed using the adaboost algorithm and the sentiment will be predicted [2]. In this research, due to the different number of words in the sample data and the limited number of words in document 3, the results that will be used are features 1, 2 and 3 (TF-IDF results of the 1st, 2nd, and 3rd words). The actual sentiment result for positive is 1 and negative is -1 [11].

The following is a table of sample data that will be used to perform manual calculations.

Table 1. Sample Data of Manual Calculation

Document	Feature-1	Feature-2	Feature-3	Actual Sentiment
d1	0,043	0,021	0,021	1
d2	0,023	0,047	0,023	-1
d3	0,079	0,079	0,079	1

This algorithm uses a decision stump (decision tree of depth 1) as a weak model for adaboost. Initialize the sample data to be 1/n, where n is the amount of data [12] [18]. In this example n=3. Next, it will be processed with several steps, namely:

1. Weight Initialization: Each data sample is given the same weight of 1/3
2. Iteration 1:
   a) Train the weak model (Decision stump) on the training dataset with the given weights. From the sample data above, the weak model generates the rule: "If the value of Feature-1, Feature-2, and Feature-3 ≥ 0.04 then the prediction is positive (1); otherwise negative (-1)"

Table 2. Sample Data After Being Trained using Adaboost Algorithm

Document	Feature-1	Feature-2	Feature-3	Actual Sentiment	Predicted Sentiment
d1	0,043	0,021	0,021	1	-1
d2	0,023	0,047	0,023	-1	1
d3	0,079	0,079	0,079	1	1

   b) Evaluation of the weak model on the training dataset.The weak model incorrectly predicts document 1 and document 2 on feature-2 with an error

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weight of $\in_1 = \frac{1}{3} + \frac{1}{3} = \frac{2}{3} r$

c) Calculate the model weights: $a_1 = \frac{1}{2}\ln\left(\frac{1-\in_1}{\in_1}\right) = \frac{1}{2}\ln\left(\frac{1-\frac{2}{3}}{\frac{2}{3}}\right) = -0{,}346$

d) Update data sample weights Document 1 : $w_1 = \frac{1}{3} * e^{-0{,}346} = 0.235$

$$w_2 = \frac{1}{3} * e^{-0{,}346} = 0.235$$

Then the results of the prediction table are as follows:

Table 3. Output Data of Adaboost Algorithm

Document	Feature-1	Feature -2	Feature -3	Actual Sentiment	Predicted Sentiment
d1	0,043	0.235	0,021	1	1
d2	0,023	0.235	0,023	-1	1
d3	0,079	0,079	0,079	1	1

The adaboost algorithm successfully predicted d1 which was previously mispredicted but in d2 the prediction results remained wrong with the initial rule in iteration 1, namely "If the value of Feature-1, Feature-2, and Feature-3 ≥ 0.04 then the prediction is positive (1); otherwise negative (-1)" [19].

3. Combine models: since we only do one literation, the adaboost model will use the results from Iteration 1.
4. Output: the resulting adaboost model will predict the sample data based on the result of Iteration 1 [20].

3. RESULT AND DISCUSSIONS

In this sub-chapter we will explain the results that have been analysis of public sentiment towards Sea Games eSports on twitter using the Adaboost algorithm. Twitter by using the Adaboost algorithm. This section consists of data collection, text preprocessing, TF-IDF, and implementation of the Adaboost algorithm as well as the results of the confusion matrix. This research has collected data as many as 1153 records using the Twitter API (Application Programming Interface).

In this study, the Adaboost algorithm was tested 4 times. The reason researchers use 4 tests is to compare the results of the number of positive and negative sentiments based on the amount of training data and testing data.

Table 4. Sentiment Analysis Results using Adaboost Algorithm

Dataset Number	Actual Sentiment	Predicted Sentiment
947	Positive	Positive
363	Positive	Positive
1096	Positive	Positive
678	Positive	Positive
311	Positive	Positive
783	Positive	Positive
733	**Positive**	**Negative**
224	Positive	Positive
491	Positive	Positive

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202	Positive	Positive

Table 4 is a display of 10 sentiment result data using the Adaboost algorithm, the dataset number attribute is the order in the Excel data, the actual sentiment is an automatically generated label, and the predicted sentiment attribute is the result of the label created using the Adaboost algorithm.

Table 5. Matrix Evaluation

Pengujian	Training Data	Testing Data	Accuracy
1	60 %	40 %	97 %
2	70 %	30 %	97 %
3	80 %	20 %	98 %
4	90 %	10 %	98 %

Based on Table 5, it can be seen that in this study there were 4 tests with different data proportions, namely test 1 with 60% training data and 40% testing getting an accuracy of 97%, test 2 with 70% training data and 30% testing getting an accuracy of 97%, test 3 with 80% training data and 20% testing getting an accuracy of 98%, and test 4 with 90% training data and 10% testing getting an accuracy of 98%.

Table 6. Performance Evaluation Results

Training: Testing	Accuracy (%)	Precision (%)	Recall (%)	F1-Score(%)
60:40	96.97	97.08	99.77	98.41
70:30	96.82	97.86	98.77	98.31
80:20	98.27	98.64	99.54	99.09
90:10	98.28	99.10	99.10	99.10

To provide a more comprehensive evaluation of the AdaBoost classifier, additional performance metrics including Precision, Recall, and F1-Score were calculated from the confusion matrix results of each testing scenario.

Based on Table 6, the AdaBoost classifier achieved consistently high performance across all experiments. The highest accuracy was obtained in the 90:10 training-testing data composition with a value of 98.28%. Precision values ranged from 97.08% to 99.10%, while Recall values ranged from 98.77% to 99.77%. Furthermore, all F1-Score values exceeded 98%, indicating that the classifier maintained a strong balance between precision and recall. These findings demonstrate that the AdaBoost algorithm is effective in classifying public sentiment toward SEA Games eSports on Twitter.

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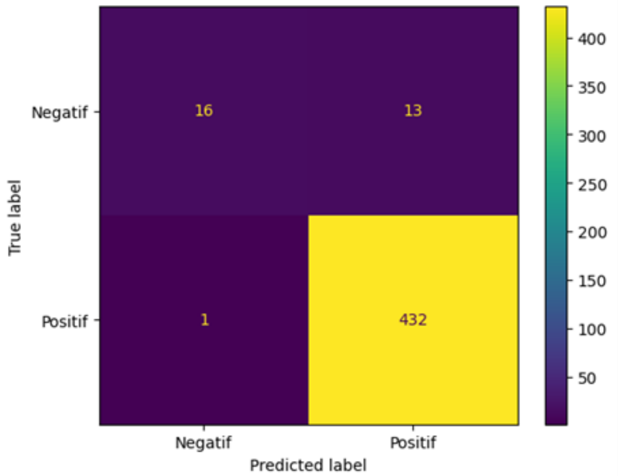

Figure 2. Confusion Matrix of Testing Scenario 1

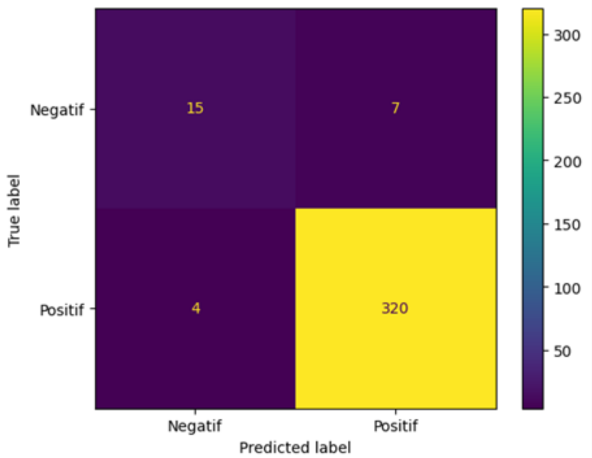

Figure 3. Confusion Matrix of Testing Scenario 2

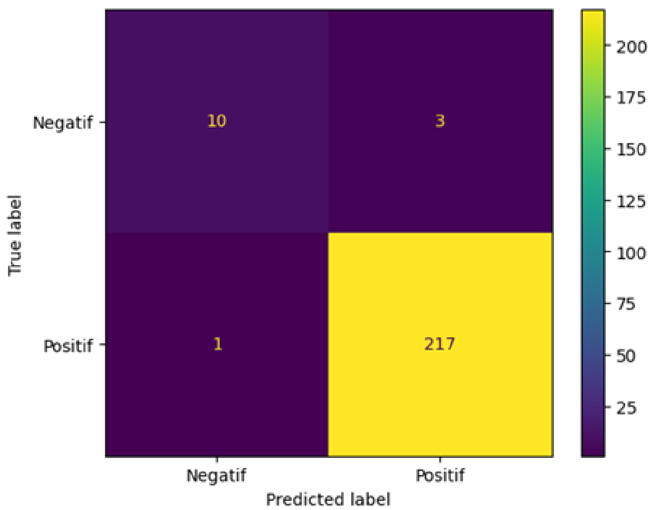

Figure 4. Confusion Matrix of Testing Scenario 3

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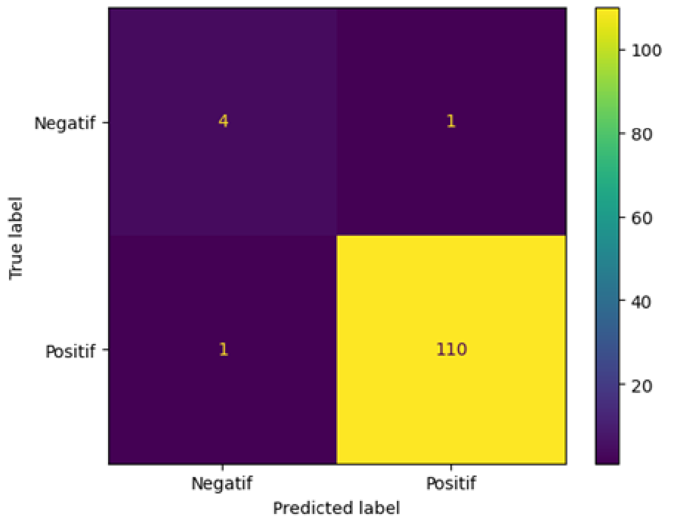

Figure 5. Confusion Matrix of Testing Scenario 4

The confusion matrix results show that the AdaBoost model successfully classified most sentiment instances correctly. In the first testing scenario (60% training and 40% testing), 432 positive tweets and 16 negative tweets were correctly classified, while only 14 tweets were misclassified. Similar trends were observed in the remaining testing scenarios, where the number of correctly classified tweets was substantially higher than the number of misclassified tweets.

Most classification errors occurred when negative tweets were predicted as positive. This may be caused by the dominance of positive sentiment within the dataset, which influenced the learning process of the classifier. Nevertheless, the high Precision, Recall, and F1-Score values indicate that the AdaBoost algorithm was able to classify sentiment accurately and consistently across different training-testing data compositions.

3.1 Sentiment Interpretation and Sample Tweets

The sentiment classification results indicate that public opinion toward SEA Games eSports was predominantly positive. This finding is supported by the high number of correctly classified positive tweets in all testing scenarios and the consistently high performance metrics achieved by the AdaBoost classifier.

An example of a positive tweet identified in the dataset is: "Raih 6 Medali di SEA Games, Atlet Timnas Esport Terima Bonus Rp 3,8 Miliar." This tweet reflects public appreciation for the achievements of Indonesian eSports athletes and demonstrates positive perceptions toward SEA Games eSports participation. Positive sentiment was generally influenced by athlete achievements, medal acquisition, team performance, and public enthusiasm toward eSports competitions.

In contrast, an example of a negative tweet is: "cabang olahraga apaan ini makin aneh aneh, aturan fokus cabor yg ada di olimpic aja kali." This tweet indicates skepticism regarding the recognition of eSports as a competitive sporting event. Negative sentiment was primarily associated with criticism of eSports legitimacy, event organization, and differing opinions regarding the inclusion of eSports in international sporting competitions.

Furthermore, the classification results demonstrate that the AdaBoost algorithm was capable of distinguishing positive and negative sentiment effectively. The consistently high Precision, Recall, and F1-Score values across all testing scenarios indicate that the classifier successfully captured sentiment patterns contained in Twitter discussions related to SEA Games eSports. These findings suggest that AdaBoost is a reliable method for sentiment classification on social media data characterized by diverse textual expressions and public opinions.

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This research has several limitations that need to be considered. One of them is the limitation in data representation, where the use of data from Twitter may not represent the entire sentiment of the community as a whole. In addition, the Adaboost algorithm used in this study has certain advantages and disadvantages that need to be considered in the interpretation of the results. Other limitations may be related to the data collection, analysis, and interpretation methods used in this research.This research has several limitations that need to be considered. One of them is the limitation in data representation, where the use of Twitter data may not fully represent the overall sentiment of the public. In addition, the Adaboost algorithm used in this research has certain strengths and weaknesses that need to be taken into account in interpreting the results. Other limitations may be related to the methods of data collection, analysis, and interpretation used in this study.

4. CONCLUSION

This study successfully applied the AdaBoost algorithm to classify public sentiment toward SEA Games eSports using Twitter data. The experimental results demonstrated that AdaBoost achieved high classification performance across different training-testing data compositions. The highest performance was obtained using 90% training data and 10% testing data, achieving an accuracy of 98%. In addition, public sentiment toward SEA Games eSports was predominantly positive, with 111 positive tweets (95.7%) and 5 negative tweets (4.3%). The main contribution of this study lies in the application of an ensemble learning approach for analyzing public opinion regarding SEA Games eSports and providing empirical evidence of the effectiveness of AdaBoost for sentiment classification on social media data.

The findings of this study provide practical implications for eSports organizers, sponsors, and policymakers. The sentiment analysis results can be utilized to understand public perceptions, evaluate audience responses, identify potential issues, and support strategic decision-making processes aimed at improving future eSports events and increasing community engagement.

Despite the promising results, this study has several limitations. The dataset was collected exclusively from Twitter, which may not fully represent public opinion across different social media platforms. Furthermore, the study focused on sentiment classification and did not perform additional analyses such as topic modeling, dominant word analysis, or sentiment trend analysis.

Future research may utilize larger and more diverse datasets obtained from multiple social media platforms and compare AdaBoost with other machine learning or deep learning approaches. Further studies may also incorporate topic modeling, dominant word extraction, and temporal sentiment analysis to provide a more comprehensive understanding of public perceptions toward eSports events.

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