Sentiment analysis and classification of Ghanaian football tweets from the 2022 FIFA World Cup

Eshun Michael[1], Gyening Mensah Rose-Mary Owusuaa[2], Takyi Kate[2], Appiahene Peter[3], Peasah Ofosuhene Kwame[2], Banning Amoako Linda[2]
[1]Department of Computer Science, Brock University, St Catherines, Canada
[2]Department of Computer Science, Faculty of Physical and Computational Sciences, Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana
[3]Department of Information Technology and Decision Sciences, University of Energy and Natural Resources, Sunyani, Ghana

Article Info

Article history:

Received Nov 15, 2023
Revised Jan 6, 2024
Accepted Jan 14, 2024

Keywords:

BERT
Football
Sentiment analysis
Support vector machines
Twitter
Vader

ABSTRACT

Football as an attractive sport generates huge volumes of tweets concerning fans' opinions, feelings, and judgments during prime events. Such data can be leveraged in sentiment analysis, an algorithmic approach to analyzing text in tweets by extracting emotional tones. This paper presents a novel benchmark dataset of 132,115 tweets collected during the 2022 world cup on 𝕏 (formerly Twitter) for football-related sentiment classification. We also performed sentiment analysis on the dataset using lexicon-based tools, traditional machine learning algorithms, and pre-trained models, robustly optimized bidirectional encoder representations from transformers (BERT)-pretraining approach RoBERTa and distilled version of BERT (DistilBERT) to understand the emotions and reactions of football fans during different phases of the football matches. Results from the study indicate that most tweets had neutral sentiments in both context-aware and context-free analysis. We also describe our novel GhaFootBERT, a sentiment classification model based on transfer learning on BERT, which provides an effective approach to sentiment classification of football-related tweets. Our model performs robustly, outperforming the traditional models with 92% accuracy.

Corresponding Author:

Gyening Mensah Rose-Mary Owusuaa
Department of Computer Science, Faculty of Physical and Computational Sciences
Kwame Nkrumah University of Science and Technology
Kumasi, Ghana
Email: mensahowusuaa@gmail.com

1. INTRODUCTION

The proliferation of the internet has simplified communication on social media platforms and led to a surge in user-generated content. Researchers are leveraging these platforms for data collection and training machine learning models for sentiment analysis, recommender systems, and identifying patterns of human behaviour. Twitter (𝕏) as a social media platform has many registered users and generates substantial data volumes daily. However, due to the word limit of tweets and unstructured data formats, machine learning algorithms could be utilized to understand tweet patterns and derive meaningful insights into the data. This paper focuses explicitly on sentiment analysis of Ghanaian football-related tweets and the training of a novel sentiment classification model. The rationale is to present a domain-specific dataset and share research findings concerning sentiment analysis of football-related tweets in Africa. Understanding the behaviour and emotions of football fans concerning prime win or loss scenarios, player substitutions, and coach decisions would enhance innovative decision-making in sports and inform future strategies for stakeholders in football. Four-time African Cup of Nations winner, Ghana's national football team, also known as the Black Stars, is one of the elite football teams in Africa. The Black Stars team came into the spotlight due to its impactful performance during the 2010 World Cup, held in South Africa. The football team became the third African team to reach the quarterfinals, following Senegal and Cameroon. Since then, it has competed in subsequent tournaments, failing to qualify for Russia's 2018 International Federation of Football Association (FIFA) World Cup. The highly anticipated return of the Black Stars, having qualified for the 2022 FIFA World Cup in Qatar, led to a surge in data on online social networking (OSN) platforms.

This paper's analysis focuses on tweets collected from the handles of key players and staff of the Ghana football association, since they were the primary subjects of discussion among Ghanaian 𝕏 users during the World Cup. The research sought to analyze the sentiments expressed by 𝕏 users during the 2022 FIFA World Cup and compare the effectiveness of lexicon-based approaches and machine learning algorithms in analyzing the sentiments expressed in tweets. We analyzed sentiments in 132,115 tweets accumulated from November 18 to December 3, 2022. Tweet sentiments were examined using lexicon-based tools, TextBlob, valence aware dictionary for sentiment reasoning (VADER), machine-learning algorithms, support vector machines (SVM) and Naive Bayes (NB), and pre-trained models robustly optimized BERT pre-training approach (RoBERTa) and distilled version of BERT (DistilBERT). We also created a sentiment classification model, GhaFootBERT, by fine-tuning the bidirectional encoder representations from transformers (BERT) model using 10,000 labeled tweets from the dataset.

Several studies have explored sentiment analysis during events such as the 2018 FIFA World Cup [1], [2], the 2014 FIFA World Cup [3]–[6], the Champions League [5]–[7], and the English Premier League [7]. These studies have demonstrated that sentiment analysis can provide insights into public opinion and emotions related to football events and explore the robustness of machine learning algorithms for sentiment analysis. Venkatesh *et al.* [1], [2] analyzed sentiment during the 2018 FIFA World Cup to build a classifier and benchmarked its performance with other machine learning classifiers. Venkatesh *et al.* [1] employed the global vectors for word representation (GloVe) word embedding technique with hybrid convolutional neural networks and long short-term memory (CNN-LSTM). Venkatesh *et al.* [2] used domain-specific lexicons, term frequency-inverse document frequency (TF-IDF) feature selection, and the count vectorizer technique to build a sentiment classifier. A study of sentiment analysis of tweets by [3] during the 2014 FIFA World Cup had more positive than negative sentiments. Barnaghi *et al.* [4] explored the effectiveness of using logistic regression to identify sentiments in tweets about the 2014 World Cup. They found strong negative opinions towards unethical behaviour, and the potential for improving matches by addressing controversial player behaviours.

Aloufi and Saddik [5] presented a football-specific sentiment classifier trained on 54,526 manually labeled tweets using SVM, multinomial Naive Bayes (MNB), and random forest (RF), with the SVM classifier exhibiting the most robust performance. Pacheco *et al.* [6] discovered increased audience engagement on 𝕏 as teams exited the competition. Their research revealed the emergence of team alliances and rivalries among fans as the tournament progressed. For instance, the Brazilian team's popularity decreased as the tournament advanced since supporters from countries that had lost to Brazil aligned themselves with rival teams like Argentina and Spain. Wunderlich and Memmert [7] tested the feasibility of using existing lexicon-based sentiment analysis tools to examine football-specific tweets. They found that the tools used performed poorly in classifying single or small sets of tweets but were better when categorizing larger groups of realistic tweets (at least 1,000). Kumar and Jaiswal [8] thoroughly assessed literature to identify research gaps and examine trends using soft computing (SC) techniques for sentiment analysis on 𝕏. They discovered that applying SC approaches to social media sentiment categorization is a promising research field with practical implications for interpreting and studying human emotions in unstructured online data.

Elankath and Ramamirtham [9] examined the efficiency of using the BERT model for sentiment analysis on a Malayalam dataset constructed from 2,000 tweets from 𝕏. They found that BERT outperforms other machine learning (ML) and deep learning (DL) models with an accuracy of 88.61%. Naznin and Mahanta [10] focused on categorizing 𝕏 users using the clustering ML technique with the k-means algorithm based on sentiment-related words in the users' tweets. Their research revealed that the content of tweets relates to the users' intrinsic opinions on varying topics. Acosta *et al.* [11] surveyed sentiment analysis of U.S. airline 𝕏 posts using the Word2Vec algorithm and three ML algorithms, with results indicating that SVM and logistic regression classifiers achieved 72% accuracy using the Word2Vec skip-gram training model. Kharde and Sonawane [12] explored various sentiment analysis techniques, including machine learning and lexicon-based approaches, cross-domain and cross-lingual methods, and evaluation metrics.

There has been limited research on sentiment analysis of tweets during football competitions in Africa. A study by Moreau *et al.* [13] investigated tweets and Facebook comments to identify controversies surrounding canceling the 2015 African Cup of Nations in Morocco. They found that data from OSN media is platform-specific, and discussions transcended football on some platforms. In Ghana, football is one of the most popular sports. Although the Black Stars team has been a significant focus of attention for Ghanaians, to our knowledge, there is no research on football-related sentiment analysis of Ghanaian tweets. This gap in the literature highlights the relevance of researching this domain. While there has been limited research on sentiment analysis of Ghanaian tweets during sporting events, existing studies have demonstrated the potential of sentiment analysis to better comprehend public opinion and emotions related to sporting events, motivating our study. The rest of the work follows in the order of method, results, discussions, and conclusion.

2. METHOD

2.1. Data collection

The proposed dataset [14] encompasses 132,115 tweets collected from various 𝕏 handles and mentions associated with the Ghana national football team. Tweets were collected from multiple prime sources, including the official 𝕏 pages of the 26-man squad, the coach, the Ghana football association (GFA), the GFA president, seven backroom staff members, and the Ghana national team. The dataset collection process was initiated on November 18, 2022, using the 𝕏 streaming application programming interface (API) and a Python script based on Tweepy library [15]. The official 𝕏 account names of the players, their known names or nicknames, and relevant hashtags were used to retrieve the tweets. Four players from the 26-man squad did not have active 𝕏 accounts; hence, tweets relating to the players were generated using their names and hashtags to ensure their representation in the dataset. Additionally, seven backroom staff members were selected to gather tweets based on their prominence and recognition among the public. The dataset offers researchers an extensive collection of tweets that reflect the online discourse surrounding the Ghana national football team during the 2022 FIFA World Cup. Its breadth, diversity of sources, and inclusion of player and staff member tweets make it a valuable resource for studying various aspects of social media activity, sentiment analysis, and fan engagement in Ghana football.

2.2. Data preprocessing

Football-specific tweets often lack structure. Hence, preprocessing is crucial for data quality and accuracy in analysis. The study explored several preprocessing steps to prepare the dataset for sentiment analysis. To ensure text clarity, we cleaned the dataset by removing noise and unwanted tweets, including retweets, duplicates, non-English tweets, uniform resource locator (URLs), mentions, and stop words. The tweet analysis process was improved by excluding punctuations and special characters (emojis), given their potential for ambiguity. The tweets were tokenized into words and converted to lowercase to ensure uniformity and eliminate duplication of words. Lemmatization was applied to words to consider their variants as a single entity in the sentiment analysis stage.

2.3. Sentiment analysis using lexicon and machine learning-based methods

Sentiment analysis is a commonly used method for understanding sentiments expressed in a dataset. Lexicon-based sentiment analysis tools and pre-trained language models were employed to gain insights into the emotional tones and opinions conveyed in the tweets. TextBlob, VADER, DistilBERT, and RoBERTa were used to analyze tweets for their sentiments, while the GhaFootBERT model was trained to classify sentiments in tweets. TextBlob is a widely utilized sentiment analysis tool, known for its user-friendly and intuitive interface. TextBlob evaluates tweets by comparing them against a sentiment dictionary, yielding sentiment scores [16]. In the context of this research, TextBlob was applied to analyze Ghanaian tweets, with the primary objective of discerning patterns in emotional responses concerning the World Cup events. VADER employs pre-established linguistic rules or patterns to predict emotional tones within texts. VADER integrates sentiment intensifiers, negations, and context-specific sentiment rules to adequately account for the intricate nature of sentiments expressed on microblogging platforms [17]. By harnessing the power of VADER, a heightened precision in comprehending Ghanaian sentiments during the World Cup was attained, leading to a more insightful and nuanced understanding of the emotional landscape surrounding the tournament.

Pre-trained language models, RoBERTa (Twitter-RoBERTa-base) [18] and DistilBERT (DistilBERT-base-uncased) [19], which are excellent for tweet sentiment prediction tasks, were applied to the dataset for sentiment classification. RoBERTa improves upon the BERT model by employing a deep transformer architecture and fine-tuning a larger corpus of textual data, resulting in enhanced performance and higher inference accuracy [20], [21]. DistilBERT is a condensed version of the BERT model that offers a more petite model size and faster inference time [19], [21]. These state-of-the-art natural language processing models were used to analyze the Ghanaian tweets. By combining the strengths of these lexicon-based sentiment analyses and powerful pre-trained language models, the research aimed to provide a comprehensive understanding of the sentiments conveyed in Ghanaian tweets during the 2022 FIFA World Cup. To further enhance our analysis, a subset of the dataset was trained and tested on two popular classification algorithms: NB and SVM. The dataset comprised 10,000 manually labelled tweets categorized as positive (3,200), negative (1,400), or neutral (5,400). The NB classifier is a probabilistic model grounded in Bayes' theorem (1) and operates under the feature independence assumption [22]. This classifier computes the likelihood of a tweet belonging to a specific sentiment class by considering the occurrence of distinct words or features. We used the labeled dataset to train the NB algorithm to construct a robust model capable of effectively categorizing sentiment in tweets, drawing from the patterns acquired during the training phase. NB can be mathematically represented as (1).

$$P(Se|Fs) = \frac{P(Fs|Se) * P(Se)}{P(Fs)} \tag{1}$$

Where:
$P(Se|Fs)$ is the posterior probability of the sentiment, given the features (words) of the tweet.
$P(Fs|Se)$ is the likelihood probability of observing the given features given the sentiment.
$P(Se)$ is the prior probability of the sentiment occurring in the dataset.
$P(Fs)$ is the probability of observing the given features in the dataset.

SVM is a supervised learning algorithm that uses a hyperplane to separate data points into different classes [23]. SVM seeks to find the best decision boundary that maximally separates positive and negative sentiment tweets. SVM was trained to build a sentiment classification model using the labeled dataset. NB and SVM were tested against feature extraction models, including bag-of-words (BOW), TF-IDF, and Word2Vec. The BOW model simplifies text representation by considering individual word occurrences without grammar or context [24]. TF-IDF measures word frequency and importance in a text [25]. Word2Vec captures semantic relationships and contextual information between words [26]. The most effective approach for sentiment classification of Ghanaians’ World Cup tweets was determined based on the highest-performaning classification algorithms and feature extraction techniques shown in Table 1.

Table 1. Classification algorithms, feature extraction techniques, and combinations

Classification algorithms	Feature extraction	Classification models
SVM	BOW	SVM and BOW
NB	TF-IDF	NB and BOW
	Word2vec	SVM and TF-IDF
		NB and TF-IDF
		SVM and Word2vec
		NB and Word2vec

By leveraging NB and SVM in training the dataset, robust models capable of accurately classifying the sentiments conveyed in the tweets were developed. The performance of the models were analyzed using accuracy, precision, recall, and F1-score (APRF) evaluation metrics. Figure 1 presents an overview of the sentiment classification and prediction process.

The research also proposes a novel sentiment classification model, GhaFootBERT, which utilizes transfer learning on BERT-base-uncased. Transfer learning involves leveraging knowledge and understanding from a previous task to improve performance in a different or related problem [27]. BERT is a state-of-the-art pre-trained transformer-based natural language processing model designed to understand and capture the contextual patterns in textual data [28]. GhaFootBERT differs from the BERT-base-uncased model by undergoing further training on the Ghanaian football tweets dataset. GhaFootBERT was trained on 10,000 labeled tweets from our dataset. This additional training fine-tunes the model to capture more effectively the nuances and sentiments unique to the context of Ghanaian football discussions. The model was fine-tuned with hyperparameters of batch size 16 and a learning rate of 2e-5 and trained for 10 epochs. GhaFootBERT architecture was based on the BERT-base-uncased architecture, which consists of 12 transformer blocks, 768 hidden units for individual tokens, 12 attention heads, and a total of 110 million parameters [28]. Transfer learning improved the model’s effectiveness in accurately classifying sentiments in Ghanaian tweets.

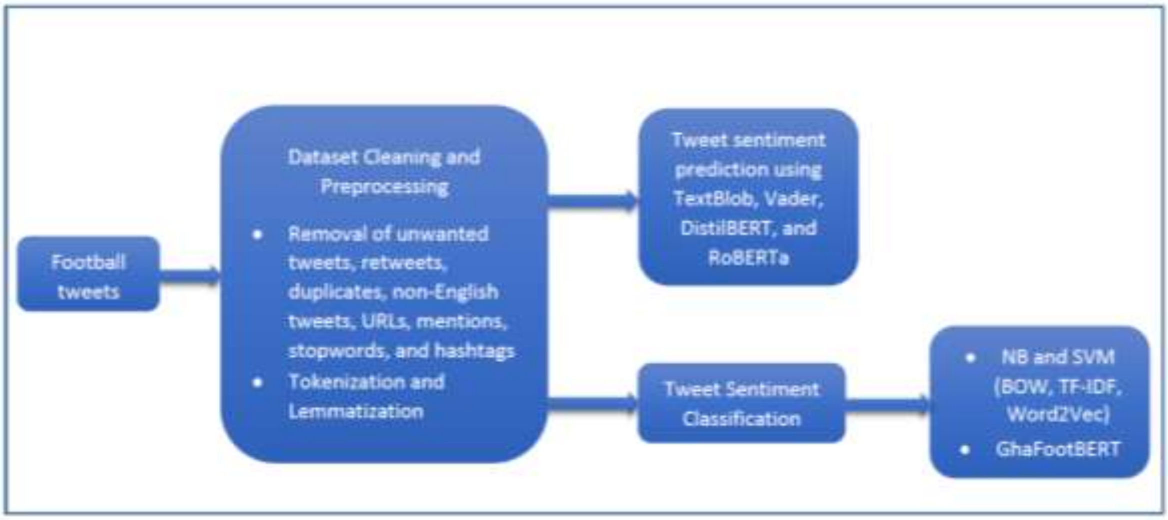

Figure 1. Overview of the sentiment analysis and classification process

3. RESULTS AND DISCUSSION

3.1. Dataset description

The proposed dataset consists of 132,115 tweets, of which 13,625 were identified as duplicates and 2,897 as retweets, resulting in 115,593 unique tweets for analysis. Figure 2 shows the tweets generated daily during the data collection stage. Tables 2 and 3 present the top ten hashtags and the dataset summary. Figure 3 presents a word cloud from the dataset, excluding hashtags and player names. We also developed a word cloud highlighting hate speech in the dataset using Python's multilingual toolkit Pysentimiento [29], depicted in Figure 4.

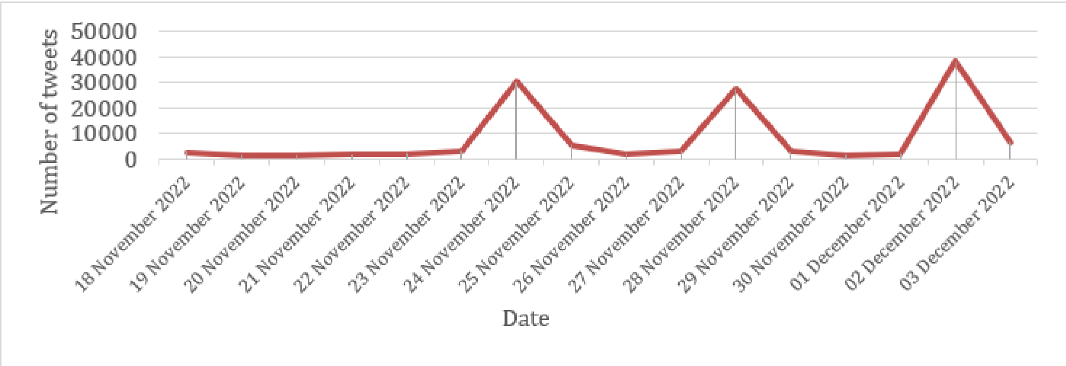

Figure 2. Number of tweets generated daily

Table 2. Top ten hashtags

Hashtags	Number of tweets
#blackstars	22,522
#fifaworldcup	11,549
#qatar2022	8,719
#teamghana	4,988
#ghana	2,943
#gha	2,885
#porgha	1,828
#fifaworldcupqatar2022	1,729
#ghauru	1,395
#worldcupqatar2022	1,259

Table 3. Summary of generated tweets

Description	Frequency
Total tweets	132,115
Duplicate tweets	13,625
Unique tweets	118,499
Retweets	22,448
Daily average tweets	8,260
Average tweets per player	2,520
Tweets with location	91,256

Figure 3. Word cloud from the dataset excluding player names and hashtags

Figure 4. Word cloud of hate speech from the dataset

3.2. Result from TextBolb, VADER, RoBERTa, and DistilBERT

Figures 5 and 6 show the classified sentiments and frequency and the daily average sentiments for TextBlob, VADER, RoBERTa, and DistilBERT. Figure 5 reveals that most tweets had neutral sentiments, as classified by the sentiment analysis tools. Notably, an emphasis has also been drawn on the average sentiments of matchdays in Figure 6.

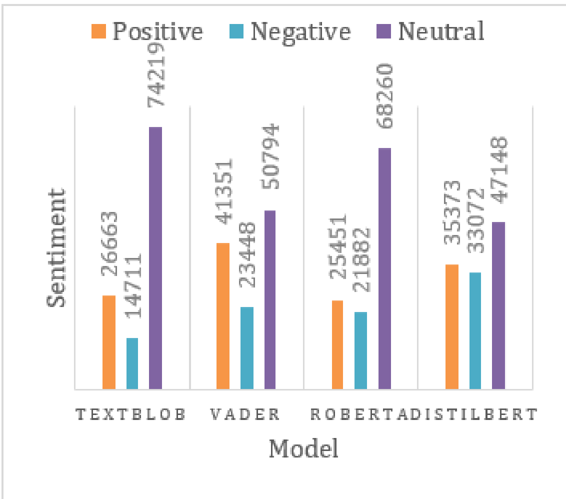

Figure 5. Frequency of predicted sentiment for TextBlob, Vader, RoBERTa, and DistilBERT

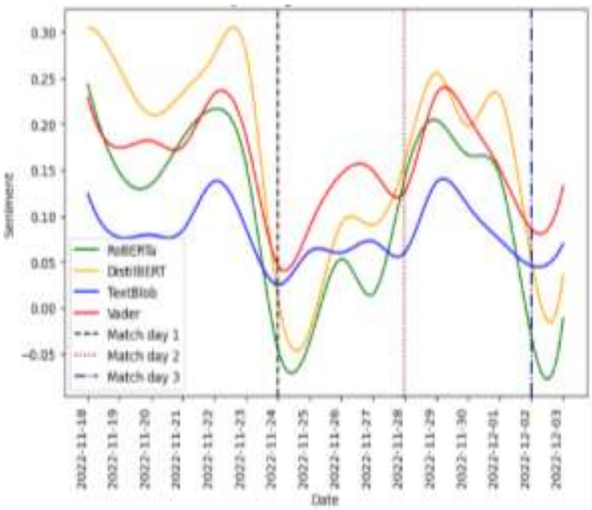

Figure 6. Daily average sentiment prediction for Vader, TextBlob, DistilBERT, and RoBERTa

3.3. Sentiment classification algorithms and corresponding feature extraction techniques

We analyzed the performance of GhaFootBERT and traditional machine learning algorithms SVM and NB algorithms on the labelled datasets against different feature extraction methods using APRF. From Hackeling [30], accuracy is the ratio of correct classifications, precision signifies the ratio of correct positive classifications, recall is the ratio of correctly classified positives to the total positives, and F1-score represents the harmonic mean of precision and recall. GhaFootBERT demonstrated robustness in its predictions with 92% accuracy. The SVM algorithm follows the GhaFootBERT model, achieving a higher accuracy across the three feature extraction models. SVM with the Word2Vec model had 87% accuracy, SVM with TF-IDF attained 86% accuracy, and SVM with BOW achieved 85% accuracy. Table 4 and Figure 7 showcase each classifier and feature extraction model's result and receiver operating characteristic (ROC) curve. A higher area under the curve (AUC) score shows a better efficiency or performance of a classification model in classifying positive, negative, and neutral tweets.

Table 4. Results of sentiment classification models

Classification models	Accuracy	Precision	Recall	F1-score
SVM and BOW	0.85	0.86	0.85	0.85
NB and BOW	0.84	0.84	0.84	0.83
SVM and TF-IDF	0.86	0.87	0.86	0.85
NB and TF-IDF	0.84	0.84	0.84	0.83
SVM and Word2vec	0.87	0.87	0.87	0.87
NB and Word2vec	0.74	0.75	0.74	0.74
GhaFootBERT	0.92	0.92	0.92	0.92

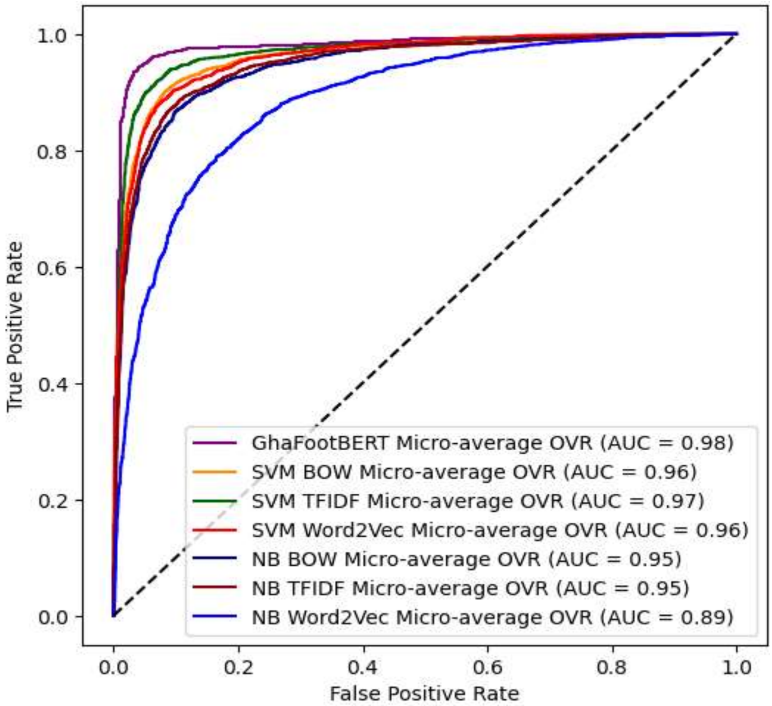

Figure 7. ROC curve of sentiment classification models

3.4. Discussions

The experimental results of this study present insights into activities on 𝕏 during the tournament. The highest frequencies of daily tweets, as shown in Figure 2, were recorded on match days, indicating the increased engagement of Ghanaians during those periods. Notably, the second match against South Korea on November 28, 2022, had the lowest number of tweets among the top three. It was the only game the Ghanaian team won in the tournament. This analysis suggests that Ghanaians are more active on 𝕏 during moments of disappointment or sadness, as observed on match days that ended in defeat. Engagement was relatively lower for the team on victorious match days. The Ghana football association can monitor public sentiment patterns on 𝕏 to make informed decisions and strategies to improve the team's performance. Although many tweets were classified as neutral, the sentiment classifiers detected some positive Ghanaian tweets throughout the tournament. Figure 3 word cloud further substantiates this inference by emphasizing the prevalence of positive words such as "good," "win," "better," and "best" in the tweets. However, the hostile comments in Figure 4 show Ghanaians' frustrations and disappointments regarding the team's performance in some matches.

The average sentiment per day depicted in Figure 6 reveals a tweet pattern. Predictions fall to negative after the first match, rise to positive after the second match, and decline again after the final fixture. The rise and fall in the graph show Ghanaians' reactions during the competition. It reflects Ghanaian's passion and enthusiasm for the national team and football. These findings set grounds for the sports ministry, authorities, and stakeholders to model sports-related initiatives and infrastructures that will promote and harness a positive impact on football in Ghana. GhaFootBERT model, leveraging the prediction abilities of the pre-trained BERT outperformed the other models, corroborating a study by [31]. SVM with Word2Vec feature extraction technique followed next, achieving a higher accuracy of 87% among the classification algorithms and feature extraction techniques. This result aligns with previous research conducted by [10], [11] who also obtained an accuracy of 72% using the SVM algorithm with the word2vec model in predicting sentiment in United State Airline tweets and classifying Turkish tweets, respectively. The results from the study are consistent with [5]. SVM outperformed NB irrespective of the feature extraction technique, implying SVM's robustness in classifying sentiment in Ghanaian football tweets.

While our study provides valuable comprehension into Ghanaians' sentiment during the 2022 FIFA World Cup, certain limitations and challenges must be acknowledged. The analysis relied on the availability of data from 𝕏. Although a substantial number of tweets were collected, there may still be a sampling bias, as the dataset does not represent the entire population of Ghanaian 𝕏 users. The dataset primarily focused on the 26-man Ghanaian squad and backroom staff members, which may have overlooked sentiments related to other aspects of the tournament. Sentiment analysis tools like TextBlob, Vader, and RoBERTa are valuable for understanding sentiment in text data. However, they may not always capture the sentiments accurately. Lexicon-based tools rely on predefined sentiment scores, which might not account for the peculiarities and cultural context specific to Ghanaian sentiments. Similarly, while pre-trained models like RoBERTa and DistilBERT provide a better understanding of sentiments, their performance may vary depending on the quality and diversity of the training data.

Sentiment analysis faces challenges in comprehending the contextual meaning of tweets. The tools can misinterpret sarcasm, irony, and colloquial expressions common in online discourse, leading to less accurate sentiment classifications. Factors beyond match outcomes, such as individual player performances, controversial referee decisions, or off-field events, could influence tweet sentiments. These complexities make accurate sentiment analysis challenging. Manually labeling a large dataset can be time-consuming and resource-intensive. Due to time constraints, a subset of the dataset could be labeled. Ghana is a multilingual country with diverse linguistic communities. The analysis focused on English-language tweets, potentially excluding sentiments expressed in other Ghanaian languages.

3.5. Ethical considerations

In conducting this research, the importance of addressing ethical considerations, including data privacy, representation, sharing, transparency, and reproducibility, was recognized to ensure the responsible use of social media data. All collected tweets were anonymized and stripped of personally identifiable information to adhere to 𝕏 users' privacy policy. Publicly making the dataset available, while respecting 𝕏's terms and conditions [32], and adhering to their data usage and sharing guidelines were acknowledged. Focus analysis was placed on aggregate sentiment patterns and did not single out individual users for criticism or scrutiny. By sharing the findings and approach, other researchers could reproduce and validate the results, fostering scientific integrity and accountability. This research was conducted responsibly and ethically, preserving the privacy of social media users while generating a significant understanding of fan sentiments during the 2022 FIFA World Cup.

4. CONCLUSION

This paper makes significant contributions, including developing a novel dataset comprising football-related tweets for natural language processing applications. It delves into sentiment analysis within the dataset, offering insights into the emotions of football fans and their correlation with match outcomes. The paper introduces a novel sentiment classification model based on deep learning. Findings indicated that the predominant sentiment expressed by Ghanaians in their tweets was neutral. Nevertheless, we observed a surge in positive reactions following victories and increased hostile tweets after defeats. The sentiment analysis tools employed in this study provided valuable insights into the emotional tone and opinions conveyed in the tweets, offering a profound understanding of sentiment patterns during the world cup. Considering the successes reported on the application of BERT in natural language processing tasks, we sought to evaluate the efficiency of the BERT variant BERT-base-uncased in sentiment classification. Notably, our proposed sentiment analysis model, GhaFootBERT, exhibited the highest accuracy, achieving a sentiment prediction accuracy of 92%. The results of our research hold significant implications for various football stakeholders, particularly the GFA, as it sheds light on the sentiments and engagement of football fans on social media. By leveraging this knowledge, stakeholders can make informed decisions and devise effective strategies for engaging fans. This study underscores the importance of social media platforms in capturing and analyzing football fans' sentiments, opening new avenues for research in this domain.

REFERENCES

[1] Venkatesh, S. U. Hegde, Z. A. S, and N. Y, "Hybrid CNN-LSTM model with GloVe word vector for sentiment analysis on football specific tweets," in *2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, Feb. 2021, pp. 1–8, doi: 10.1109/ICAECT49130.2021.9392516.

[2] V. Venkatesh, C. Keerthi, Y. Nagaraj, and S. Swetha, "Comprehensive Analysis of classifier to identify sentiment in football specific tweets," in *Proceedings of the Fist International Conference on Advanced Scientific Innovation in Science, Engineering and Technology, ICASISET 2020, 16-17 May 2020, Chennai, India*, 2021, p. 283, doi: 10.4108/eai.16-5-2020.2304099.

[3] R. Patel and K. Passi, "Sentiment Analysis on twitter data of world cup soccer tournament using machine learning," *IoT*, vol. 1, no. 2, pp. 218–239, Oct. 2020, doi: 10.3390/iot1020014.

[4] P. Barnaghi, P. Ghaffari, and J. G. Breslin, "Text analysis and sentiment polarity on FIFA World Cup 2014 tweets," in *The Workshop on Large-Scale Sports Analytics (LSSA 2015) at the 21st ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD 2015)*, 2015, pp. 10–13.

[5] S. Aloufi and A. El Saddik, "Sentiment Identification in football-specific tweets," *IEEE Access*, vol. 6, pp. 78609–78621, 2018, doi: 10.1109/ACCESS.2018.2885117.

[6] D. Pacheco, F. B. De Lima Neto, L. Moyano, and R. Menezes, "Football conversations: what twitter reveals about the 2014 world cup," Aug. 2015, doi: 10.5753/brasnam.2015.6771.

[7] F. Wunderlich and D. Memmert, "Innovative approaches in sports science—lexicon-based sentiment analysis as a tool to analyze sports-related twitter communication," *Applied Sciences*, vol. 10, no. 2, p. 431, Jan. 2020, doi: 10.3390/app10020431.

[8] A. Kumar and A. Jaiswal, "Systematic literature review of sentiment analysis on Twitter using soft computing techniques," *Concurrency and Computation: Practice and Experience*, vol. 32, no. 1, p. e5107, Jan. 2020, doi: 10.1002/cpe.5107.

[9] S. M. Elankath and S. Ramamirtham, "Sentiment analysis of Malayalam tweets using bidirectional encoder representations from transformers: a study," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 3, pp. 1817–1826, Mar. 2023, doi: 10.11591/ijeecs.v29.i3.pp1817-1826.

[10] F. Naznin and A. Kakoti Mahanta, "Grouping of Twitter users according to contents of their tweets," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 2, pp. 876–884, Aug. 2023, doi: 10.11591/ijeecs.v31.i2.pp876-884.

[11] J. Acosta, N. Lamaute, M. Luo, E. Finkelstein, and A. Cotoranu, "Sentiment analysis of Twitter messages using Word2Vec," in *Proceedings of Student-Faculty Research Day, CSIS, Pace University*, 2017, pp. C8-1-C8-7.

[12] V. A. Kharde and S. S. Sonawane, "Sentiment analysis of Twitter data: a survey of techniques," *International Journal of Computer Applications*, vol. 139, no. 11, pp. 5–15, Apr. 2016, doi: 10.5120/ijca2016908625.

[13] N. Moreau, M. Roy, A. Wilson, and L. Atlani Duault, "Life is more important than football": Comparative analysis of Tweets and Facebook comments regarding the cancellation of the 2015 African Cup of Nations in Morocco," *International Review for the Sociology of Sport*, vol. 56, no. 2, pp. 252–275, Mar. 2021, doi: 10.1177/1012690219899610.

[14] M. Eshun, R.-M. O. M. Gyening, and K. Takyi, "Ghana-FIFA2022-WorldCup-Dataset," *Mendeley Data*, vol. V1, 2023, doi: 10.17632/5sgxm3jnw4.1.

[15] J. Roesslein, "Tweepy documentation," *tweepy.org*, 2009. http://tweepy.readthedocs.io/en/. (accessed: Jan 1, 2024).

[16] S. Loria, "TextBlob documentation," 2018. [Online]. Available: https://media.readthedocs.org/pdf/textblob/latest/textblob.pdf.

[17] C. Hutto and E. Gilbert, "VADER: a parsimonious rule-based model for sentiment analysis of social media text," in *Proceedings of the International AAAI Conference on Web and Social Media*, May 2014, vol. 8, no. 1, pp. 216–225, doi: 10.1609/icwsm.v8i1.14550.

[18] F. Barbieri, J. Camacho-Collados, L. Espinosa Anke, and L. Neves, "TweetEval: unified benchmark and comparative evaluation for tweet classification," in *Findings of the Association for Computational Linguistics: EMNLP 2020*, 2020, pp. 1644–1650, doi: 10.18653/v1/2020.findings-emnlp.148.

[19] V. Sanh, L. Debut, J. Chaumond, and T. Wolf, "DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter," *arXiv preprint*, Oct. 2019, [Online]. Available: http://arxiv.org/abs/1910.01108.

[20] Y. Liu *et al.*, "RoBERTa: A robustly optimized BERT pretraining approach," *arXiv preprint*, Jul. 2019, [Online]. Available: http://arxiv.org/abs/1907.11692.

[21] I. Staliūnaitė and I. Iacobacci, "Compositional and lexical demantics in RoBERTa, BERT and DistilBERT: a case study on CoQA," *arXiv preprint*, Sep. 2020, [Online]. Available: http://arxiv.org/abs/2009.08257.

[22] G. I. Webb, "Naïve Bayes," in *Encyclopedia of Machine Learning*, Boston, MA: Springer US, 2011, pp. 713–714.

[23] S. Suthaharan, "Support vector machine," in *Machine learning models and algorithms for big data classification: thinking with examples for effective learning*, 2016, pp. 207–235.

[24] W. A. Qader, M. M. Ameen, and B. I. Ahmed, "An overview of bag of words;importance, implementation, applications, and challenges," in *2019 International Engineering Conference (IEC)*, Jun. 2019, pp. 200–204, doi: 10.1109/IEC47844.2019.8950616.

[25] M. J. Lavin, "Analyzing documents with TF-IDF," *Programming Historian*, no. 8, May 2019, doi: 10.46430/phen0082.

[26] L. Ma and Y. Zhang, "Using Word2Vec to process big text data," in *2015 IEEE International Conference on Big Data (Big Data)*, Oct. 2015, pp. 2895–2897, doi: 10.1109/BigData.2015.7364114.

[27] L. Torrey and J. Shavlik, "Transfer learning," in *Handbook of Research on Machine Learning Applications and Trends*, IGI Global, 2010, pp. 242–264.
[28] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: pre-training of deep bidirectional transformers for language understanding," in *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference*, 2019, vol. 1, pp. 4171–4186, doi: 10.18653/v1/N19-1423.
[29] J. M. Pérez, J. C. Giudici, and F. Luque, "Pysentimiento: a Python Toolkit for sentiment analysis and SocialNLP tasks," *arXiv preprint*, pp. 1–4, 2021.
[30] G. Hackeling, *Mastering machine learning with scikit-learn*. Packt Publishing Ltd., 2014.
[31] M. P. Geetha and D. K. Renuka, "Improving the performance of aspect based sentiment analysis using fine-tuned BERT base uncased model," *International Journal of Intelligent Networks*, vol. 2, pp. 64–69, 2021, doi: 10.1016/j.ijin.2021.06.005.
[32] "Developer agreement and policy," *developer.twitter.com*, 2023. https://developer.twitter.com/en/developer-terms/agreement-and-policy. (accessed: Jan 1, 2024).

BIOGRAPHIES OF AUTHORS

Eshun Michael is a graduate of Kwame Nkrumah University of Science and Technology with B.Sc. degree in Computer Science. He is currently pursuing his master's study at the Department of Computer Science, Brock University. His research areas are evolutionary computation, software engineering, and natural language processing. He can be contacted at email: me22eh@brocku.ca.

Gyening Mensah Rose-Mary Owusuaa is a lecturer at the Department of Computer Science. She holds Ph.D. Computer Science from Kwame Nkrumah University of Science and Technology (KNUST). She has been interested in machine learning, robotics and IoT, human computer interaction and cybersecurity. She can be contacted at email: mensahowusuaa@gmail.com.

Takyi Kate holds Ph.D. Degree at Lovely Professional University, Punjab, India in Computer Applications. She is currently a lecturer in the Computer Science, Department of KNUST. Her research areas of interest include machine learning, data science wireless networks, internet of things, network communications. She can be contacted at email: takyikate@knust.edu.gh.

Appiahene Peter is a senior lecturer with over 10 years working experience in the Computer Science Industry and Academic Institutions both Domestic and International. He has a Ph.D. in Computer Science with specialization in reinforcement learning and machine learning. He can be contacted at email: peter.appiahene@uenr.edu.gh.

Peasah Ofosuhene Kwame is a lecturer with the Department of Computer Science. He holds first and doctoral degrees in Computer Science. He however branched to the area of mathematics after his first degree and had his M.Sc. in Industrial Mathematics all in KNUST. His areas of expertise are digital forensic, operating systems and database forensics. He can be contacted at email: kpeasah@gmail.com.

Banning Amoako Linda is a lecturer at the department of Computer Science at KNUST. She holds a Ph.D. in Computer Science from University of Cape Coast. She is a natural language processing researcher, computational linguistics and artificial intelligence enthusiast. She can be contacted at email: labanning@knust.edu.gh.