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Tweeting democracy: analyzing twitter's role in public participation during the 2022 Philippine election

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Abstract

This study displays Twitter's relevance in collecting sentiments and evaluating social networks, notably in election processes. This study examines 10,000 tweets on the 2022 Philippine presidential election, gathered during the key week of May 9–13, 2022, to show Twitter's influence in molding the public conversation. The study found the most popular hashtags, including #halalan2022 and #eleksyon2022, highlighting their importance in the digital discussion around the election. A thorough social network study established eight key communities, demonstrating a strong connection among Filipino netizens during election-related debates. Among these, noteworthy people such as @RexelBartolome and @daywreckoning, as well as the news site @ABSCBNEWS, emerged as essential nodes, demonstrating their influence in information dissemination. Sentiment analysis of the tweets revealed a mostly neutral public mood toward the election, with frequent phrases such as "martial law" and "never again" indicating the discourse's underlying themes. This study examines Twitter as a valuable instrument for political analysis and advocates for a more sophisticated method of picking tweets that truly reflect community attitudes. Future studies should look beyond pre-election times to provide a complete picture of online debate, using Twitter's API for easy data gathering and analysis. This study closes a fundamental gap in understanding social media dynamics in the Philippines, providing insights for academic and practical applications in political communication.

Keywords: *twitter, social network analysis, sentiment analysis, election*

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Introduction

The presidential contest in the Philippines in 2022 was highly competitive, with numerous candidates vying for the office. Mastering social media and other digital platforms was crucial to shaping public opinion during this campaign. In recent years, social media has become influential throughout Philippine society (Quitzon, 2021) due to its simplicity and widespread accessibility despite inconsistent internet connections. Political campaigns recognize that harnessing these online forums is a vital means of reaching voters; as such, they often go all out to capture attention through various tactics (Sanvictores, 2022).

Social media usage exceeds 90% among Filipinos with internet access. According to Macaraeg (2022), Filipinos' daily internet usage was approximately four hours on social media platforms. Filipinos with internet access are likelier to trust social media than traditional media. According to a 2017 survey, 87 percent of respondents said they would rely on information obtained on social media (Quitzon, 2021; Kasuya, 2024). However, due to unreliable internet service and the primarily copy-protected nature of the rest of the web, it is nearly impossible for Filipinos to verify the information they encounter on Messenger, WhatsApp, Viber, or their Twitter or Facebook pages (Tumasjan et al., 2010; Benvenisti, 2018).

This study focuses on using the social media platform Twitter in public conversation throughout the 2022 Philippine election. Twitter usage has experienced a substantial surge in the Philippines. The general public adopted Twitter as a source of information and a platform for its communication. The subscriber growth rate on Twitter is similar to that of other social media platforms (Esteves, 2016). Filipino individuals exhibit a high degree of engagement with election-related hashtags, with the majority using them to support the incumbent presidential candidate. Political campaigns used the vast quantities of information accessible on these platforms to gain an understanding of user sentiments and, consequently, formulate their campaign strategies (Soler et al., 2012). Significant monetary investments made by politicians toward social media campaigns immediately preceding an election, coupled with disputes and discussions among their supporters and competitors, strengthen the notion that user-generated thoughts and opinions influence election sentiment and social media coverage.

The basis of this study is social network analysis. Social Network Analysis (SNA) refers to the procedure of defining how an individual engages in social interaction with another person (Muzaki & Witanti, 2021; Ghermaoui, 2015). SNA can identify relationship patterns maintained by online users across various social networks, including but not limited to Twitter, blogs, webpages, and Facebook (Harkan et al., 2021; Metzgar & Maruggi, 2009). SNA finds links between people interacting socially by using nodes to show what entities are present and linkages to show how actors exchange information (Drakopoulos et al., 2020). This method from sociology uses network theory to look at how people interact within a social network structure. It can be used in computer-mediated communications or collaborative networks (Drakopoulos et al., 2020). Researchers interested in organizational behavior or inter-organizational relationships have examined these patterns for many years (Mezzanzanica et al., 2018).

Additionally, sentiment analysis serves as an anchor for the study. Opinion mining is another name for sentiment analysis, which studies the opinions, sentiments, evaluations, appraisals, attitudes, and emotions of individuals, organizations, products, services, topics, issues, events, and topics and their qualities. While Yi et al. (2004) introduced sentiment analysis first, Kushal et al. (2003) introduced the term "opinion mining." At multiple granularity levels, sentiment analysis is a Natural Language Processing task. It is employed within the realm of politics to monitor political perspectives and identify inconsistencies and concurrences between the words and deeds of the government (Singh et al., 2020). Consequently, it can be employed to predict the outcomes of elections. Sentiment analysis on Twitter starts with indexing messages against identifiers to collect all pertinent data (Agrawal & Hamling, 2021). Typically, sentiment analysis produces or reveals a compilation of terms associated with notably positive or negative sentiment. Most findings indicate that social network and sentiment analysis with Twitter data were somewhat accurate when examining worldwide elections.

Furthermore, Twitter serves as the primary source of data for this study. Twitter, a social networking and microblogging platform, was established in 2006 by Biz Stone, Evan Williams, and Jack Dorsey. Users can post and read tweets on this social media network, which are text-based communications limited to 280 characters. Twitter has

336 million monthly active users (Jungherr, 2015; (Mislove et al., 2021). Retweeting is vital to Twitter's functionality, enabling users to share or repost someone else's tweet with their entire audience. A reversing arrow frequently denotes The Retweet button at the bottom of the tweet. Hashtags are non-separated words beginning with the "#" symbol that monitor who discusses a particular subject (M & Ravikumar, 2015; Kwak et al., 2010). The prevalence of frequent hashtags in Twitter discussions may elevate the hashtag's status as a trending topic. Specifically, it references the username of another Twitter user in a tweet that may be viewed by their followers (Ramteke et al., 2016; Suh et al., 2010). This functionality facilitates user-to-user communication on Twitter, where all exchanges are publicly accessible. A reply is a public response to a tweet directed at the tweet's originator. The purpose of the reply option is to stimulate conversation (Harkan et al., 2021). The schematic diagram shows the paradigm of the study.

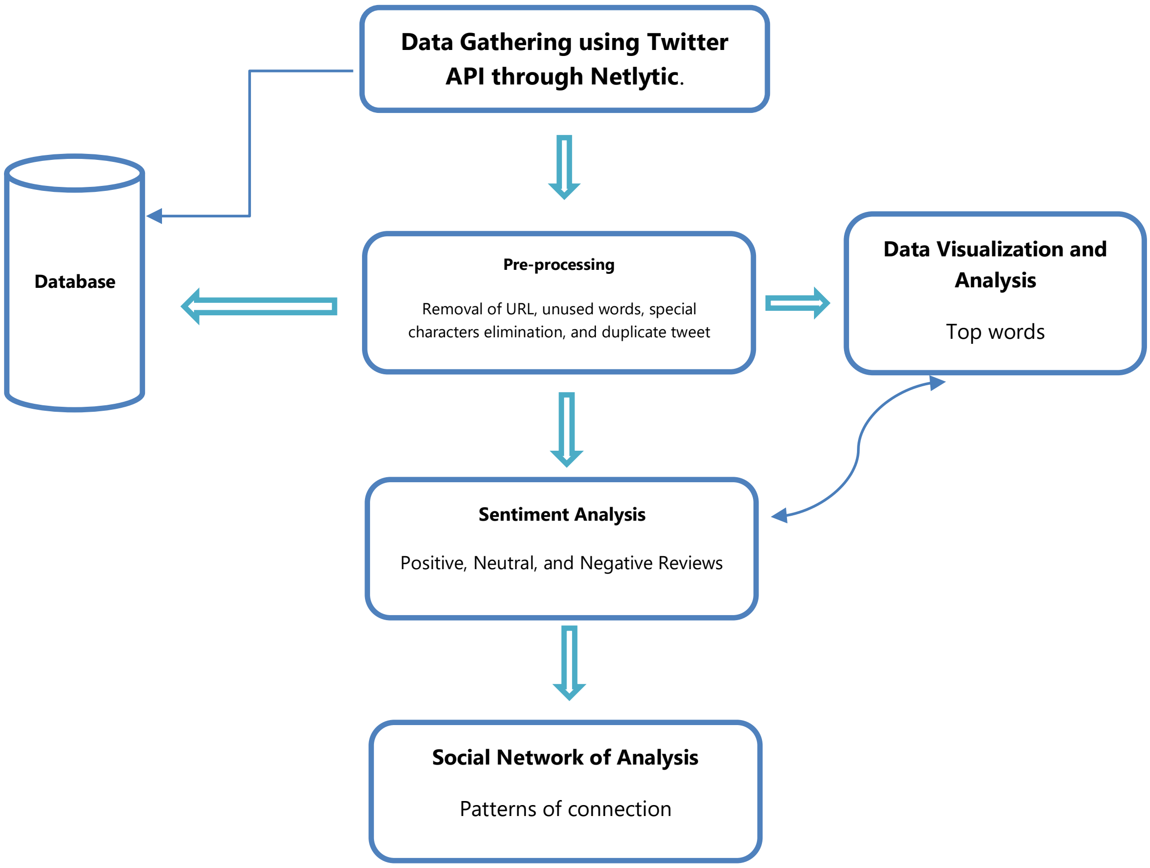

Figure 1. Schematic Diagram
Source: processed by author, 2024

Furthermore, to organize the procedure, the study was divided into subtasks. The researchers converted the data from the Twitter streaming API via Netlytic to CSV format as the initial phase to obtain data for our model, which can be processed, analyzed and developed. Following the pre-processing and cleansing of tweets, the researchers conducted a preliminary analysis focusing on the top terms to understand the data's fundamentals and generate narratives from the available information. The following phase involved applying RapidMiner sentiment analysis to the cleaned tweets and analyzing the results according to the percentage of positive, negative, and neutral tweets. Subsequently, a social network analysis was conducted on the dataset utilizing Gephi. Retweets served as edges connecting users as nodes, and online users' influencers were identified to determine the perspective of online users and show the slight world trend in the data.

In order to gain a deeper understanding of Twitter's role in the public discourse surrounding the 2022 Philippine election, this study employed Social Network Analysis (SNA). SNA is a sociological method that utilizes network theory to analyze patterns of connections and interactions between social agents and identify the underlying structure of social networks (Cheong, 2011). Sentiment analysis makes it easier to understand whether internet users respond positively, negatively, or neutrally. Sentiment analysis recognizes an online user's comment, opinion, like, dislike, or feedback on the content and classifies it as positive, negative, or neutral. Twitter is a social networking platform that uses text messaging and microblogging. Tweets are messages shared on this social media platform, unlike the other two social media networks, which rely on photographs and may include lengthy written papers. Twitter helps you express yourself more concisely and meaningfully (Budiharto & Meiliana, 2018).

This study focuses on Twitter data to provide more precise information for social networks and sentiment analysis in analyzing public conversations surrounding the 2022 Philippine presidential election. Moreover, there needs to be more research on this topic in the Philippines; thus, its goal is to collect data through the Twitter API while employing various classifiers that could reveal diverse trends in election discussions. Additionally, social network and sentiment analyses have aided in concluding the collected data.

This research explore how much Twitter contributes to being used as a platform for public discussion throughout the 2022 Philippine presidential election. The study employed sentiment analysis and social network methodologies. The fundamental objective of the study is to reveal the complex interrelationships and interactions among online users involved in political discussions relevant to the election. Specifically, the purpose is to thoroughly analyze user behaviors about election-focused content, including but not limited to likes, dislikes, comments, opinions, and feedback. The study analysis classified user responses into three emotional states: neutral, negative, and positive. This study aims to thoroughly comprehend social interactions in the digital sphere by conducting an in-depth analysis.

Research Methods

The study employs sentiment and social network analysis on Twitter data. This method provides and describes how Twitter was used in public conversation throughout the Philippine election of 2022. The researchers established a Twitter API account and subsequently linked it to their Twitter account. The authentication procedure for the Twitter API was done using Netlytic software and hashtags associated with the conversation surrounding the 2022 presidential election. The Twitter application was employed to gather tweets about the election to determine popular sentiment. Thus, using the following attributes, tweets were stored in the database: Twitter id, hashtag, number of retweets of tweet text, number of favorites, and number of tweets created. Following the collection of Twitter data by the researcher, sentiment analysis was utilized to ascertain the correspondence between the words in tweets and a catalog of positive, neutral, and negative phrases. Consequently, social network analysis was implemented to identify the interconnection patterns among online users.

The data source used for this study comprises electronic documents, which are precisely information collected through mention, reply, and retweet activity on Twitter. Netlytics.org supplies the researchers' monitoring software. Data was then crawled and analyzed using Gephi and Rapid Miner. Therefore, to determine how Twitter was utilized in public discourse throughout the 2022 Philippine Presidential election by employing social network and sentiment analysis, the research gathered tweets posted on May 1, 2022, from May 9th to May 13th.

Although software can assist researchers in collecting and managing electronic data, this method has several limitations. Two constraints of the Netlytic software were attributable to the context of the study. The first constraint pertains to the readability of the output. Twitter users may encounter the following four categories of interactions: mention, retweet, respond, and like. Unfortunately, only three of the four were readable by the software: mention, reply, and retweet. An additional constraint pertains to the volume of data that can be scanned. The free program Netlytic has a maximum crawling capacity of 10,000 submitted tweets—consequently, a mere 10,000 tweeted messages appeared in the form of mentions, replies, or retweets.

The study employs a methodology and conducts data analysis using social network analysis, sentiment analysis, and data processing. In the first stage, data is processed. The primary objective of the data pre-processing procedure is to eliminate anomalies and noise that restrict the ability to determine the sentiment of tweets or texts. Punctuation, numerals, special characters, or phrases without semantic significance within the text may constitute this extraneous noise. For instance, they remove special characters, punctuation, numerals, brief words, and Twitter usernames.The next step involves sentiment analysis, which uses text analysis tools like Rapid Miner to interpret and classify emotions into positive, negative, or neutral categories within text data. Frequently, sentiment analysis generates or uncovers a list of terms associated with notably positive, negative, or neutral sentiments. Many favorable terms and the absence of negative ones denote a positive sentiment. In contrast, a negative sentiment is expressed by an abundance of negative terms and a lack of positive terms. Preceding sentiment analysis on Twitter is scanning messages for pertinent information using hashtags.

The analysis of social networks constitutes the final stage. Important to the Social Network Analysis is the utilization of Twitter's 'retweet' feature. Individuals are more inclined to disseminate messages that they endorse and appreciate. Numerous users include political party leaders and commentators they follow daily when retweeting their messages. Two additional nodes are produced with every retweet. A node is utilized to symbolize the retweeted tweet, whereas another node is employed to represent the user who retweeted said tweet. User A, for instance, published a tweet retweeted by user B. Consequently, users A and B will be transformed into network nodes connected by an edge. This edge would be considered undirected. Despite user B repeatedly retweeting the identical tweet as user A, a single edge will remain connecting A and B.

The researchers subsequently utilized Gephi, a visualization and analysis tool for social networks. Gephi forges communities through the rapid unfolding of communities in enormous networks. The community and every individual node were both stored in a CSV file. The researchers classified the communities into distinct categories according to the on-screen identities present within each group.

Results and Discussion

To explore how Twitter social media was used in public conversation during the 2022 Philippine Presidential election using social network and sentiment analysis, the study examined a dataset of up to 10,000 tweets crawled using Netlytics. According to Kaplan and Haenlein (2012), Twitter is a popular social media platform for facilitating open discussions. With its integrated features, this tool enables rapid communication that fosters novel interaction patterns amongst multiple sectors, including government agencies, businesses, and the general public, significantly impacting communication trends and responses. Governments commonly employ this medium to engage stakeholders on specific matters or policies. The Social Network study method assesses online interactions to identify consistent outcomes (Haupt et al., 2021). Burnap et al. (2016) examined Twitter data from the UK General Election to forecast election outcomes using a straightforward model that accurately allocated parliament seats by considering previous party support rates and sentiment analysis. Soler et al. (2012) employed another tool that facilitated the definition of experimental designs, capturing impassioned discourse surrounding three Spanish elections held across years covering 2011 and 2012.

The study collected tweets made on the first day of the election, May 9-13, 2022, often known as election week. Furthermore, the data-cleansing technique grouped tweet subjects into generic categories and network links between users based on their Twitter behavior. As shown in Table 1, the researchers chose hashtags that were popular on Twitter and represented the conversation around the election.

Table 1. Trending hashtags related to the Presidential election in the Philippines

Hashtags			
#halalan2022	#eleksyon2022	#election2022ph	#votesafepilipinas

Source: processed by author, 2024

Social Network Analysis

The social network analysis based on popular hashtags consisted of interactions between 8,864 distinct Twitter users. This approach is carried out by displaying the interaction network of public conversation during the 2022 Philippine Presidential election on Twitter using the Gephi tool. Gephi uses the fast unfolding of communities in massive networks to build communities. The researchers claimed their approach was the quickest for huge networks. A CSV file was created for each node and its community. We categorized communities based on their on-screen names. The data is represented in a sociogram, in which the individual in the image's center is referred to as a node and is connected by a line known as an edge.

It indicates user engagement, such as retweets and replies. The outcomes of the application of social network analysis are as follows. Table 2 provides the network attribute values that are based on the Twitter activity identified (reply, retweet, retweet & comment, and mention). The social network analysis was divided into two groups: mention and reply. The mention network consists of users based on Twitter behaviors such as retweeting, commenting, and mentioning, while the reply network includes actors based on Twitter replies. The mentioned network and reply network had 8864 nodes and 9367 edges. Users who did not mention other accounts were classified as having no relationship activity or lines linking to different actors.

Table 2. Network Attributes Value

Network Attributes	Value
Total Nodes	8864
Total Edges	9367
Average Degree	2.113
Average Weighted Degree	2.256
Network Diameter	11
Average Path Length	4.03
Number of Communities	124

Source: processed by author, 2024

Force Atlas 2 was used to visualize the network. Force Atlas 2 is a typical layout approach for Gephi, an open-source network visualization and analysis program. This technique works exceptionally well for displaying vast and complicated networks. Force Atlas 2 is a force-directed layout technique that arranges network nodes by simulating a physical system. Nodes are characterized as electrically charged particles that repel one another. Edges are considered as springs, attracting the nodes they link. In Figure 2. the first graphic was made with Force Atlas 2 without text labels or statistics on top Twitter users. This resulted in a network that was difficult to interpret because of the difficulties in determining node positions. As a result, it is possible to derive that the persons in this network are close to one another.

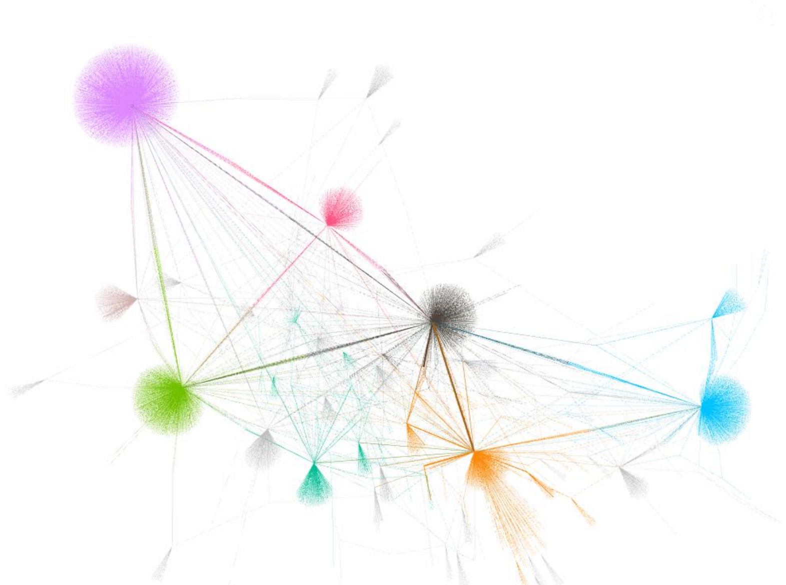

Figure 2. Force Atlas2 without labels
Source: processed by author, 2024

As shown in Figure 3. the expanded graphic was created with Force Atlas 2, which included text labels and identified significant Twitter users. These top users were identified as indicators of node centrality in the network. The study revealed that the most influential users are @rexelbartolome, @daywreckoning, @ABSCBNEWS, @AmbMacArthur, @pat_delacerna, @pinoyweekly, @alltoojohn, and @altermidya. An examination of their Twitter accounts revealed that three top entities are news media sources, while the others are important Twitter personalities with a large following. This set of users played a crucial role in influencing interactions inside this social network, identifying them as key influencers in the conversation.

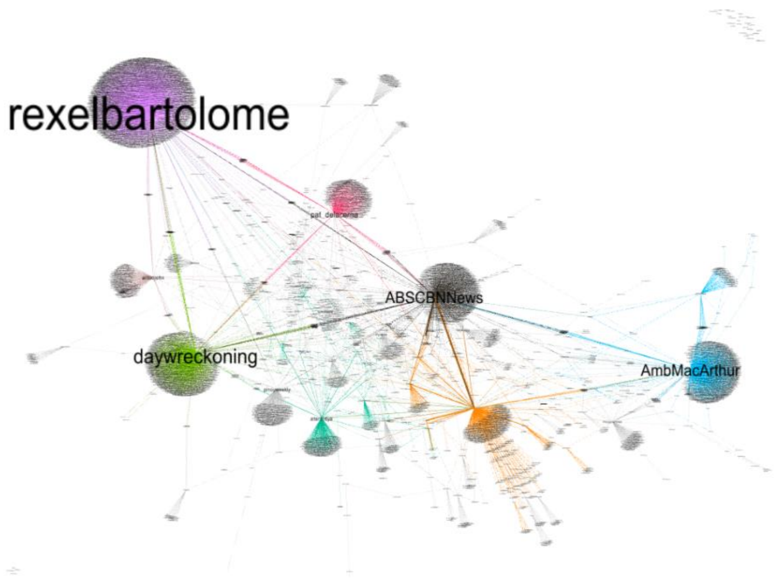

Figure 3. Force Atlas2 with labels
Source: processed by author, 2024

Based on the centrality calculation findings, Table 3 lists the central actors in each community in the network.

Table 3. Central Actor

Communities	Actor
Purple	Rexelbartolome
Green	Daywreckoning
Black	ABSCBNEWS
Blue	AmbMacArthur
Pink	Pat_delacerna
Gray	Pinoyweekly
Peach	Alltoojohn
Aqua	Altermidya

Source: processed by author, 2024

In SNA, each node is considered an actor. Nodes may be institutions, states, or cities, not just individuals. This character's behavior on Twitter is significant. On Twitter, the actor is identified by their username or Twitter account. Individuals may have many accounts, but major organizations only have one official account. A bot may be managing the account(s). Actors on Twitter do not always do activities like tweeting, responding, mentioning, or liking. Actors may be passive, such as those noted, liked, responded to, or retweeted by other accounts on the network. In the Mention and

Reply networks, @rexelbartolome has the greatest centrality, betweenness centrality, and eigenvector centrality but is always passive. This phenomena also happened under #halalan2022, #eleksyon2022, #election2022ph and #votesafepilipinas. In comparison SNA has been utilized in various settings to examine social interactions. Numerous studies, including "Mixed Methods Analysis of the #Sugar Tax Debate on Twitter" (Bridge et al., 2021), "E-Cigarette Themes on Twitter: Dissemination Patterns and Their Relationship to Online News and Search Engine Questions in South Korea (Paek et al.., 2018) and "Analyzing Public Discourse on Social Media with Geographical Context: A Case Study of the 2017 Tax Bill," have analyzed tax policy using SNA analysis (Park & Tsou, 2020). Past research has delved into utilizing SNA to detect actors, connections, and discussion topics through content, sentiment, and thematic examination. The consequent findings may benefit governments while devising relevant policies and strategies for citizens' welfare (Ferdiana et al., 2019).

The research revealed that Twitter networks exhibit similarities and differences from real-life social networks. Both networks consist of players, relations, and discussions, but their communication patterns vary. In a real-life network, people often connect with those they know. To approach strangers in real life, people might ask an acquaintance to introduce them. In SNA, this idea is known as six degrees of separation. This notion claims that even in the most significant network, everybody may link through no more than five intermediates, such as acquaintances. In this context, steps represent the contacts needed to connect with an unknown person in your life. However, this is only sometimes true on social media platforms like Twitter. Strangers may connect by directly referencing one another's accounts (Harkan, 2021).

The under #halalan2022, #eleksyon2022, #election2022ph and #votesafepilipinas. The network also experiences this form of connection. Accounts or other prominent figures may not have a personal connection to the account owner. The observed network structure may have a diameter greater than six steps. The observed network's communication pattern varies from real-life networks with six degrees of separation.

Sentiment Analysis

The researcher performed sentiment analysis using 10,000 crawled Tweets from Netlytic. This approach involves text-mining conversations on Twitter during the 2022 Philippine Presidential election using Rapidminer. Twitter sentiment analysis in comments and tweets may serve as valuable indications for several reasons. Sentiment falls into two categories: negative and positive words. Sentiment analysis is a natural language processing approach that quantifies stated opinions or sentiments in tweets (Annett & Kondrak, 2008). Sentiment analysis is a field of natural language processing, text mining, and computational linguistics that analyzes feelings, views, and emotions in text (Pak & Paroubek, 2010). Emotion-based views or attitudes are sometimes referred to as sentiments, which lend themselves to sentiment analysis or opinion mining (Boyd et al., 2010). Sentiment mining has many applications in accountancy, law, research, entertainment, education, technology, politics, and marketing. Previously, social media platforms allowed individuals to communicate their views and opinions freely.

In their study published in 2024, Nguyen and colleagues utilized Twitter data from the 2016 US election to conduct an exhaustive analysis of internet tweets. By employing the software they developed, which gathered all mentions of either candidate on Twitter by state and sorted them according to sentiment for each tweet (either supporting one candidate or being neutral), the researchers evaluated how major candidacy announcements affect party affiliation, personality traits conveyed via social media posts, as well as policy impact (Rauniyar et al., 2023). Similarly focused on political elections but with a different approach was Bansal and Srivastava's research project that used alternate keywords such as usernames and hashtags during data collection processes geared towards Uttar Pradesh polling activities in India, reported two years later. Their methodology primarily entailed manually searching various users' profiles within specified tags while simultaneously seeking out namesake parties alongside official handles linked therein, resulting in numerous results of due diligence comparisons among political affiliations across Twitter messages captured. Additionally, pre-existing pre-processing efforts were carried out, including removing special characters (punctuation marks), URLs, and the omission exclusion of stop words upon factual scrutiny confirmation (Daga et al.,2017).

The tool utilized in this study is Rapid Miner. Rapid Miner is a software platform that offers integrated capabilities for machine learning, data mining, text mining, predictive analytics, and business analytics (Tripathi et al., 2015). With over 1500 drag-and-drop operators, this smart product allows for rapid and efficient data mining tasks. We applied text mining, categorization, and validation operators in our work. We employ text processing methods to transform natural language text for data mining.- Tokenization is the process of splitting a document's text into tokens. Transform Cases converts all characters in a document to either lower or upper case. Filter stop words remove English stop words from a text by deleting tokens that match the built-in list.

The dataset utilized in this study consists of natural language tweets sourced from twitter.com. Rapid Miner uses tokenization, filtering, stemming, and other text-mining operations to prepare data for classifiers and testing. We manually divided tweets into positive, negative, and neutral. The class labels were used as a classifier to predict the labels of tweets in the testing dataset.

Table 4 displays the results of the classifying feelings about public conversation during the 2022 Philippine Presidential Election. Positive attitudes toward the public conversation amounted to 2707 or 27.07% of the entire sentiment, while negative sentiment amounted to 1005 or 10.05%, and neutral sentiment amounted to 6288 or 62.88% of the total sentiment implemented. Based on the findings, most public opinion about the 2022 Philippine Presidential election is neutral. In the study "Emotion Analysis of Twitter using Opinion Mining" aimed beyond classifying opinions as positive, negative, or neutral; it categorized them into five emotions: joy, anger, fear, sorrow, and disgust (Galarnyk 2019). The researchers used a two-step technique that involved identifying opinion words and applying an innovative algorithm that calculated emotional values in these terms (Castro et al., 2017). Jungherr's research, conducted in 2015, focused on discerning how social media data could effectively predict election outcomes. However, political parties often use propaganda techniques like fake news stories to promote their candidates through actors who manipulate people (Jungerherr, 2015). Although comparing tweets to votes is not considered helpful information, according to Stepanyan et al. (2010), Twitter remains poised to discover public perspectives about voting choices

Table 4. Sentiment Analysis

Positive	2707
Negative	1005
Neutral	6288
Total	10, 000

Source: processed by author, 2024

The subsequent text provides a sample of sentiment analysis derived from the public discourse surrounding the 2022 Philippine Presidential election.

Table 5. Sentiment Classification

Sentiment	Text
Positive	This is not the time to give up on our country.
Negative	It's a shameful senate composition.
Neutral	Wedding suppliers pledge services for couples who dreamt of Leni's presidency.

Source: processed by author, 2024

Analysis of the 10,000 tweets collected reveals that the predominant topics in public discussions during the 2022 Philippine Presidential election encompassed a range of subjects, including martial law, challenges in literacy ('nahihirapan magbasa'), the 'never again' sentiment, and references to key figures and concepts such as Marcos, Leni, knowledge ('alam'), internet trolls, 'people strength', and democracy.

Figure 4. Top words

Source: processed by author, 2024

Twitter has emerged as a vital platform for public discourse in the Philippines, with recent data underscoring its significant impact on the country's digital landscape. The social media site has become an essential forum for Filipinos to engage in discussions on various topics, from politics and current events to entertainment and social issues. Its real-time nature and wide reach have made it a go-to source for breaking news, opinion sharing, and community building. The platform's popularity in the Philippines reflects the country's high social media engagement rates and its increasingly digitally connected population. As a result, Twitter has become an influential tool for shaping public opinion, disseminating information, and fostering civic engagement among Filipino users.

Conclusion

Twitter showed its effectiveness as an instrument for sentiment extraction and social network analysis. Multiple studies have demonstrated that Twitter data can be used to analyze elections from around the world with a certain degree of accuracy. The researchers employed sentiment and social network analysis to examine 10,000 tweets in this study. The authors employ Twitter data spanning from May 9-13, 2022, which corresponds to the week of the election when public discourse regarding the election first began to emerge. The most frequently used hashtags during that period were #halalan2022 #eleksyon2022 #election2022ph #votesafepilipinas, all data associated with the 2022 Philippine presidential election.

An examination of the communities that have developed within the network can be obtained by performing a thorough social network analysis on the dataset comprising retweeted tweets. According to the research, eight significant communities have emerged. Furthermore, this confirms that online communities exhibit a strong sense of camaraderie in their public conversation about the Philippine election in 2022. The three Filipino netizens with the largest communities or highest betweenness centrality values are @Rexelbartolome and @daywreckoning. The third community was from the news organization @ABSCBNEWS. It visually represents the Filipino online community that seeks and shares information through social network analysis (SNA). In addition, a sentimental analysis was conducted on tweets; the findings revealed that the prevailing sentiment among the general public regarding the 2022 Philippine presidential election was neutral. During the 2022 Philippine presidential election, the public discourse on Twitter exhibited three predominant words: martial law, nahihirapan magbasa, and never again.

Given the lack of research on this topic in the Philippines, the results of a social media community's behavior as determined by sentiment analysis and social network utilization are essential. The following suggestions for future research: Selecting a tweet that genuinely reflects community sentiment rather than relying on popular hashtags is imperative. More Twitter data mining and analysis should be unrestricted to the period immediately preceding elections; it should continue to the post-election period to obtain more precise analyses of online conversation. Collecting messages through the Twitter API is considerably easier than alternative approaches and has demonstrated its suitability in generating dependable outcomes.

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