Temporal Sentiment Analysis of Politician XYZ on Social Media X Using FastText Word Embedding and Graph Neural Network Model

Nurul Aini Afiqah
School of Computing
Telkom University
Bandung, Indonesia
nurulainiafiqaah@student.telkomuniversity.ac.id

Fitriyani
School of Computing
Telkom University
Bandung, Indonesia
fitriyani@telkomuniversity.ac.id

Toufan Diansyah Tambunan
School of Computing
Telkom University
Bandung, Indonesia
tambunan@tass.telkomuniversity.ac.id

***Abstract*— Social media has become a primary platform for the public to express their opinions. Since 2023, politician XYZ has been one of the most widely discussed figures, particularly on Social Media X. Several political events between 2023 and 2024 make the public sentiment toward this figure interesting to analyze. This study conducts a temporal sentiment analysis of public opinion on politician XYZ from August 2023 to March 2024, using FastText word embeddings and a Graph Neural Network (GNN) model. The approach involves data collection, text processing, and sentiment classification, utilizing FastText to capture the semantic relationships between words and a Graph Neural Network (GNN) to model sentiment dynamics over time. The focus of this study is to explore the temporal aspect of sentiment shifts, providing insights into how public opinion evolves over time in response to political events, in contrast to static sentiment. The temporal sentiment analysis reveals that the public's perception of politician XYZ initially began with positive sentiment but shifted to negative sentiment in the following months, influenced by key political events. With an accuracy of 72%, this study highlights the potential of integrating FastText and GNN for capturing complex and evolving political sentiments. The findings offer practical implications for political communication strategies, enabling stakeholders to better understand and anticipate shifts in public opinion during critical political moments.**

Keywords—Temporal Sentiment Analysis; Politics; FastText; Graph Neural Network.

I. INTRODUCTION (*HEADING 1*)

The rapid growth of social media has transformed how people share and access information, fostering a platform for public discussion and self-expression [1][2]. By early 2024, 5.16 billion individuals, or 59.3% of the global population, were active on social media [3]. Among these platforms, X (formerly Twitter) stands out as a leading channel for information exchange and public discourse, with 24.85 million users in Indonesia as of April 2024, positioning the country as the fourth-largest global user base for the platform [4][5]. This makes social media X a valuable resource for analyzing public sentiment, especially during politically significant periods.

Politician XYZ emerged as a central figure in public discourse throughout 2023 and 2024 due to his involvement in pivotal political events crucial to Indonesia's stability. Understanding the dynamics of public sentiment toward him is essential, as it reflects broader societal and political trends. Temporal analysis serves as a powerful tool for tracking how public opinion shifts in response to specific events, offering insights into the interaction between political developments and public perception. This approach can also identify anomalies within specific timeframes that trigger shifts in public perspectives [6]. Using advanced computational methods, this study examines how sentiment toward politician XYZ evolved from August 2023 to March 2024, addressing gaps in temporal sentiment analysis within political contexts.

The study by Garcia, C.M. et al. [7] highlights the shift in focus of the hashtag #mybodymychoice, from women's rights to vaccination issues in 2021. Similarly, Vivek, M. et al. [8] conducted a spatio-temporal crime analysis in India, using statistical and machine learning techniques to track changes over time. These studies demonstrate the power of temporal analysis in tracking topic evolution. Additionally, Zhao Lin's [6] work on global network properties such as reciprocity and assortative reveals correlations with real-world phenomena, aiding in anomaly detection and refining analysis to more appropriate time granularities. This study similarly applies temporal sentiment analysis to explore how public opinion and perceptions of politician XYZ evolved from August 2023 to March 2024, identifying shifts in sentiment over time.

The focus of this study is on analyzing social media X users' sentiment regarding politician XYZ from August 2023 to March 2024. The analysis utilizes FastText word embedding. MR Ilham and AD Laksito [9] in their study found that FastText outperformed the GloVe method with an accuracy of up to 90%. Additionally, the sentiment analysis model used in this study is the Graph Neural Network (GNN), with research by Yao et al. [10] demonstrating that the GNN model is effective in text classification, particularly in sentiment analysis.

While previous studies, such as those by Garcia, C.M. et al. [7] and Vivek, M. et al. [8], have explored temporal and spatio-temporal dynamics in various contexts, they primarily focus on topic-level or spatial patterns without addressing the evolution of sentiment over time or its implications for public opinion in political scenarios. Furthermore, models such as FastText and GNN, which have individually demonstrated strong performance in text classification and semantic analysis [9], [10] have not been applied in combination to the specific domain of political sentiment analysis over time. This leaves a gap in understanding how advanced methods can capture nuanced sentiment dynamics in response to key political events.

By addressing this gap, this study introduces an enhanced approach by integrating FastText and GNN into temporal sentiment analysis, with a focus on public perceptions of Politician XYZ. This approach not only illuminates the evolution of sentiment within the politically dynamic context of Social Media X, but also provides new insights into how technological tools can enhance our understanding of the interplay between public opinion and political developments.

II. LITERATURE REVIEW

A. *Temporal Sentiment Analysis*

Temporal analysis is a method used to understand changes in data over a specific time range. The temporal approach focuses on analyzing the entire timeline of the data, without the need to simplify it into a single representation [11]. Temporal analysis is used for identifying phenomenon, trends, or changes in a topic or event over time. Additionally, understanding the relationships between events is crucial for predicting future developments [12]. For instance, it is important for businesses to monitor and develop strategies to ensure that their products are engaging the target market with the analysis of previous events.

Common methods used in temporal analysis include time series approaches like Auto-Regressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM) for machine learning, or graph-based methods such as GNN. These temporal analysis methods can also be applied in sentiment analysis to detect changes in public opinion regarding an event. This approach can be used to identify sentiment patterns that emerge before, during, or after a particular event, offering deeper insights into public response and perception of ongoing events.

B. *Social Media X*

Social media X is a popular platform for sharing information and opinions, transforming how the public engages in discussions. It has become an effective tool for businesses and researchers to gather insights on current topics and public sentiment [13]. The platform offers features that enable users to easily share opinions and news, fostering dynamic discussions. Additionally, Social media X provides an Application Programming Interface (API) that allows researchers to collect data from tweets, likes, comments, and mentions, based on specific keywords and time periods, for research purposes.

C. *FastText Word Embedding*

FastText, introduced by Facebook, is an efficient and fast word embedding model that represents data as vectors by decomposing words into sub-words using n-grams [14]. His sub-word processing enables FastText to handle languages with rich morphology, misspellings, and out-of-vocabulary words by analyzing word structures. The architecture, as shown in Fig. 1, includes an input layer, a hidden layer, and an output layer. Words are broken down into sub-words at each layer and represented as vectors in the output layer, facilitating the discovery of similar words and enhancing tasks like sentiment analysis

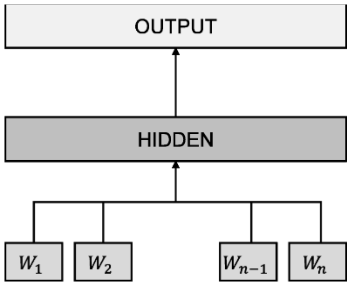

Fig. 1. FastText Architecture [15].

A study published in 2021 on emotion detection in Twitter social media compared several word embedding methods, with Word2Vec achieving an accuracy of 73.15%, GloVe reaching 60.10%, and FastText also yielding an accuracy of 73.15% [16]. In 2023, MR Ilham and AD Laksito [9] further compared FastText and GloVe, and found that FastText outperformed GloVe, achieving an accuracy of up to 90%. Given these findings, FastText was chosen for the current study. The dataset used in this research contain of tweets in Indonesian, which feature a diverse range of expressions and informal language. FastText is particularly effective for handling linguistic variations, as it can manage out-of-vocabulary (OOV) words by leveraging subword information. This ability to capture nuances in language makes FastText well-suited for analyzing the complexity and variety of the Indonesian language in Twitter data.

D. *Graph Neural Network (GNN)*

Graph Neural Network (GNN) is an artificial neural network designed to process graph-structured data, consisting of nodes and edges. GNN excels in handling complex data like social networks and molecular networks. According to Yao et al. [10] GNN is effective for tasks like text classification, including sentiment analysis, showing its versatility in both graph and textual data processing.

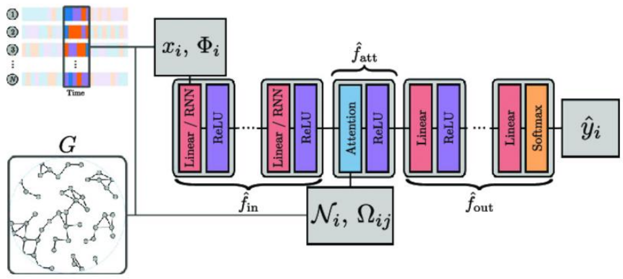

Fig. 2. Graph Neural Network (GNN) Architecture [17].

Fig. 2. illustrates the architecture of the GNN model. The GNN architecture processes input data through hidden layers with specific functions. Red blocks represent functions influenced by weights and biases, purple blocks indicate activation functions, and orange blocks transform outputs to generate results. This structure illustrates how GNN transforms input into meaningful outputs.

The sentiment analysis model employed in this research is based on the Graph Neural Network (GNN) approach, which has been shown to be effective in text classification tasks, particularly sentiment analysis, as highlighted in studies like the one by Yao et al. [10]. GNNs excel at managing complex structured data by capturing relationships between words, documents, and the overall corpus, making them especially suited for analyzing diverse, human-written text with varying