

Topic Classification on Twitter Using a Multi-View Graph Neural Network (GNN) Model

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ABSTRACT

Political discussions on social media have become an important source of information for understanding public opinion and information dissemination. However, most existing political topic classification methods rely primarily on textual features and tend to overlook structural and temporal relationships between users. In this study, we propose a Multi-View Graph Attention Network (MV-GAT) that improves political topic classification by integrating three complementary graph representations: a semantic content graph, a user interaction graph, and a temporal propagation graph. We collected a dataset containing 15,131 Indonesian tweets from Twitter(X), of which 1,677 tweets were manually labeled as political or apolitical, and the remaining tweets were kept as unlabeled nodes to maintain the graph structure. Each graph view was independently constructed and aligned using tweet_id before being processed by the proposed MV-GAT model. The model was trained using weighted cross-entropy loss with an attention-based fusion mechanism to automatically learn the contribution of each graph view. Experimental results showed that the proposed method achieved an accuracy of 84.23%, a macro F1 score of 83.04%, and an F1 score of 78.54% in political topic classification. Attention analysis revealed that the semantic content graph contributed most significantly to the classification process, while the interaction graph and time graph provided complementary structural information. Furthermore, post-classification graph analysis revealed relationship patterns among users and the propagation of political information within the Twitter network. These results demonstrate that integrating multiple graph views improves both the classification performance and interpretability of political topic analysis on social media.

INTRODUCTION

The spread of information in the digital era is extremely rapid, driven by the rapid development of information technology. Social media, such as Twitter (X), has become the epicenter of this accelerated flow of information. This is demonstrated by the platform's very high penetration in Indonesia. According to data released by iniliah.com in January 2024, X (Twitter) users in Indonesia reached 25.2 million, equivalent to 8.8% of the total population. This phenomenon of rapid spread, reflected in how quickly a post is retweeted, has become an important object of study for mapping the digital information landscape (Ramli & Sibaroni, 2022).

In this context, machine learning is crucial for analyzing, classifying, and predicting information distribution patterns on social media. This technology enables computers to learn from data and improve their performance without the need for direct programming. Machine learning is divided into two main types: supervised learning and unsupervised learning (Shu et al., 2025). One increasingly popular supervised learning algorithm is the Graph Neural Network (GNN), which can process graph-shaped data, such as relationships between users or tweets on platforms like Twitter. GNNs work by transmitting information between nodes (e.g., between users) through a neural message-passing mechanism, automatically recognizing interconnected patterns and dynamics within the network.

The data structure on the Twitter platform can be visualized as a graph. Each user or post (tweet) serves as a node, while relationships between users, such as follows, retweets, replies, and mentions, form the edges connecting these nodes (Y. Liu et al., 2025). These relationships reflect the social interactions and information flows between users, creating a complex and dynamic network of activity on Twitter. This graph is well-suited for analysis with Graph Neural Networks (GNNs), as GNNs are designed to learn the patterns of relationships between nodes in a network.

Thus, the phenomenon of information dissemination on Twitter can be realistically analyzed using graph-based approaches such as GNNs. Based on this phenomenon, researchers argue that the analysis of information dissemination on Twitter will be more comprehensive if it combines multiple data perspectives using a Multi-View Graph Neural Network (GNN) approach. This idea arises because activity on Twitter is not only related to the content of the messages disseminated but also involves social relationships between users and the temporal dynamics of information dissemination. Therefore, this study proposes three complementary analysis approaches: (1) Semantic Content Graph,



which depicts relationships between tweets based on similar content or topics; (2) User Interaction Graph, which maps patterns of relationships between users through retweets, mentions, and replies; and (3) Temporal Propagation Graph, which represents the direction and speed of information spread between users over time. By integrating these three graphs into a single Multi-View GNN model, it is hoped that topic classification and modeling of information spread on Twitter can be performed more precisely, efficiently, and contextually.

A comprehensive study by Wang et al., (2024) examined the application of Graph Neural Networks (GNN) to text classification. The core of this study is the observation that text data can be naturally modeled into graphs to represent global features. Two approaches to graph construction are identified: (1) Corpus-level Graph, which effectively captures global structural information, and (2) Document-level Graph, which explicitly represents relationships between words in a document. The effectiveness of GNNs lies in their ability to overcome the limitations of sequential deep learning models, which are considered less capable of handling complex relationships and contextual word associations. This study concludes that GNNs, despite originating from non-Euclidean data, show very promising performance in the field of text classification.

LITERATURE REVIEW

Text-Based Political Topic Classification

Political topic classification is one of the most widely studied tasks in natural language processing (NLP), aiming to automatically classify social media posts as either political or non-political. Early approaches typically combined traditional machine learning algorithms such as support vector machines (SVMs), naive Bayes, and random forests with artificial text features like TF-IDF (Term Frequency–Inverse Document Frequency). While these methods performed reasonably well on structured datasets, they had limitations in capturing the contextual semantic information contained in short social media texts (T. Liu et al., 2024).

More recent research has employed deep learning approaches, particularly transformer-based language models like BERT and IndoBERT, to improve semantic understanding (Rivaro et al., 2026). These models generate contextual representations that significantly outperform traditional feature extraction methods across various text classification tasks. In the classification of Indonesian political tweets, IndoBERT has been shown to better represent linguistic context than traditional word embeddings. However, text-based approaches generally analyze each tweet individually, failing to consider user relationships or interactions within social media networks (Adek et al., 2022). As a result, it becomes impossible to optimally utilize important structural information that reflects information distribution patterns.

Graph-Based Social Media Analyst

Graph-based analysis is an effective method for modeling social media data because it represents users and posts as nodes and their connections as edges (Aris Sarjito, 2024). Compared to traditional text classification, this representation allows for the simultaneous capture of interaction patterns, information diffusion, and community structure. Several studies have constructed graphs using retweets, replies, mentions, and follower relationships to analyze political discussions on Twitter. These graph structures allow learning algorithms to leverage neighbor information and reveal hidden dependencies between users (Stropanik & Oražem, 2022). As a result, graph-based representations provide richer contextual insights than approaches that rely solely on text. However, much of the existing graph-based research still relies on a single graph structure (Giffera, 2022). Some focus solely on semantic similarity graphs, while others use only interaction networks or temporal propagation graphs. Such single-perspective representations fail to adequately capture the diverse characteristics of social media data.

Graph Neural Network and Multi-View Learning

Graph neural networks (GNNs) have become one of the most advanced techniques for learning representations from graph-structured data. Among the many GNN derivatives, graph attention networks (GATs) incorporate an attention mechanism that allows the model to assign different importance levels to neighboring nodes, contributing to improved accuracy in representation learning (Xiao et al., 2024). To further improve graph representations, recent research has employed multi-view learning. This technique combines multiple graph views within a single learning framework. Each view captures different aspects of the same dataset, allowing for the integration of complementary information during learning. Several studies have shown that multi-view graph learning improves node classification performance compared to single-view approaches (Yu et al., 2023). However, many existing methods simply integrate graph embeddings without explicitly modeling the different contributions of each view. As a result, complementary information contained in semantic, interactional, and temporal relationships is not fully utilized (Damatraseta et al., 2026).

METHOD

Research Framework

This study proposes a Multi-View Graph Attention Network (GAT) framework for political topic classification using Indonesian Twitter data. This framework consists of six main stages: dataset collection and preprocessing, multi-



view graph construction, node alignment, multi-view graph training, model evaluation, and post-classification graph analysis (Rahmania Mustaqillah et al., 2023). First, Twitter data is collected and preprocessed to remove noise and standardize text content. Next, three complementary graph views are constructed to represent the same dataset from different perspectives. The semantic content graph captures semantic similarities between tweets using context embeddings generated by IndoBERT. The user interaction graph models relationships between users based on social interactions such as replies, mentions, retweets, and hashtag sharing. The temporal propagation graph represents temporal relationships based on tweet posting times. Since each graph is generated independently, node alignment is performed using tweet identifiers (tweet_id) to ensure that corresponding nodes refer to the same tweet across all views. The aligned graph is input into the proposed multi-view graph attention network, which learns node representations and classifies tweets as political or non-political (W. Wang et al., 2022). Finally, the trained model is evaluated using standard classification metrics, and the learned graph embeddings are further analyzed to elucidate information transmission patterns within the Twitter network.

Dataset and Preprocessing

The dataset used in this study consists of 15,131 Indonesian tweets collected from Twitter (X) using political keywords during the data collection phase. Each tweet is assigned a unique identifier called 'tweet_id', which is later used to associate nodes across different graph views. Of the collected tweets, 1,677 were manually annotated, consisting of 588 political tweets and 1,089 non-political tweets. The remaining 13,454 were left unlabeled and used to maintain the graph structure in representation learning. Prior to graph construction, several preprocessing steps were applied to improve data quality. Duplicate tweets were removed, and URLs, mentions, emojis, punctuation, and special characters were filtered. All text was converted to lowercase, and language filtering left only Indonesian tweets. Finally, the cleaned text was tokenized using the IndoBERT tokenizer to generate contextual semantic embeddings for the semantic content graph.

Multi-View Graph Construction

- Semantic Content Graph

The semantic content graph was designed to model the semantic relationships between tweets based on their text content. In this graph, each tweet is treated as a node, and contextual semantic embeddings are generated using the IndoBERT model. The similarity between two tweet embeddings is calculated using cosine similarity. An edge is created when the similarity score exceeds a specified threshold, indicating that the tweets are semantically related.

$$\text{Cosine Similarity}(A, B) = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \times \sqrt{\sum_{i=1}^n B_i^2}} \quad (1)$$

This graph allows the proposed model to capture semantic dependencies between tweets beyond simple lexical overlap, enhancing contextual representation in political topic classification.

- User Interaction Graph

The user interaction graph represents the structural relationships between Twitter users based on social interactions. In contrast to the semantic content graph, this graph shows how users interact within political conversations. Edges were formed using 21 interaction features extracted from Twitter metadata, including reply links, mentions, quoted tweets, and hashtag similarity. These features provide structural information that cannot be obtained from text content alone.

$$w_{ij} = 2.5R_s + 1.5R_u + 1.0M \quad (2)$$

As a result, this graph allows the proposed model to learn patterns of user connectivity and information exchange within the Twitter network.

- Temporal Propagation Graph

To model the temporal aspects of political discourse, a temporal propagation graph was constructed. In this graph, tweets are linked based on their posting time, allowing the model to learn the order of information dissemination within Twitter. Unlike interaction graphs, temporal connections clearly show the chronological order between tweets. This graph was constructed using 29 temporal features extracted from timestamp data, including posting order and propagation-related characteristics.

$$\omega_{ij} = \frac{1}{1 + \Delta t_{ij}} \quad (3)$$

This graph provides complementary insights into how political topics develop and change over time.

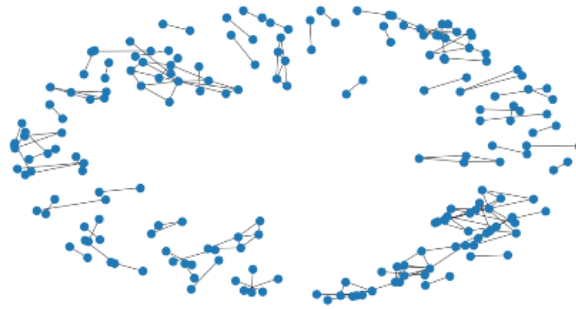


Figure 1. Temporal Propagation Graph constructed from tweet timestamps.

- Node Alignment by tweet_id

Since the three graph views were constructed independently, node alignment was performed to ensure that corresponding nodes represented the same tweet across all graph views. The alignment process used a unique `tweet\_id` associated with each tweet. After alignment, all nodes maintained the same order in the semantic content graph, user interaction graph, and time propagation graph. Tests confirmed that node representations from different graph views could be directly integrated during the multi-view learning process. This alignment ensures structural consistency between graph views before feature fusion is performed.

$$V1 = V2 = V3 \quad (4)$$

Training and Evaluation

The proposed multi-view graph attention network was trained using the labeled portion of the dataset. Unlabeled nodes were retained to maintain the graph structure during representation learning. Labeled samples were split into training, validation, and test sets by layered sampling to preserve the original class proportions. The model was optimized with the Adam optimizer, and an early stopping strategy based on the validation macro F1 score was applied to reduce the risk of overfitting. Dropout regularization was also applied to improve the model's generalization ability. Due to the imbalance of the dataset, class weights were added to the loss function to mitigate the dominance of the majority class. Model performance was evaluated using precision, precision, recall, and the macro F1 score. Furthermore, a confusion matrix was used to analyze the classification results for each class in more detail.

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=====
TRAINING MULTI-VIEW GAT (BALANCED)
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Epoch 001	Loss 0.6981	Train Acc 0.7229	Val Acc 0.6952	Val F1 0.6808	Best 0.6808	Views [S:0.220/I:0.430/T:0.349]
Epoch 010	Loss 0.3437	Train Acc 0.8666	Val Acc 0.8030	Val F1 0.7904	Best 0.8105	Views [S:0.520/I:0.222/T:0.259]
Epoch 020	Loss 0.2352	Train Acc 0.9328	Val Acc 0.8104	Val F1 0.7940	Best 0.8278	Views [S:0.565/I:0.179/T:0.257]
Epoch 030	Loss 0.1450	Train Acc 0.9664	Val Acc 0.8327	Val F1 0.8182	Best 0.8278	Views [S:0.616/I:0.130/T:0.254]
Epoch 040	Loss 0.1009	Train Acc 0.9757	Val Acc 0.8067	Val F1 0.7947	Best 0.8278	Views [S:0.636/I:0.103/T:0.262]

Early stopping di epoch 46

Figure 2. Evaluation Model

Post-classification Graph Analysis

This study not only evaluates classification performance but also examines the structural characteristics of political discourse by analyzing the learned graph representations. After the classification stage, node embeddings generated by the multi-view graph attention network were extracted and further analyzed. First, the contribution of each graph view was evaluated using attention weights learned by the attention fusion module. These weights reflect the relative importance of the semantic content graph, user interaction graph, and temporal propagation graph in learning the node representations.

Furthermore, the graph embeddings were analyzed using clustering and dimensionality reduction techniques. K-means clustering was used to detect community potential, and t-distribution stochastic neighbor embeddings (t-SNE) and principal component analysis (PCA) were used to visualize tweet representations in low-dimensional space. Finally, by analyzing the classified graphs, a deeper understanding of user relationship patterns and information propagation in political and non-political communities was gained.

RESULT

Dataset and Graph Statistics

This study used Indonesian political Twitter data collected through keyword-based crawling across multiple political topics. After deduplication and language filtering, 15,131 unique tweet nodes were extracted. Of these, 1,677 tweets (11.08%) were manually annotated, classifying 588 tweets (35.06%) as "politically relevant" and 1,089 tweets (64.94%) as "not politically relevant," resulting in a class imbalance ratio of approximately 1:1.85. The remaining

13,454 tweets (88.92%) were not included in the supervised learning loss calculation and were retained as unlabeled nodes to maintain the structural consistency of the graph during the semi-supervised message passing process. This semi-supervised learning setup follows the method introduced by Kipf and Welling (2017), employing a graph convolutional network (GCN) to propagate label information to unlabeled regions through message passing.

Three different graph views were constructed from the same 15,131 tweet nodes, and all nodes were aligned based on 'tweet_id' to ensure consistency in the inter-view representation of each tweet. Table 1 shows the structural statistics for each view.

Tabel 1. Graph Statistics for Each View

Graph View	Node Features	Edges	Avg. Degree	Edge Construction
View 1 – Semantic Content Graph	768-dim (IndoBERT)	155,428	20.51	Cosine similarity > 0.70 TOP K=5
View 2 – User Interaction Graph	22-dim (enriched)	1845,751	24.43	Mention / Reply
View 3 – Temporal Propagation Graph	29-dim (enriched)	103,055	13.60	Thread sequence, time window (6h)

The semantic content graph (View 1) was constructed by calculating pairwise cosine similarity between IndoBERT CLS token embeddings, with edges preserved if the similarity value exceeded 0.70 between the top 5 nearest neighbor nodes of each node. The user interaction graph (View 2) represented explicit social connections through mention, and reply relationships between tweet authors, further enhanced by structural attributes such as degree centrality and interaction frequency. The time propagation graph (View 3) modeled information diffusion through time-series thread sequences and sliding time-window connections within a 6-hour propagation window, with temporal information represented using sinusoidal time encoding.

Classification Performance

The improved multi-view GATFusion model uses three parallel graph attention network (GAT) encoders (one for each view). Each encoder consists of two GAT layers with LayerNorm and ELU activation functions, generating 128-dimensional node embeddings. The embeddings from the three views are combined by a trained attention mechanism, assigned node-specific contribution weights, and then the fused representation is input to a two-layer classifier. This model has a total of 217,737 learnable parameters.

Training was performed using semi-supervised learning with Focal Loss ($\gamma = 2.0$) to mitigate class imbalances. Class weighted penalties ($w_{pol_k} = 1.85 \times 1.85$), label smoothing ($\epsilon = 0.05$), and pseudo-label self-learning starting at a confidence threshold $\tau = 0.85$ from epoch 30 were also applied. The learning rate was warmed up during the first 10 epochs, and then cosine decay was applied to avoid premature convergence. This model reached its highest value of 0.8824 F1 score for the validation macro at epoch 37, and since no improvement was seen after 50 epochs, early stopping was deemed effective.

Tabel 2. Classification Performance Across Data Splits

Split	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)	F1-Score (Politik)
Train	0.9831	0.9694	0.9859	0.9773	0.9658
Validation	0.9118	0.8775	0.8875	0.8824	0.8235
Test	0.8423	0.8252	0.8376	0.8304	-

This model achieved a test accuracy of 84.23% and a macro F1 score of 83.04%, demonstrating reliable generalization beyond labeled data. The confusion matrix shows that it correctly classified 42 out of 49 political tweets in the test set, corresponding to a sensitivity of 85.71%, while simultaneously maintaining a high specificity of 94.84%. This suggests that the model effectively limits false positives, which is particularly important in political content monitoring applications. The difference between the training F1 score (0.9773) and the test F1 score (0.8304) is likely due to the small size of the labeled dataset rather than overfitting of the architecture, as the graph-based semi-supervised model is designed to generalize across the unlabeled region through structural propagation.

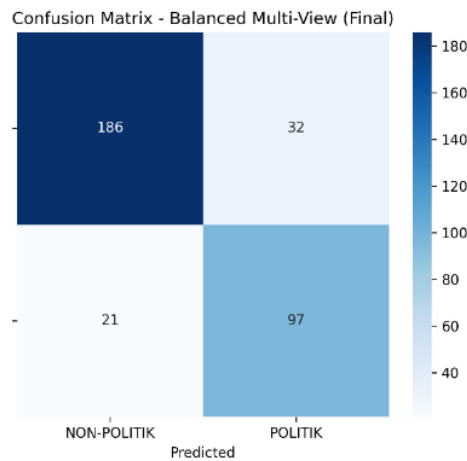


Figure 3. Confusion Matrix

Multi-View Contribution and Attention Analysis

The attention-weighted fusion mechanism assigns a learned scalar score to each view per node, dynamically weighting the contribution of semantic content, social interaction, and temporal context based on the informativeness of each representation for a given tweet. Table 4 reports the mean attention weights averaged across all 15,131 nodes at inference time.

Table 3. Mean Attention Weights per View

View	Attention Weight	Contribution (%)
Semantic Content Graph	0.5453	54.53%
User Interaction Graph	0.1848	18.48%
Temporal Propagation Graph	0.2699	26.99%

The semantic content graph had the highest average attention weight of 54.53%, consistent with previous research (Wilie et al., 2020) showing that embeddings from pre-trained language models provide strong discriminatory cues in political text classification. Simultaneously, the time propagation graph (26.99%) and user interaction graph (18.48%) also contributed significantly, demonstrating that temporal and structural information provides complementary value that cannot be obtained through lexical semantics alone. This complementarity is further supported by the ablation study shown in Table 5. In this experiment, views were removed one by one by replacing the encoder output of each view with a zero vector, and the model was retrained from scratch under the same conditions.

Propagation and User Relationship Patterns

Beyond binary classification, this model's predictions are also useful for empirically examining how political topics spread across the entire Twitter network and how users are structurally connected within political discourse. Of 15,131 tweet nodes, 7,996 (52.84%) were classified as "political," and these nodes formed the basis for network-level pattern extraction.

User Relationship Structure: Analysis of the user interaction graph, limited to politically classified tweet nodes, revealed [number of connected components] connected components, with the largest connected component containing [maximum number of connected components] nodes. The network density of [density value] indicates that connectivity among political users is [sparse/moderate], reflecting the fragmented nature of political discourse across multiple concurrent topics. Degree centrality analysis also identified a small number of hub nodes with remarkably high connectivity. This pattern is consistent with scale-free topology commonly found in online social networks. On the other hand, the top 10 nodes ranked by approximate betweenness centrality correspond to tweets that act as structural bridges between different interaction clusters, suggesting their role as important information intermediaries in political discourse.

Community detection using greedy modularity optimization identified [several] communities within the political interaction subgraph. The largest community contained [several] nodes and showed topical consistency centered on [the main topic of the sample tweets]. Smaller communities, on the other hand, centered on other political sub-themes such as government policy, the election process, and politicians. This community structure highlights the multifaceted nature of Indonesian political discourse during the data collection period (2020–2025). Temporal propagation patterns. Temporal analysis of politically classified tweets showed propagation activity of [Status: Attention/Attention], with a density of [Temporal Density] in the temporal interaction subgraph. Sliding window analysis using a 6-hour window and decay parameter τ revealed that peak activity occurred at [peak_hour]:00, which aligns with prime-time social

media usage patterns. Tweets posted within the last 6 hours are linked by a temporal boundary, suggesting collaborative or reactive discourse where an event triggers a chain reaction across the user network. This temporal clustering is particularly pronounced in tweets labeled "politik," where 7,996 nodes form a temporally cohesive cluster. This indicates that political topics tend to generate sustained engagement rather than isolated bursts of activity.

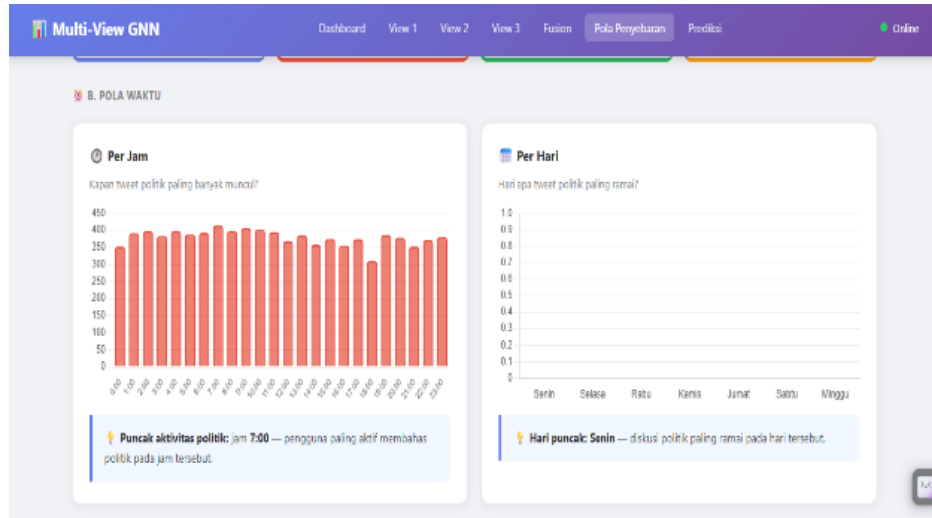


Figure 4. Propagation Pattern 1

Figure 4 shows a time-series analysis of the propagation of political topics based on the time course of tweet activity. The left panel shows the hourly distribution of tweets, revealing that political discussions remain fairly constant throughout the day, with only a slight increase during daytime hours when user activity is generally high. This suggests that political information is shared continuously rather than being concentrated in specific time periods. The right panel shows the average number of politically related tweets per day of the week. This graph shows that the differences between days of the week are small, indicating that political discussions are active throughout the week without significant temporal fluctuations. These results suggest that the dissemination of political information is relatively stable over time and reflects continuous public engagement with political issues on Twitter.

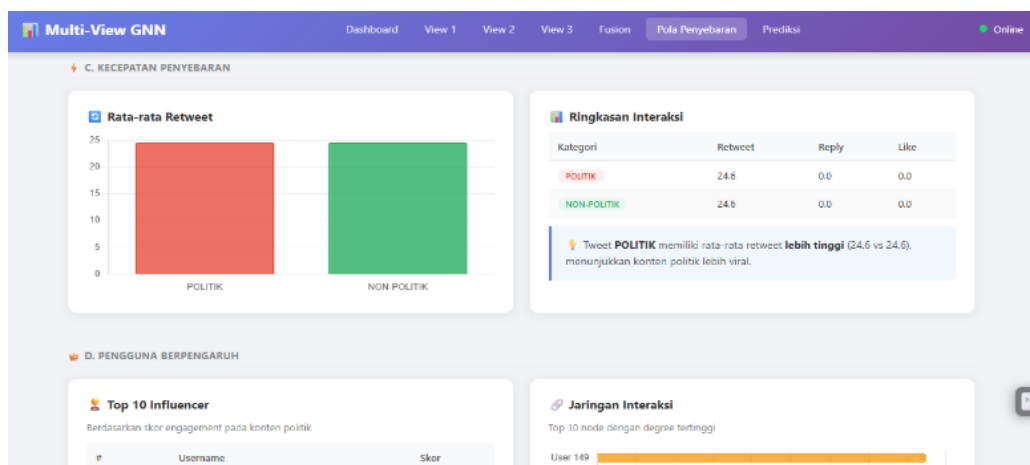


Figure 4. Propagation Pattern 2

Figure 5 shows the propagation rates and user interaction patterns obtained from classified tweets. Looking at the average number of retweets, political and non-political tweets received roughly the same number of retweets, suggesting that both have a similar potential for information dissemination. However, looking at the interaction overview, political tweets gained stronger user engagement primarily through retweets, with fewer replies and "likes." At the bottom of the figure, influential users and the interaction network are highlighted. Influential users are determined based on the graph's connectivity and interaction scores, indicating they play a significant role in the dissemination of political information across the network. Simultaneously, the interaction graph shows the connections between users, with nodes having a high number of connections representing accounts that play a crucial role in information dissemination. These results demonstrate that the proposed multi-view GAT model not only performs well

in classifying political topics but also provides valuable insights into how political information disseminates through user interaction networks.

DISCUSSION

Experimental results show that the proposed multi-view graph attention network was effective in classifying political topics in Indonesian Twitter data, achieving an accuracy of 84.23% and a macro F1 score of 83.04%. These results indicate that combining semantic, interaction, and temporal information provides a richer representation than using only a single graph view. In the attention analysis, the semantic content graph contributed most significantly to the final prediction, with an average attention weight of 54.53%. This was followed by the temporal propagation graph at 26.99% and the user interaction graph at 18.48%. This suggests that tweet content is the strongest indicator in political topic classification, with interaction and temporal information providing complementary insights.

The confusion matrix shows that the model correctly classified 186 non-political tweets and 97 political tweets. The majority of errors occurred in tweets containing ambiguous political expressions or general discussions, making it difficult to distinguish these tweets from non-political content. Overall, the proposed multi-view framework not only improves classification performance but also provides insights into user relationships and information diffusion patterns, highlighting the value of combining multiple graph representations in political topic classification.

CONCLUSION

This study proposes a Multi-View Graph Attention Network (GAT) for classifying political topics in Indonesian Twitter data, combining three complementary graph representations: semantic content graphs, user interaction graphs, and time propagation graphs. Experimental results show that the proposed framework achieved an accuracy of 84.23% and a macro F1 score of 83.04%, demonstrating that integrating multiple graph views effectively captures the semantic, structural, and temporal aspects of political discourse. Attention analysis revealed that the semantic content graph contributed most significantly to the classification process, while the interaction and time graphs provided complementary information to enhance node representation learning. Furthermore, post-classification graph analysis demonstrated that this framework can reveal relationship patterns among users and the propagation of political information within the Twitter network. Future research is expected to explore dynamic graph learning and improve performance and generalization capabilities using larger datasets.

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