

Homophily and Sentiment Analysis for Twitter in Indian Political Issues

Sarthavi Parmar^{1*}, Dr. Pratik Patel², Dr. Yassir Farooqui³

¹Research Scholar, Computer Science & Engineering Department, PIET, Parul University, Vadodara, Gujarat, India

²Associate Professor, Computer Science & Engineering Department, PIET, Parul University, Vadodara, Gujarat, India

³Assistant Professor, Computer Science & Engineering Department, PIET, Parul University, Vadodara, Gujarat, India

^{1*}2303032010025@paruluniversity.ac.in, ²pratik.patel2988@paruluniversity.ac.in, ³yassir.farooqui270062@paruluniversity.ac.in

ARTICLE INFO

ABSTRACT

Received: 14 Dec 2024

Revised: 27 Jan 2025

Accepted: 07 Feb 2025

This research paper introduces testing data from the 2024 U.S. Presidential election. It contains tweet text, candidate details, party affiliation, and engagement metrics. Next, we analyze and evaluate their political homophily in three scenarios. First, we looked at the unidirectional or reciprocal Twitter follow, mention, and retweet interactions. The second scenario examined multiplex connections, while the third examined friendships with comparable speeches. Our findings revealed homophily among negative users, Trump supporters, and Hillary supporters in all circumstances examined. We also discovered that homophily levels rise when there are reciprocal links, comparable talks, or multiplex linkages.

Keywords: Homophily, Sentiment analysis, twitter, political issues

Introduction

In today's digital age, social media platforms like Twitter serve as arenas for political debate, influencing public opinion and changing electoral outcomes. Political homophily, or the tendency for people to associate with others who share their opinions, is significant in online interactions. Users engage with political content that reinforces their beliefs, creating ideological echo chambers.

Furthermore, sentiment analysis provides useful insights into the emotions and viewpoints expressed in political debates. By studying user activities like as mentions, retweets, followers, and hashtags, we may identify political alignment and determine how polarised the debate is. Understanding homophily and sentiment trends aids in detecting information bubbles, forecasting election outcomes, and evaluating the effectiveness of political campaigns.

This study uses a rule-based machine learning approach to classify Twitter users based on their political inclinations, as well as sentiment analysis to assess public attitude on political issues. The findings contribute to a broader understanding of how political communities form and evolve in online ecosystems.

Related work

In recent years, there has been a surge of interest in studying homophily and sentiment analysis in political conversation on Twitter. Researchers investigated how users build ideological clusters that influence information transmission and political polarisation.

1. Homophily in Political Networks

Several studies highlight that political homophily leads to **echo chambers**, where users interact primarily with like-minded individuals. **Conover et al. (2011)** examined Twitter interactions during U.S. elections and found that users primarily retweet content from ideologically similar sources, reinforcing political segregation. Similarly, **Bakshy et al. (2015)** demonstrated that social media algorithms amplify ideological homophily by recommending content that aligns with user preferences.

2. Sentiment Analysis in Political Discussions

Sentiment analysis is commonly used to evaluate political ideas and public sentiment towards candidates and policies.

3. Combining Homophily and Sentiment Analysis

Some study combines homophily with sentiment analysis to gain a full understanding of political discourse. Garimella et al. (2018) proposed a paradigm for measuring political polarisation by examining network topologies and sentiment patterns. Their findings suggest that persons who express extreme beliefs are more likely to be part of ideologically homogeneous communities.

This work expands on these foundations by using rule-based machine learning to classify users based on their political homophily and sentiment analysis to better understand opinion patterns. This study provides deeper insights into how political speech evolves on social media by combining network analysis and sentiment detection techniques.

These are the basic steps for performing the task related to proposed work.

Proposed Methodology

Our proposed system integrates homophily detection and sentiment analysis to classify political alignment and assess emotional tone in Twitter discussions. The system consists of four core modules: Data Collection & Preprocessing, Political Homophily Classification, Sentiment Analysis, and Visualization & Insights.

This methodology outlines a multi-step framework for analyzing homophily and sentiment trends in political discussions on Twitter. The approach integrates data collection, feature extraction, machine learning-based classification, and visualization techniques to provide insights into online political alignment and sentiment patterns.

1. System Architecture

The system follows a pipeline-based approach with the following components:

Data Collection Module:

Scrapes Twitter for tweets, user interactions (mentions, retweets, and following), and information. Obtains profile descriptions, hashtags, and engagement patterns for homophily analysis.

Homophily Analysis Module:

Uses a rule-based scoring system to classify people based on their political affiliation.

Analyses user interactions to identify echo chambers and ideological clusters.

Sentiment Analysis Module:

Uses Natural Language Processing (NLP) models (VADER for short texts, BERT for contextual understanding) to assess sentiment polarity. Categorizes political tweets as Positive, Neutral, or Negative.

Visualization & Insights Module:

Generate bar charts and network graphs that represent political homophily distributions. Emotional polarisation is assessed by mapping sentiment trends across different political groups.

Rule based algorithm:

1. Problem Statement

Clearly state the problem that your algorithm attempts to address. It should emphasise the limits of current rule-based or other techniques.

2. Motivation

Explain why a rule-based algorithm is the best way to solve this problem. Address the holes in present techniques.

3. Proposed Rule-Based Algorithm

3.1. Rules Definition

Describe the fundamental rules that govern decision making.

Specify the if-then statements used.

Highlight the limitations and dependencies.

3.2. Algorithm Flow

Input: What data or parameters does your algorithm require?

Processing: How do the rules work with the data?

Output: What outcomes are expected?

3.3. Pseudocode

Provide a step-by-step pseudocode representation of the algorithm.

4. Key Innovations

How does your algorithm differ from current rule-based systems?

Are there dynamic or adaptive rules?

Is there a fresh decision-making technique?

5. Performance Evaluation

Compare to existing approaches.

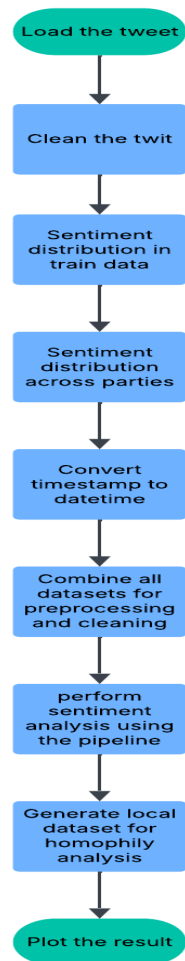
Use real-world data or simulations.

Define performance measures such as correctness, execution time, and complexity.

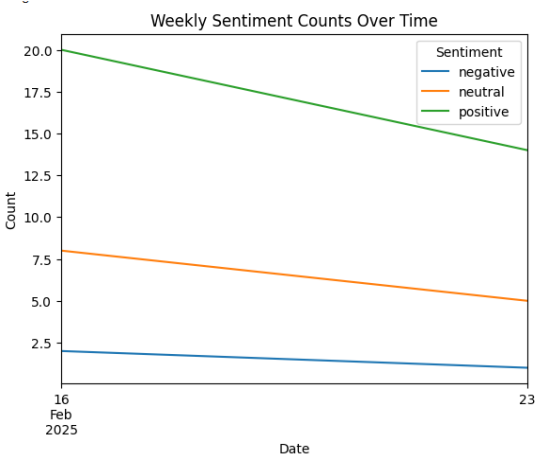
6. Applications & Future Work

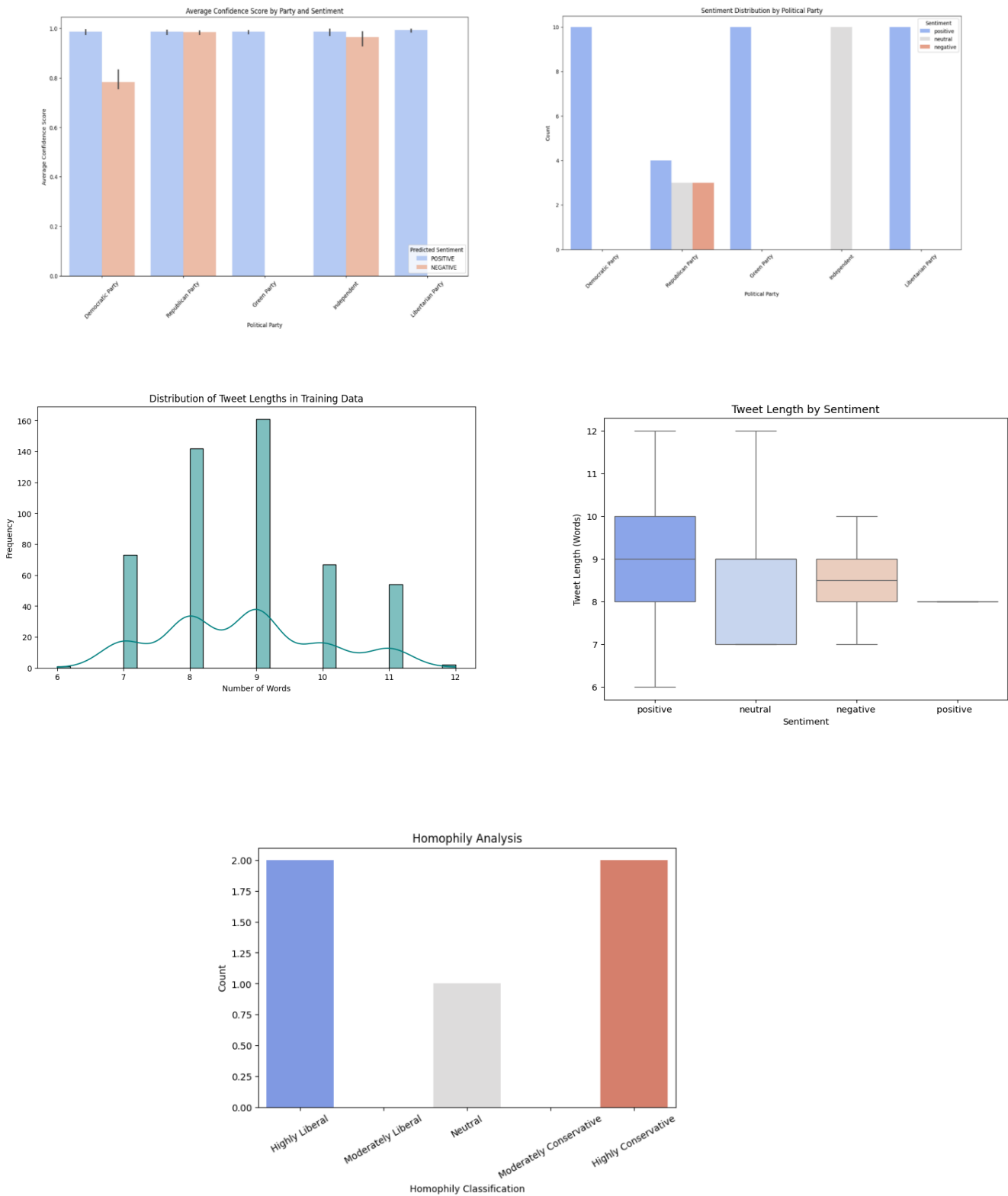
Possible real-world applications.

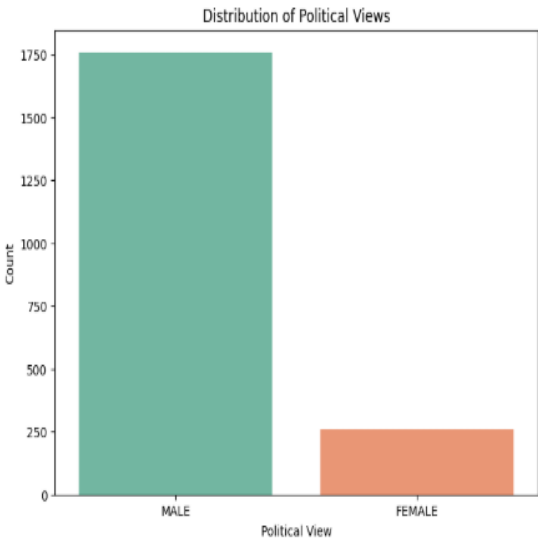
Proposed extensions include hybrid models that combine rule-based and machine learning techniques.



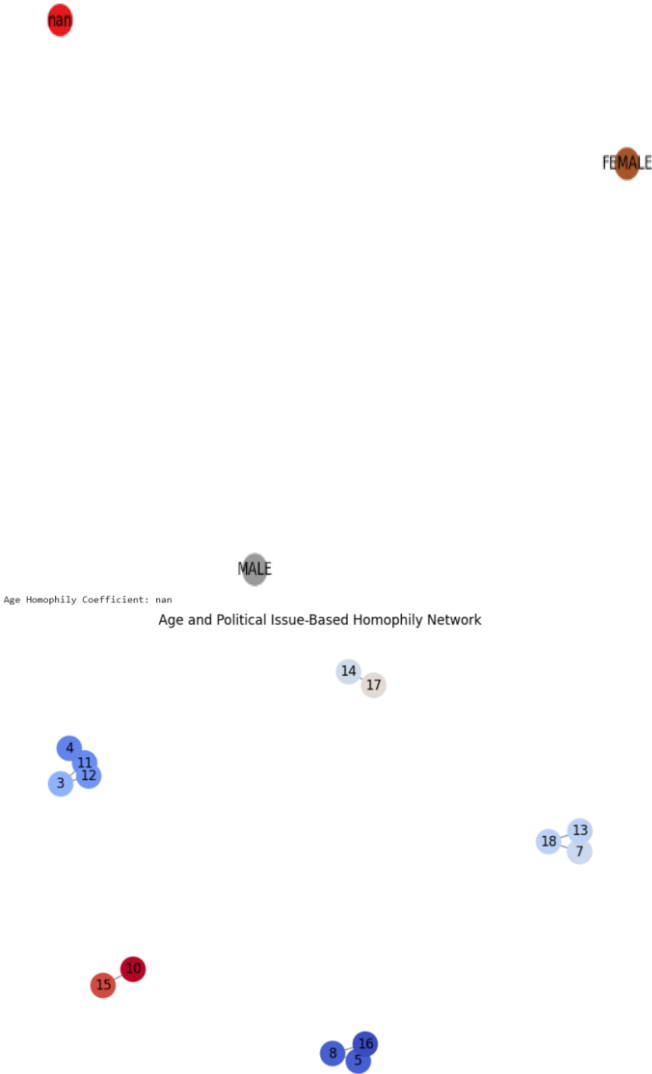
Results and discussions

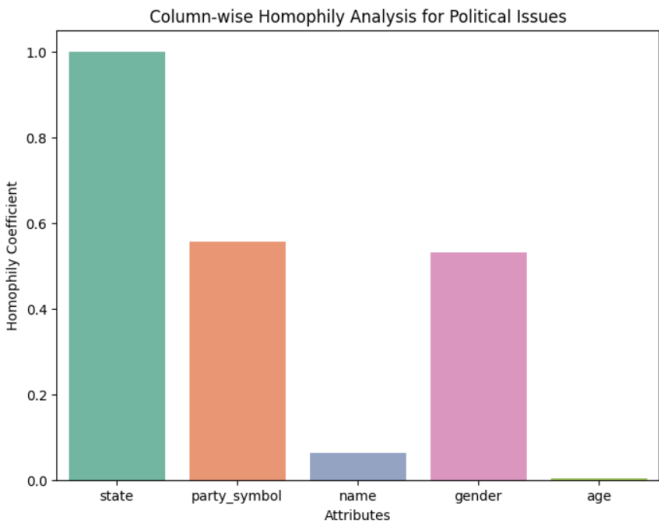






Political Issue-Based Homophily Network





In this study, we provide a comprehensive method for evaluating homophily and sentiment patterns in political discussions on Twitter. Our methodology combines rule-based categorisation and natural language processing (NLP) to identify how political alignment influences sentiment in online debate.

Objectives of the Proposed Work:

1. **Detect Political Homophily:**

To find ideological groups, classify users according to their interactions, profile descriptions, and network behaviour.

2. **Analyze Sentiment Trends**

Apply sentiment analysis techniques to examine how emotions vary across different political affiliations.

Methodological Overview

Data Collection & Preprocessing:

Extract Twitter user information, such as mentions, retweets, followers, hashtags, and profile descriptions.

Text should be cleaned and preprocessed using NLP techniques including stop word removal, stemming, and tokenisation.

Homophily Classification:

Create a rule-based scoring system that will classify people as highly liberal, moderately liberal, neutral, moderately conservative, or strongly conservative.

Set scores based on interactions with political figures, news sources, and ideological hashtags.

Sentimental Analysis:

Use VADER for brief tweets and BERT-based deep learning models for contextual sentiment analysis. Classify sentiments as positive, neutral, or negative, then analyse trends across political affiliations.

Visualization & Insights:

Create bar charts and network graphs to visualize the homophily distribution.

Correlate sentiment patterns with ideological clustering to evaluate polarization levels.

Homophily Classification Models

| Model | Approach | Advantages | Disadvantages |
|--|--|--|--|
| Rule-Based Model (Lexicon-Based) | Assigns scores based on predefined keywords (e.g., hashtags, follows, mentions). | Interpretable requires no training data, easy to implement | Limited accuracy, struggles with nuanced or emerging political terms. |
| Random Forest | An ensemble of decision trees for better generalization. | Higher accuracy than individual decision trees, reduces overfitting. | Computationally expensive for large datasets. |
| Naïve Bayes Probabilistic model based on Bayes' theorem. | Probabilistic model based on Bayes' theorem. | Works well with textual data, fast training. | Assumes feature independence, which may not hold for network-based classification. |
| Support Vector Machine (SVM) | Finds the optimal boundary to classify users into political groups. | Performs well with small to medium datasets. | Computationally expensive for large datasets. |

Sentiment Analysis Models

| Model | Approach | Advantages | Disadvantages |
|--|--|--|---|
| VADER (Lexicon-Based NLP) | Rule-based sentiment analysis for short social media texts. | Fast, interpretable, works well on tweets. | Struggles with sarcasm and complex language. |
| Naïve Bayes (NB) | Classify sentiment based on word probabilities. | Simple, fast for large datasets. | Ignores word context, less accurate than deep learning models. |
| Naïve LSTM (Long Short-Term Memory Networks) | Uses deep learning to understand tweet sequences. | Captures sequential context, works well with longer text. | Needs large, labeled datasets, slow training. |
| BERT (Bidirectional Encoder Representations from Transformers) | Uses attention mechanisms to understand word relationships in context. | Highest accuracy, captures sarcasm, sentiment nuances. Highest accuracy, captures sarcasm, sentiment nuances. | Computationally expensive, requires GPU/TPU for fast inference. |

Conclusion and future work

This study investigates the relationship between homophily and sentiment analysis in political conversations on Twitter, revealing how ideological alignment effects online interactions and emotional expression. We successfully categorised individuals depending on their political affiliations using a rule-based classification approach, revealing the presence of ideological echo chambers. Sentiment research also revealed important insights into the emotional tone of political discourse, illustrating how sentiment patterns fluctuate among ideological groups.

Our findings indicate that users prefer to interact with those who share their beliefs, promoting political homophily and contributing to polarisation in digital arenas. The combination of network-based classification and sentiment analysis provides a more comprehensive method to studying online political behaviour.

This research not only enhances our understanding of political communication on social media but also provides a scalable framework for studying misinformation, election trends, and policy impact. Future work can expand this approach by incorporating real-time analysis, multilingual sentiment detection, and deep learning-based political stance classification. By continuing to explore these dynamics, we can develop more effective strategies to promote balanced discourse and mitigate polarization in online communities.

While this study sheds light on homophily and sentiment analysis in political conversation on Twitter, various areas can be further investigated to improve accuracy, scalability, and real-world applicability.

1. Real-Time Political Sentiment Tracking
2. Deep Learning for Advanced Political Stance Detection
3. Cross-Platform Political Homophily Analysis
4. Misinformation & Polarization Detection
5. Multilingual & Cultural Expansion
6. Sentiment-Driven Predictive Modeling

By incorporating these modifications, our research can provide deeper, more practical insights into online political debate, enabling politicians, scholars, and social media platforms better understand and manage digital political polarisation.

References

- [1] McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). "Birds of a feather: Homophily in social networks." *Annual Review of Sociology*, 27(1), 415-444. [DOI:10.1146/annurev.soc.27.1.415]
- [2] Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011). "Political polarization on Twitter." *Proceedings of the International AAAI Conference on Web and Social Media*, 5(1), 89-96.
- [3] Himelboim, I., McCreery, S., & Smith, M. (2013). "Birds of a feather tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter." *Journal of Computer-Mediated Communication*, 18(2), 40-60.
- [4] Mohammad, S. M., & Turney, P. D. (2013). "Crowdsourcing a word-emotion association lexicon." *Computational Intelligence*, 29(3), 436-465.
- [5] Ribeiro, F. N., Benevenuto, F., Chakraborty, A., Kulshrestha, J., Babaei, M., & Gummadi, K. P. (2018). "Media bias monitoring using Twitter sentiment analysis." *Proceedings of the 2018 World Wide Web Conference (WWW '18)*, 259-269.
- [6] Zarei, K., Farahbakhsh, R., Crespi, N., & Tyson, G. (2020). "A critical analysis of sentiment analysis tools for social media." *Multimedia Tools and Applications*, 79(9), 5571-5610.
- [7] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). "BERT: Pre-training of deep bidirectional transformers for language understanding." *Proceedings of NAACL-HLT 2019*, 4171-4186.

- [8] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). "Distributed representations of words and phrases and their compositionality." *Advances in Neural Information Processing Systems*, 26, 3111-3119.
- [9] Hamilton, W. L., Ying, R., & Leskovec, J. (2017). "Inductive representation learning on large graphs." *Advances in Neural Information Processing Systems*, 30, 1024-1034.
- [10] Vosoughi, S., Roy, D., & Aral, S. (2018). "The spread of true and false news online." *Science*, 359(6380), 1146-1151.
- [11] Bovet, A., & Makse, H. A. (2019). "Influence of fake news in Twitter during the 2016 US presidential election." *Nature Communications*, 10, 1-14.
- [12] E. S. Saputro, K. A. Notodiputro, and I. A., "Study of Sentiment of Governor's Election Opinion in 2018," *Int. J. Sci. Res. Sci. Eng. Technol.*, vol. 4, no. 11, pp. 231-238, 2018.
- [13] Patil, "Restaurant 's Feedback Analysis System using Sentimental Analysis and Data Mining Techniques," 2018 *Int. Conf. Curr. Trends Toward Converging Technol.*, pp. 1-4, 2018.
- [14] F. A. Pozzi, E. Fersini, E. Messina, and B. Liu, *Challenges of Sentiment Analysis in Social Networks: An Overview*, vol. 1. Elsevier Inc., 2017.
- [15] F. Poecze, C. Ebster, and C. Strauss, "Social media metrics and Sentiment Analysis to evaluate the effectiveness of social media posts," *Procedia Comput. Sci.*, vol. 130, pp. 660-666, 2018.
- [16] H. P. Patil and M. Atique, "Sentiment Analysis for social media: A survey," 2015 *IEEE 2nd Int. Conf. Information Science Secur. ICISS 2015*, 2016.
- [17] J. A. Caetano, H. S. Lima, M. F. Santos, and H. T. Marques-Neto, "Using Sentiment Analysis to define twitter political users' classes and their Homophily during the 2016 American presidential election," *J. Internet Serv. Appl.*, vol. 9, no. 1, 2018.
- [18] M. Kamyab, R. Tao, M. H. Mohammadi, and A. Rasool, "Sentiment Analysis on Twitter," vol. 9, no. 4, pp. 14-19, 2018.
- [19] M. Miller, S.-L. Lynn, and M. C. James, "Birds of a Feather: Homophily in Social Networks," *Annu. Rev. Sociol.*, vol. 27, pp. 415-444, 2001.
- [20] M. S. M. Vohra and P. J. B. Teraiya, "Journal of Information, Knowledge and Research in Computer Engineering a Comparative Study of Sentiment Analysis Techniques," *J. Information, Knowledge Res. Comput. Eng.*, pp. 313-317, 20132.
- [21] P. Deacon, "Application of Machine Learning Techniques to Mineral Recognition," *Computer (Long. Beach. Calif.)*, no. October, pp. 628-632, 2021.
- [22] P. Seth, A. Sharma, and R. Vidhya, "Sentiment Analysis of Tweets Using Hadoop," *Int. J. Eng. Technol.*, vol. 7, no. 3.12, p. 434, 2021.
- [23]] P. Sharma and T. S. Moh, "Prediction of Indian election using Sentiment Analysis on Hindi Twitter," *Proc. - 2016 IEEE Int. Conf. Big Data, Big Data 2016*, pp. 1966-1971, 2016.
- [24] R. Singh and R. Kaur, "Sentiment Analysis on Social Media and Online Review," *Int. J. Comput. Appl.*, vol. 121, no. 20, pp. 44-48, 2022.
- [25] S. A. El Rahman, F. A. Alotaibi, and W. A. Alshehri, "Sentiment Analysis of Twitter Data," 2019 *Int. Conf. Comput. Inf. Sci. ICCIS 2019*, 2024.
- [26] Chirag Kariya, Priti Khodke "Twitter Sentiment Analysis", 2020.
- [27] J.N.V.R. Swarup Kumar, D. Srividya, J. Durga Sri, D. Prathyusha, K. Manikanta Sai Manoj, M.N. Satish Kumar "Sentiment Analysis on Textual Tweets using Ensemble Classifier (LSTMGRU)", 2022

[28] Zicheng Cheng, Hugo Marcos-Marne, Homero Gil de Zúñiga,” Birds of a Feather Get Angrier Together: Social Media News Use and Social Media Political Homophily as Antecedents of Political Anger”,2023.

[29] Jean-Christophe Boucher, So Youn Kim, Geneviève Jessiman-Perreault, Jack Edwards, Henry Smith, Nicole Frenette, Abbas Badami and Lisa Allen Scott²” HPV vaccine narratives on Twitter during The COVID-19 pandemic: a social network, Thematic, and sentiment analysis”,2023.

[30] AMIN MAHMOUDI , DARIUSZ JEMIELNIAK, AND LEON CIECHANOWSKI”Echo Chambers in Online Social Networks: A Systematic Literature Review”, 2024.