Ph.D Defence Viva

on

Effective Techniques and Datasets for Detecting Political Polarization in Indian Elections on Online Social Networks

Presented by
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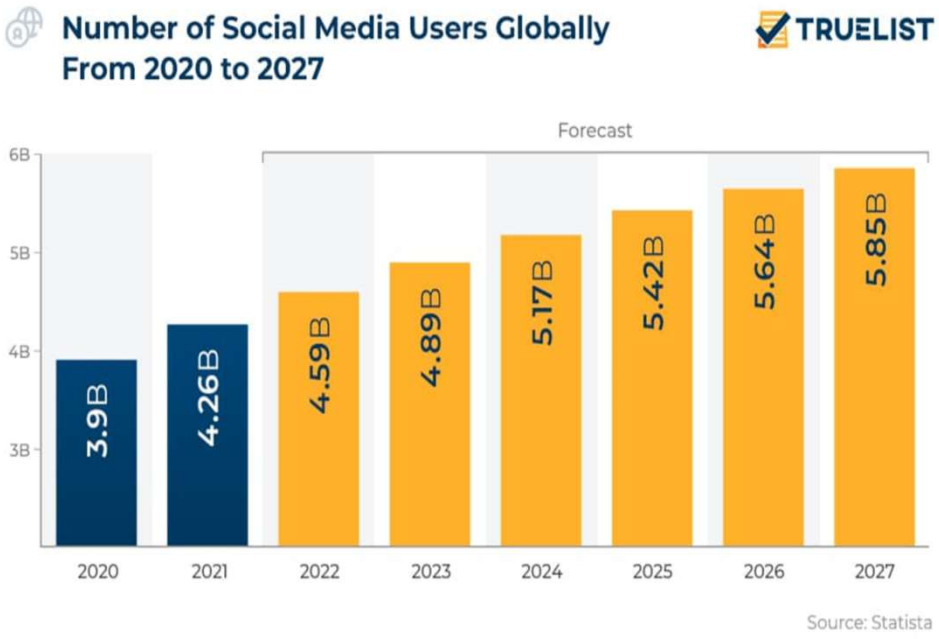
Overview…

- ❑ Introduction
- ❑ Literature Review
- ❑ Research Gap
- ❑ Research Questions
- ❑ Research Contributions
- ❑ Proposed Solution
- ❑ Conclusion

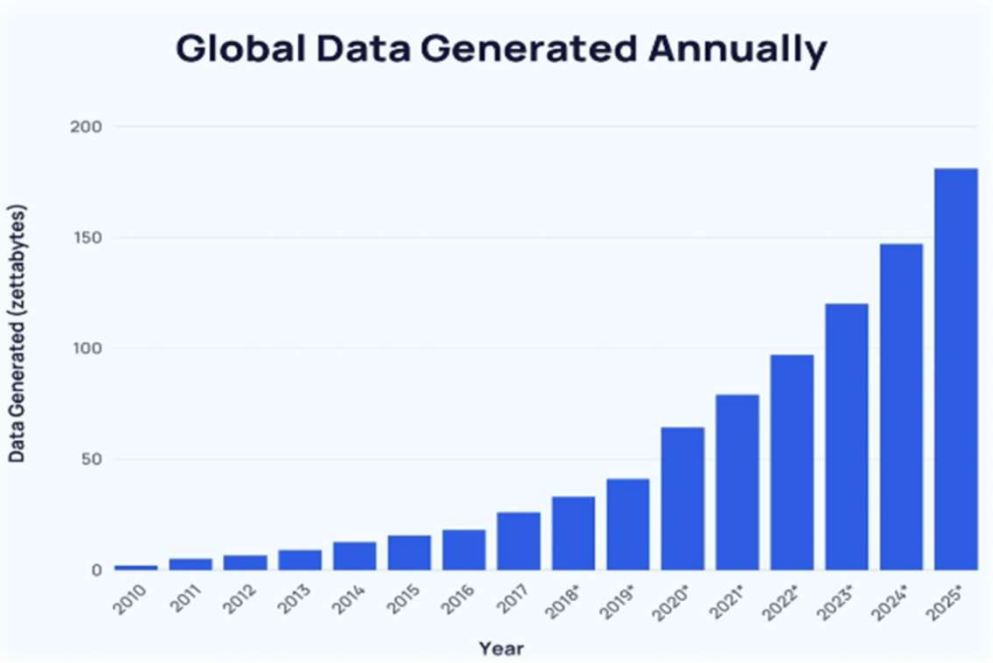
Introduction → Social Networks

- Express opinions, emotions, and stances
- News updates
- **Political discussion**

Introduction → Social Networks

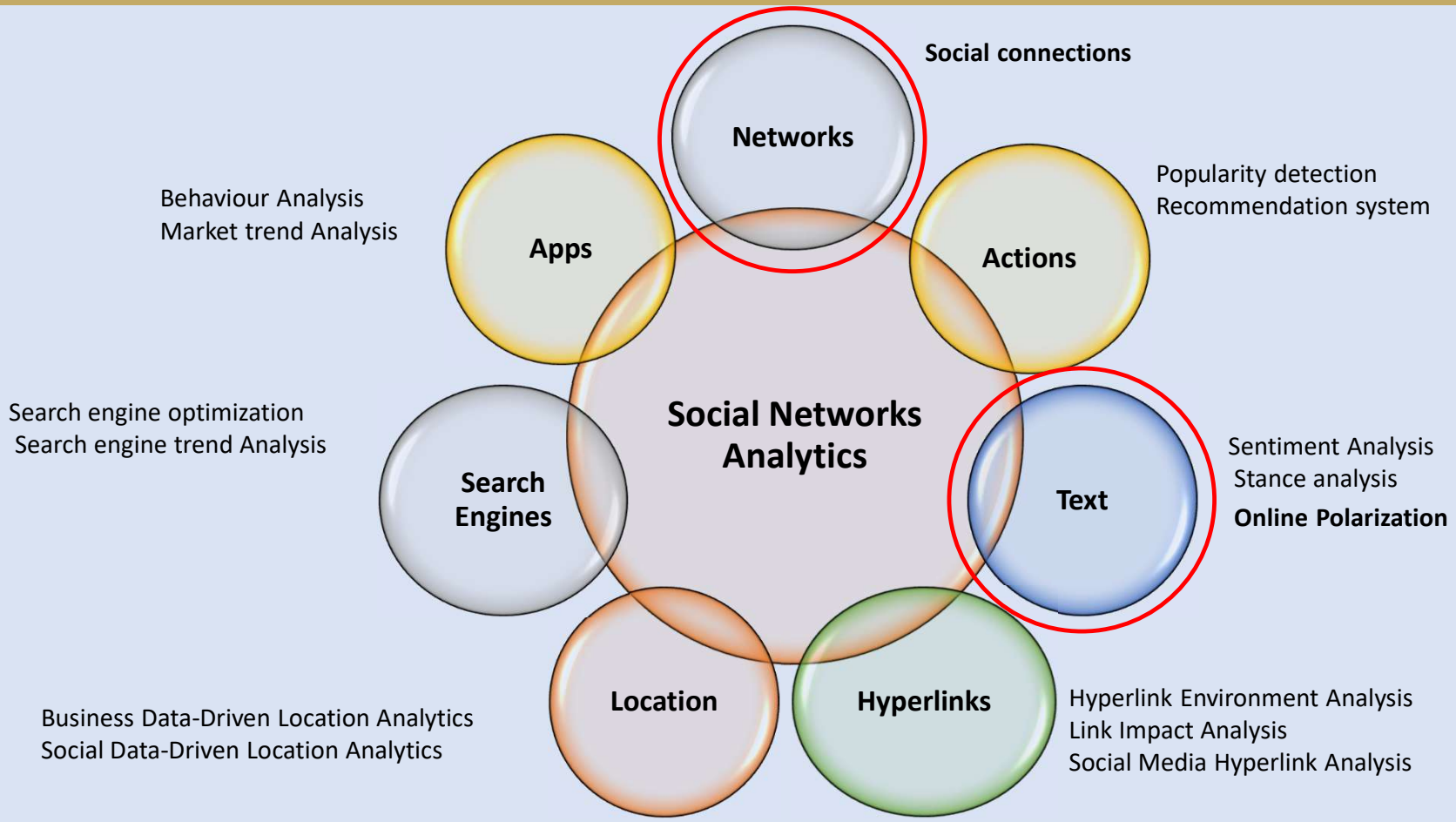


Source: https://truelist.co/blog/social-media-marketing-statistics/



Source: https://explodingtopics.com/blog/data-generated-per-day

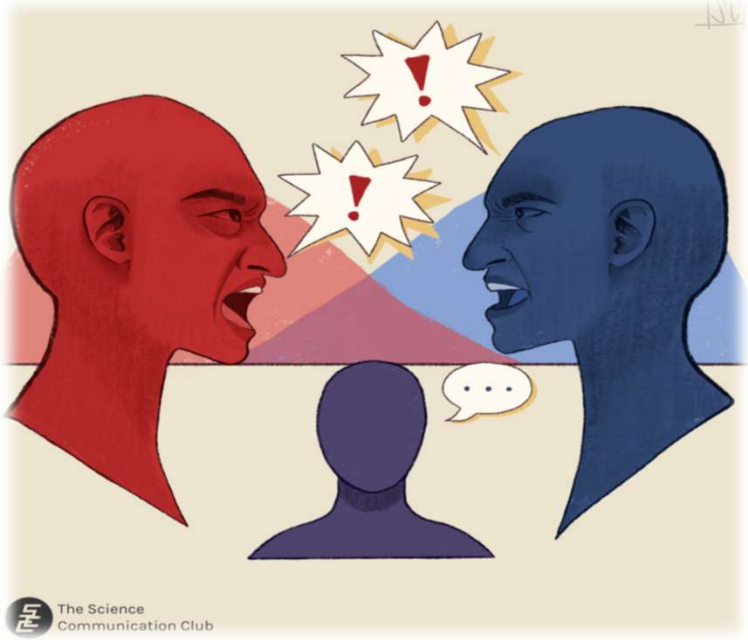
Introduction → Open Research Problems



Source: "Khan, G. F. (2015). Seven Layers of Social Media Analytics: Mining Business Insights from Social Media Text, Actions, Networks, Hyperlinks, Apps, Search Engines, and Location Data. Gohar Feroz Khan."

Introduction → Online Polarization

"Polarization is the social process whereby a social group is divided into two opposing sub-groups having conflicting, contrasting positions, goals, and viewpoints, with few individuals remaining neutral or holding an intermediate position (Sunstein, 1999)".



Introduction → Online Polarization

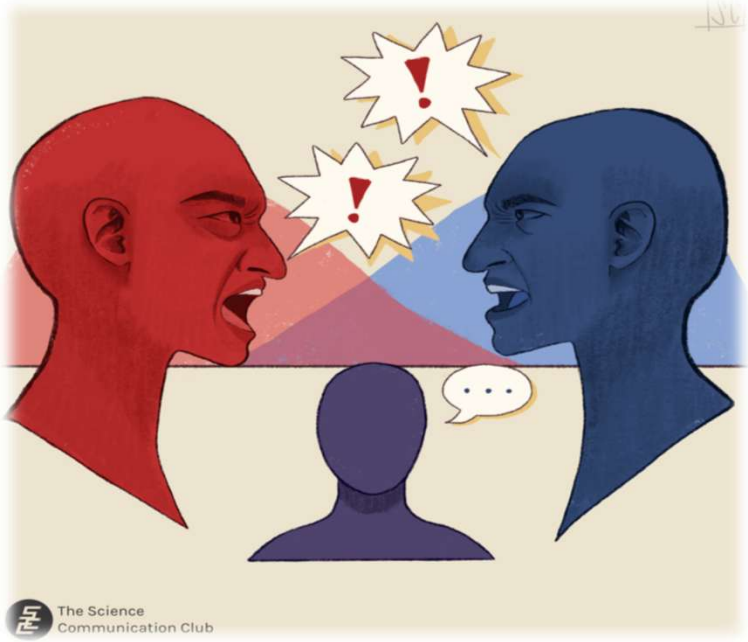
Most popular polarized topics on social networks are:

- Gun Control
- Covid 19 vaccine
- Abortion
- AI replace Jobs
- Election

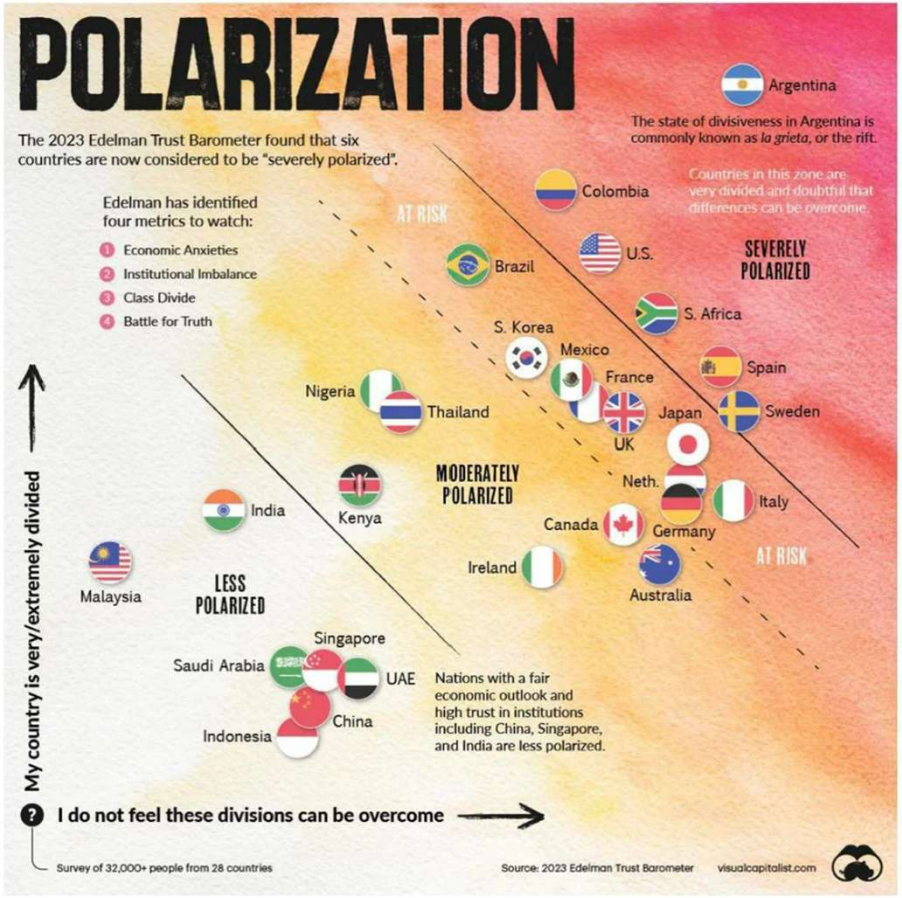
Introduction → Political Polarization

Political Polarization- "the divergence of political attitudes to ideological extremes" **[McCoy, J., & Somer, M (2022)]**

Oxford Dictionary - "Division into two sharply contrasting groups or set of opinions or beliefs"



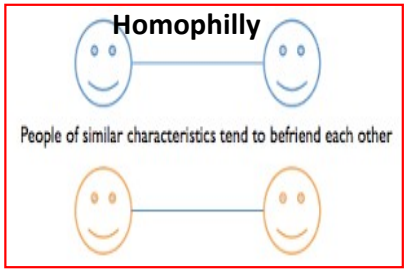
Introduction → Motivation

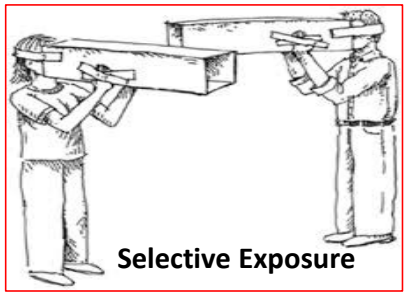


Source: https://licensing.visualcapitalist.com/product/visualized-polarization-across-28-countries/

Introduction → Political Polarization Process

User Behaviour





Leads to

Leads to

Filter Bubble

Echo Chamber

forms

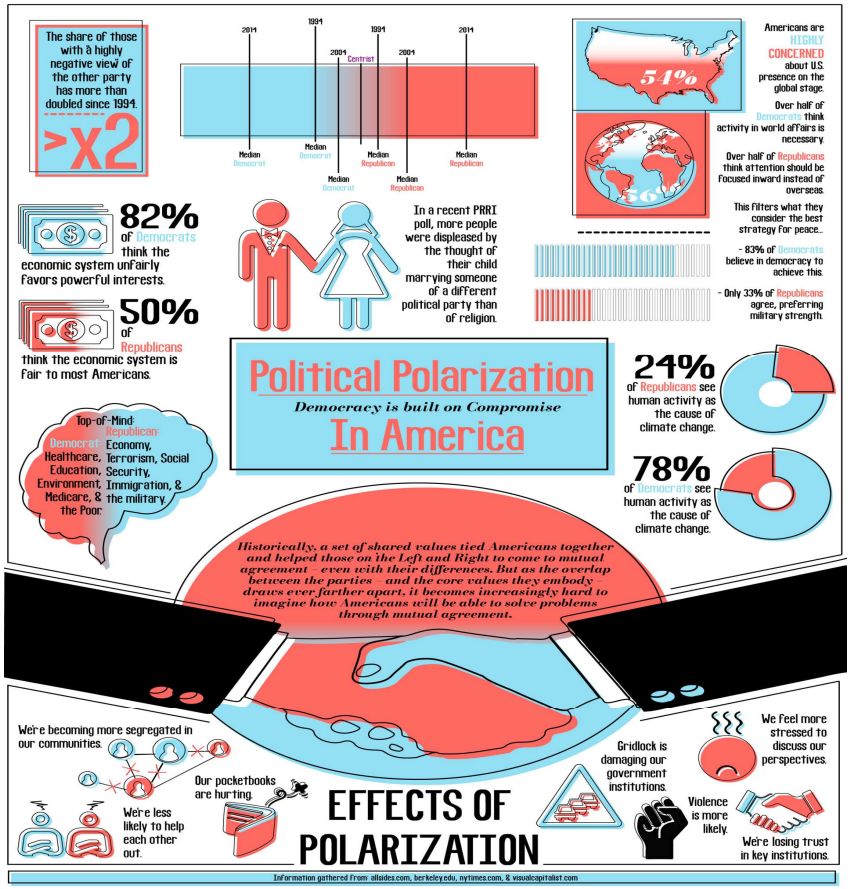
Political Polarization

Introduction → Impact of Political Polarization

- ❑ Isolated user from each other
- ❑ Threat to democracy
- ❑ Impact country economics
- ❑ Challenges for policymaker and government

Measures of Political Polarization

- ❑ User Opinion
- ❑ User Stance



Introduction → Measures of Polarization → User Opinion

User opinion refers to an individual's personal viewpoint, sentiment, or attitude.

Tweet example 1: Election are essential in a democracy and should be conducted wisely to benefits everyone. Every citizen should perform their right to vote.

Target : Election

Label : Opinionated tweet

Tweet example 2: #LokSabhaElection election date will announce next month.

Target : Election

Label : Neutral tweet

Introduction → Measures of Polarization → User Stance

User stance refers to an individual's position or attitude i.e. support, against or neutral towards a political group or ideologies.

Tweet example 1: Govt leads by XGovt most corrupt govt India ever.

Target : XGovt

Label : Against

Tweet example 2: Govt leads by XGovt have best foreign minister India ever had.

Target : XGovt

Label : Favor

Tweet example 3: We should think about leader not party. Leader matters party doesn't matter that's my political believe.

Target : Political party

Label : Neutral

Literature Review → Political Polarization

Table 1: Summary of literature survey with opinion measure

Authors	Matric	Features	Dataset	Summary
Martino et al. [2025]	Opinion	Content	YouTube, **US election dataset 2020**	• Analyze the **different opinion of users** • Impact of polarization on decision making
Pecile et al. [2024]	Opinion	Content	Facebook Post	• Show the selective exposure of user activity • Framework show the formation echo chamber
Bor et al. [2023]	Opinion	Content	Indian election user sentiment tweets dataset	• Degree of polarization in **current political narratives on key policy issues**. • Applying sentiment analysis to Twitter data and developing quantitative analysis for six political groupings
Belastro et al. [2019]	Opinion	Content	**2018 Italian general election political Tweets**	• Discovering the **behavior of social media users** during election campaigns. • Analyzes the posts published by social media users through an automatic incremental procedure based on feed-forward neural networks
Borah et al. [2022]	Opinion	Content Network	2019 Indian Election tweets	• discussions among Indian politicians. • Show communication ties in and between parties and the extent of divergence of opinions during political discourse

Literature Review → Political Polarization

Table 2: Summary of literature survey with stance measure

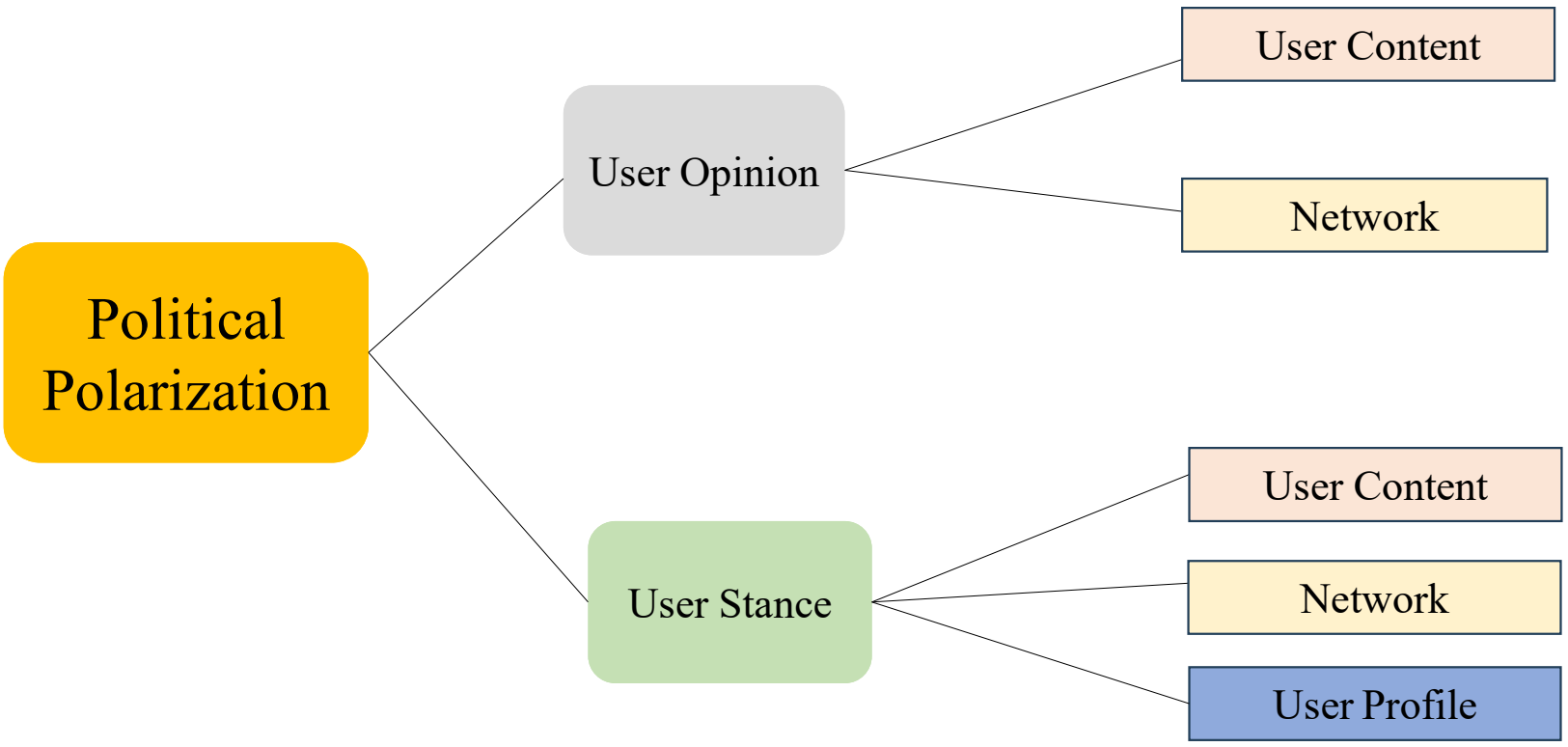
Authors	Matric	Features	Dataset	Summary
Jiang et al. [2023]	Stance	User Network	**Twitter COVID-19** and 2020 United States presidential elections dataset	• Retweet-BERT leverages the retweet network users' profile descriptions to estimate user political leanings • Show existence of **echo chambers and political polarization among the right-leaning population**
Fang et al. [2022]	Stance	Network	**Social network dataset** Cora, Pubmed, Photo, Facebook	• Pairwise similarities and dissimilarities. • Nodes are modeled with node features and topological structure information.
Tran et al. [2022]	Stance	Network	Youtube video and channels	• User-activity-based model. • Users are strongly polarized because the number of neutral users is very small
Dash et al. [2022]	Stance	Content Network	Indian Election Tweets dataset	• **Quantify influencers' political engagement on social media** • Tweet embeddings with retweet graphs help compute their stance
Lyu et al. [2022]	Stance	User Content	Twitter dataset of inflation and vaccine	• Jointly model user characteristics, multimodal post contents as well as user-item. • Bipartite graph for user embedding without labels.
Horawalavithana et al. [2021]	Stance	Content Network	**Venezuela's political dataset of Twitter ACLED and GDELT Twitter**	• **Identifying polarizing users to designing content promotion algorithms**. • Influential users contribute differently to different topics polarization of the user interaction network.

Literature Review →Political Polarization

Table 3: Summary of literature survey with sentiments

Authors	Matric	Features	Dataset	Summary
Tyagi et al. [2018]	Sentiment	Content	**Indian election**	• Predict the binary emotions of each tweet
Lopez-Chau et al. [2018]	Sentiment	Content	**Mexican Election Tweets**	• Predict the emotions of each candidate and the effects of those emotions on the other candidates
Matakos et al. [2017]	Opinion	Network	Social media dataset Karate, club, blogs elections	• Measuring and reducing polarization of opinions in a social network. • Degree of polarization consider network structure and the existing opinions of users.
Borge et. al. [2015]	Opinion	Content Network	Egypt Political tweets	• Understanding of bipolarized societies • Analyze the of users who switched polarity due to social media content

Literature Review → Summary



Identified Research Gaps

- **RG1:** Political polarization hasn't been study in the context of Indian politics because of lack datasets.

- **RG2:** Political polarization has been examined through the identification of either opinions or stances. Thus, there is a necessity to construct a matric that integrates both aspects and derived polarization.

- **RG3:** Most of the available datasets have only single attribute to measure polarization. However, multifaced attributes should consider to measure polarization.

- **RG4:** Most of the existing work have examined either user-generated content or social connections to analyze polarization. However, user profile information is also important attributes to understand the polarization.

- **RG5:** Existing reserch work limited to political emotions analysis of the user.

Research Questions

- **RQ1:** How to generate a text-based dataset of Indian Election?
- **RQ2:** How to use the user's stance along with opinion to quantify political polarization for polarization detection?
- **RQ3:** How do we detect polarization through multifaceted features that include user profile, content and structure information?
- **RQ4:** How do we generate a multifaceted feature dataset to study political polarization?
- **RQ5:** How do we perform a multi-label classification of user political emotions?

Research Contribution

- **RC1:** Generated a text-based dataset of opinion and stance attributes to study polarization (**Covers RG1, RQ1)**.

- **RC2:** Developed a hybrid model that utilize user opinion and stance measures to quantify political polarization (**Covers RG2, RQ2)**.

- **RC3:** Developed a new multifaced features dataset to detect political polarization (**Covers RG3**, **RQ3**).

- **RC4:** Developed a framework using graph neural network to model user profile, content, and structure information (**Covers RG4, RQ4**).

- **RC5:** Developed a dataset to understand the user political emotions in multi-label setup (**Covers RG5, RQ5**).

Thesis Contributions

1. Generated a text-based dataset of opinion and stance attributes to study political polarization (Covers RG1, RQ1).
2. Developed a hybrid model that utilize user opinion and stance measures to quantify political polarization (Covers RG2, RQ2).
3. Developed a new multifaced features dataset to detect political polarization (Covers RG3, RQ3).
4. Developed a framework using Graph Neural Network to model using Profile, Content, and Structure of OSM Users for polarization detection (Covers RG4, RQ4).
5. Developed a dataset to understand the multiple user political emotions with machine learning and deep learning techniques (Covers RG5, RQ5).

RC1 →Novel Text-based dataset generation → Research Objective

To generate a textual dataset for Indian election tweets that contain both user opinion and stance information.

Motivation

- ❑ Limited dataset for Indian election.
- ❑ Available dataset US election, Italy election does not comprise the both opinion and stance measures.

RC1 →Novel Text-based dataset generation →Data Collection

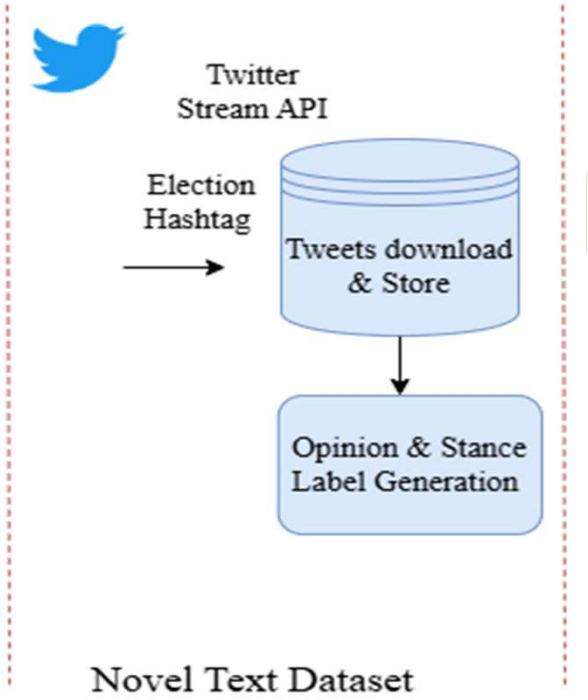


Figure 1: Dataset collection

Step 1. Trending hashtags

Step 2. Download Tweets (23 April 2019 to May 23, 2019))

Step 3. 1.5 millions tweets

Step 4. Extracted tweet-id, created_at, full_text

Election hashtags

#MumbaiVotesForNation

#IndiaVotesForNaMo

#TNElection2019

#VoteForChange

RC1 →Novel Text-based dataset generation → Label Generation for IGE

- **Manual Annotation Process :** Create a set of 250 tweets for assignment.

- **Opinion Class**

  Opinion Tweet *: Tweet content shows user's view and thought towards a target.*

  Neutral Tweet *: Tweet contains political text but cannot infer any opinion.*

- **Stance Class**

  ProGovt : *Tweet content supports the current ruling government then mark it ProGovt.*

  AntiGovt: *Tweet content against the government or in support of any other party then mark it AntiGovt.*

  Neutral : *Tweet content does not show any political alignment then mark it Neutral.*

- **Hashtag-based Search**

Tweet: #IndiaWantsXGovtAgain, this is an old story, now nobody wants him. He is a liar".

[Morales, A.J. 2015]

RC1 →Novel Text-based dataset generation → Snapshot of annotated dataset

Table 4 : Example of election tweets for opinion and stance class

Class I	Tweet Example
Opinion	In Kerala if you press symbol light shows as one symbol. How is that all ‘faulty EVMs’ select only X Govt only? #LokSabhaElections2019 #Votinground3 #BattleOf2019 #Phase3 #Trivandrum #Keralahttps://t.co/2naZ1Q5jM7
Neutral	#LokSabhaElections2019 wife Siya (2.5 years) went for Voting
Class II	**Tweet Example**
ProGovt	just met an 85 year old @ XGovt supporter who rode on a moped for 6 days and about 1500km from amravati to delhi via various constituencies in rajasthan mp up haryana etc - he campaigned for the pm.
AntiGovt	In Kerala if you press symbol light shows as one symobol. How is that all ‘faulty EVMs’ select only X Govt only? #LokSabhaElections2019 #Votinground3 #BattleOf2019 #Phase3 #Trivandrum #Keralahttps://t.co/2naZ1Q5jM7
Neutral	Do cast your vote. #Mumbai, #LokSabhaElections2019

RC1 →Novel Text-based dataset generation →Dataset Statistics

- Total annotation: 12000 (4000 tweets × 3 annotators)
- Inter-annotator agreement
- Fleiss' Kappa: 0.74

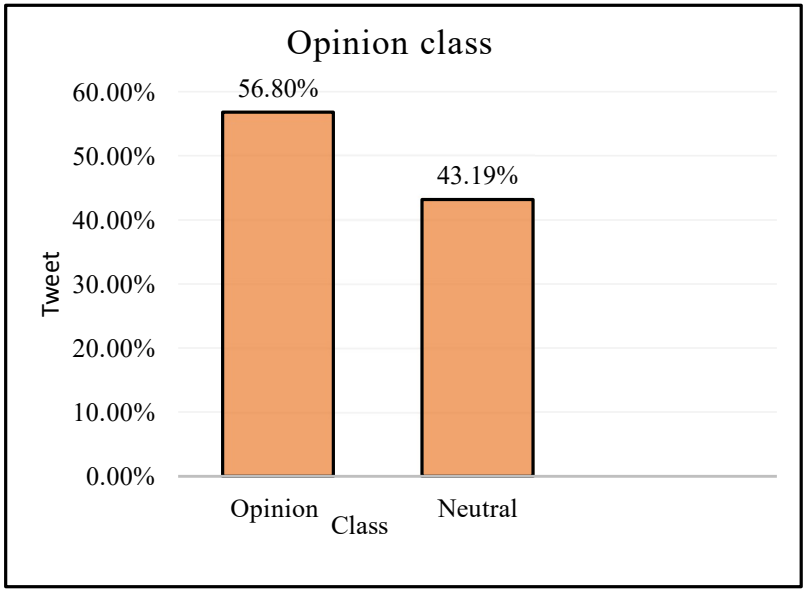


Figure 2 : Number of tweets for opinion class

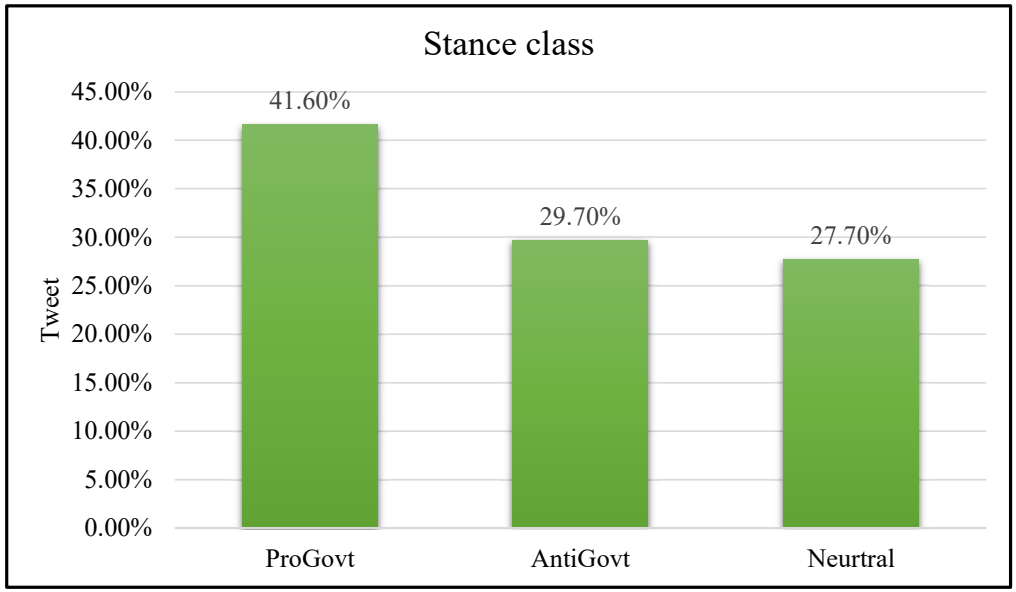


Figure 3 : Number of tweets for stance class

RC1 →Novel Text-based dataset generation → Summary

- Out of the total number of opinionated tweets, 88.3% of tweets show political stances.
  - 52.9% classified as ProGovt
  - 47.3% as AntiGovt
  - 7% as neutral

- Opinionated tweets can influence a user's political stance, as most tweets with an opinion also include the user's political stance.

Thesis Contributions

1. Generated a text-based dataset of opinion and stance attributes to study polarization (Covers RG1, RQ1).
2. Developed a hybrid model that utilize user opinion and stance measures to quantify political polarization (Covers RG2, RQ2).
3. Developed a new multifaced features dataset to detect political polarization (Covers RG3, RQ3).
4. Developed a framework using Graph Neural Network to model using Profile, Content, and Structure of OSM Users for polarization detection (Covers RG4, RQ4).
5. Developed a dataset to understand the multiple user political emotions with machine learning and deep learning techniques (Covers RG5, RQ5).

RC2 →Detection and Characterization of Political Polarization

Research Objectives

To identify whether the online social network content can make user polarized.

Key Contribution:

- ❑ Hybrid model to quantify political polarization.
- ❑ Evaluate the performance using the machine learning algorithms.

Publication

1. A. Gupta and S. Mehta, "Automatic stance detection for twitter data." 2022 1st International Conference on Informatics (ICI). IEEE, 2022.(Conference, SCOPUS).
2. 2. A. Surolia, S. Mehta and P. Kumaraguru, “Detection and characterization of political polarization using user opinion and stance features for Indian Election” to the Journal of Theoretical and Applied Information Technology, Scimago, Elsevier SCOPUS Indexing with H- index 39

RC2 →Detection and Characterization of Political Polarization → Related Work

- Research confined to keyword-based stance prediction.

  [Marozzo et al. 2017]

- Limited to consider user opinion with user political stance information.

  [Belcastro et al. 2019]

- Focuses on network structures and influencer dynamics limited to content and sentiment of the tweets.

  [Lyu et al. 2022]

RC2 → Detection and Characterization of Political Polarization → Methodology

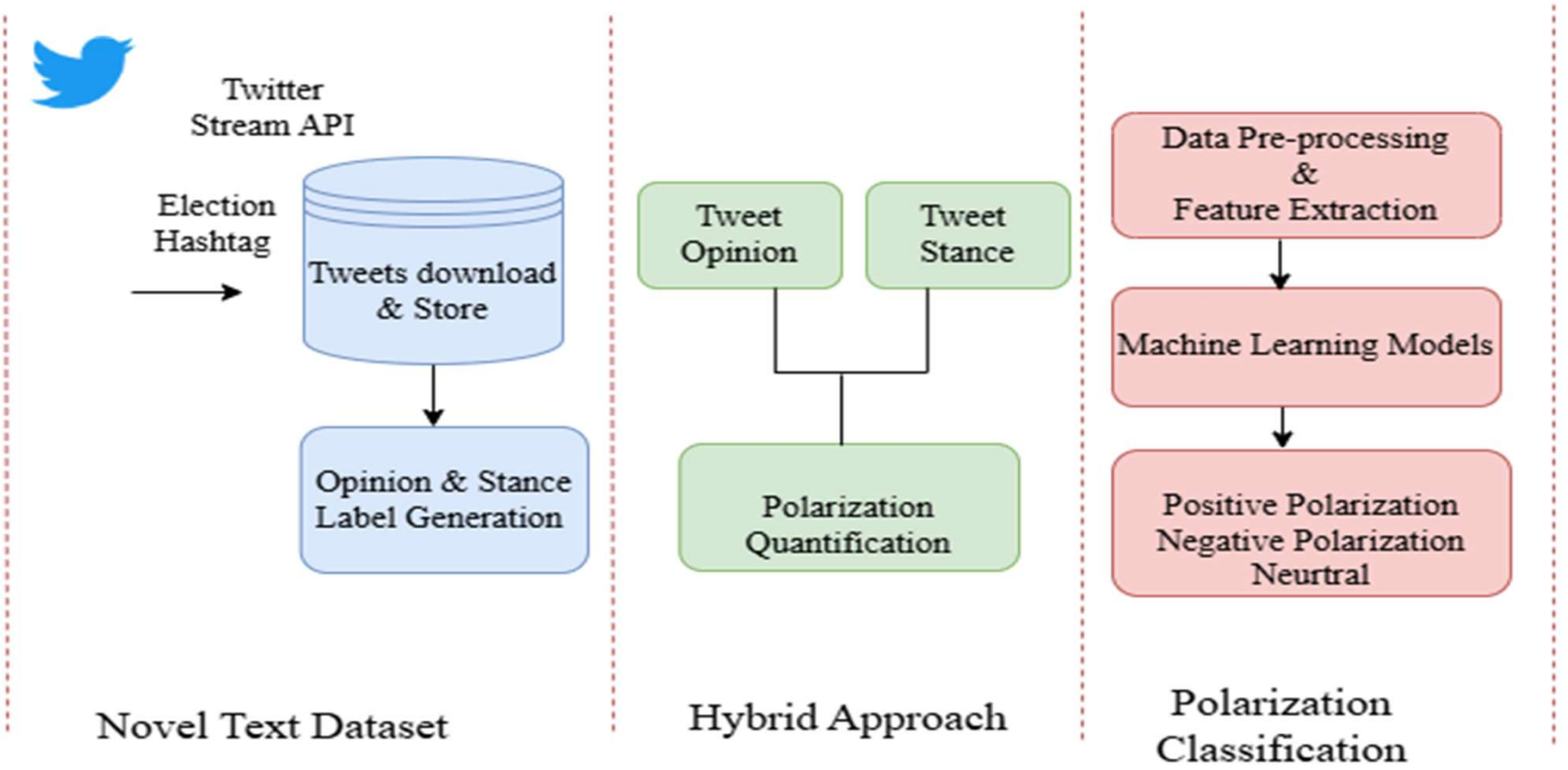


Figure 5: Work flow for political polarization detection

RC2 → Detection and Characterization of Political Polarization → Proposed Algorithm

Problem Statement:

Given a set of tweet t1, t2, t3.....tn and polarization label Pol(+v), Pol(−ve) and Pol(0). The goal is to identify the tweet label, whether it is positive polarized, negative polarized or neutral.

Algorithm 1: Quantifying Polarization by Opinion and Stance-level Information

1. Input: H = No of Hashtags
2. Input: T = No of Tweets
3. C_O = {yes, no}
4. C_S = {pro, anti, neu}
5. $\forall\ t_i \in T$: if $t_i \in Co_{(yes)}$ then
6. if $t_i \in C_{S(pro)}$ then
7. t_i(label) ←Positive Polarization
8. else if $t_i \in Cs_{(anti)}$ then
9. t_i(label) ←Negative Polarization
10. else
11. t_i(label) ← Neutral
12. end if

RC2 →Detection and Characterization of Political Polarization → Experiment Design

Dataset

IGE dataset (RC1)

Machine learning models

- Random Forest (RF)
- Support Vector Machine (SVM)
- Decision Tree (DT)
- Logistic Regression (LR)

Evaluation Parameter

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

RC2 →Detection and Characterization of Political Polarization →Results

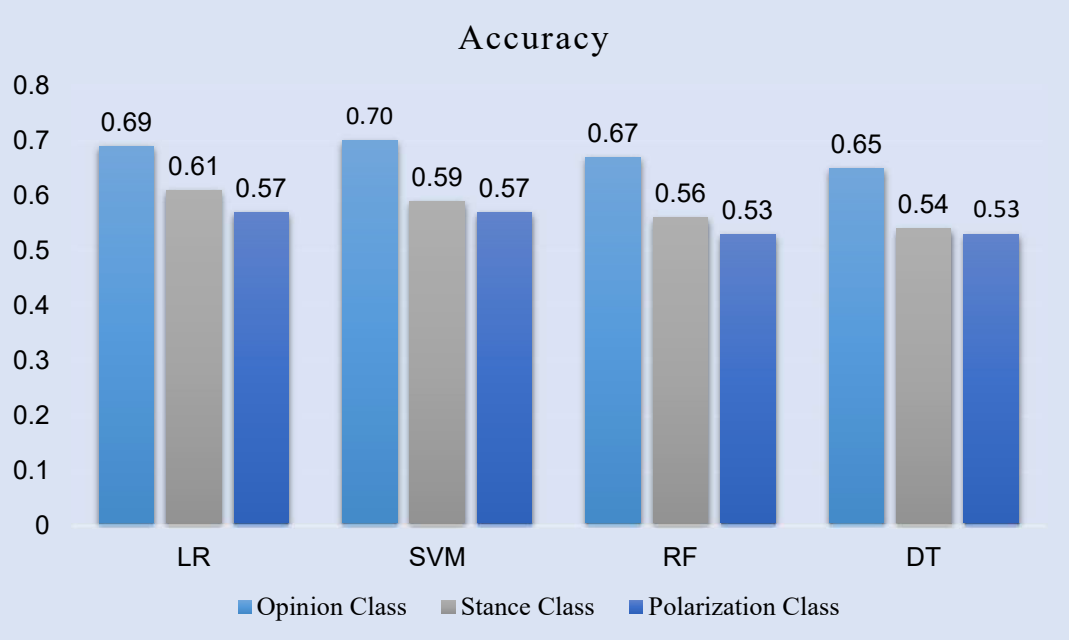
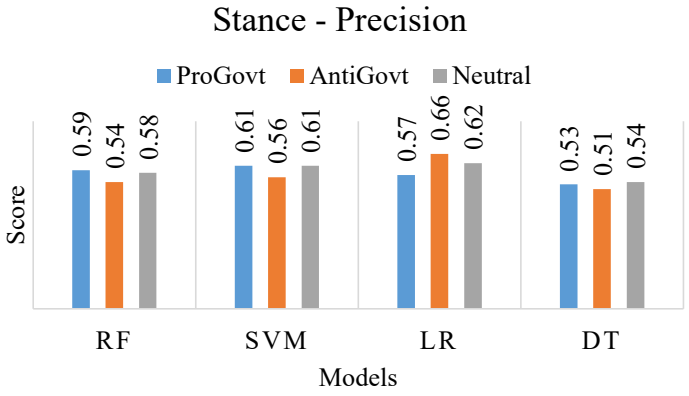
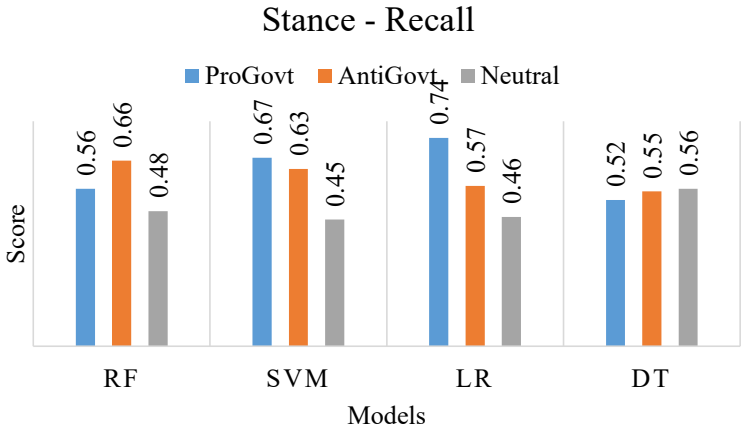
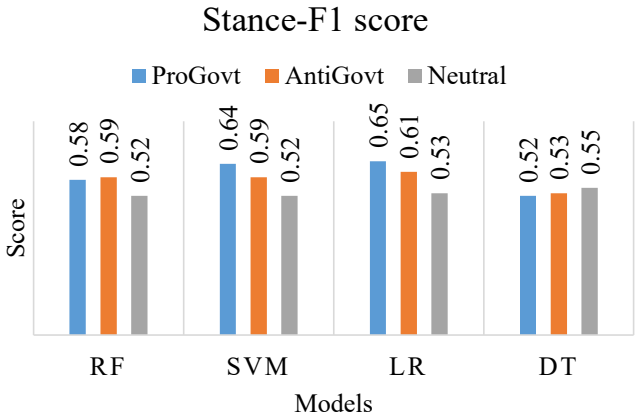


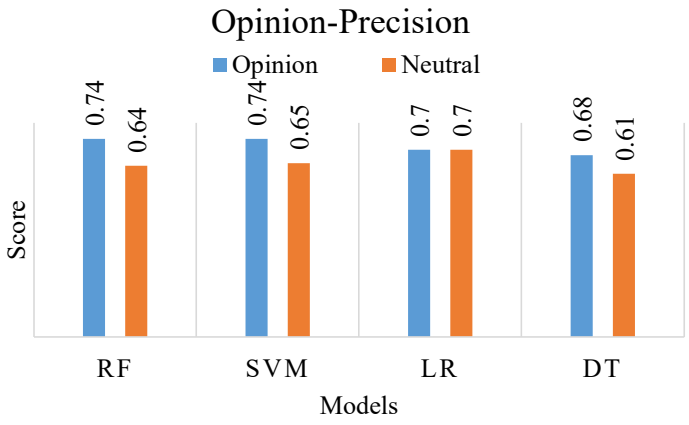
Figure 4: Accuracy for opinion, stance, and polarization respectively.

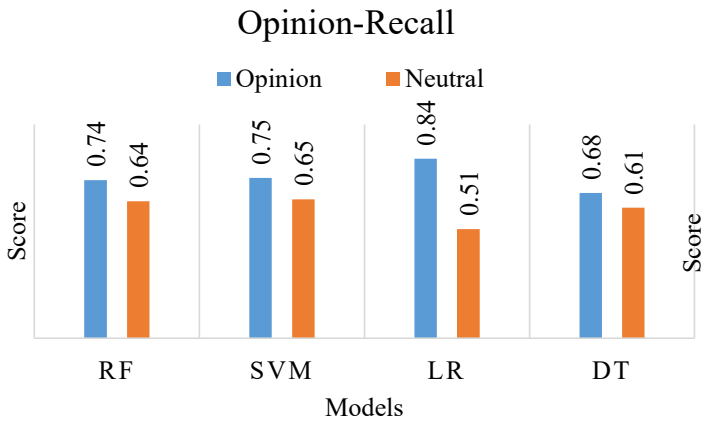
RC2 →Detection and Characterization of Political Polarization →Results











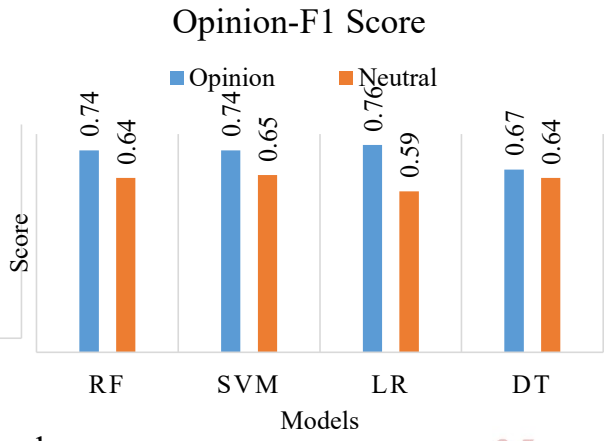
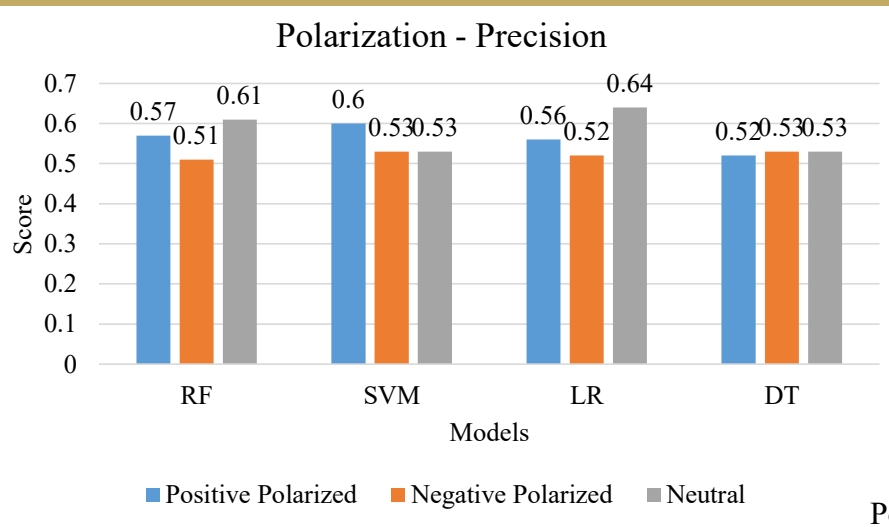
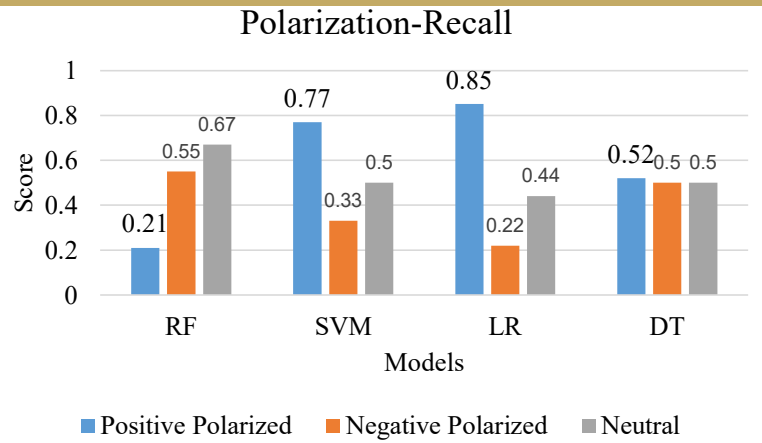


Figure 5: Precision, recall and F1 score for opinion and stance class.

RC2 →Detection and Characterization of Political Polarization →Results





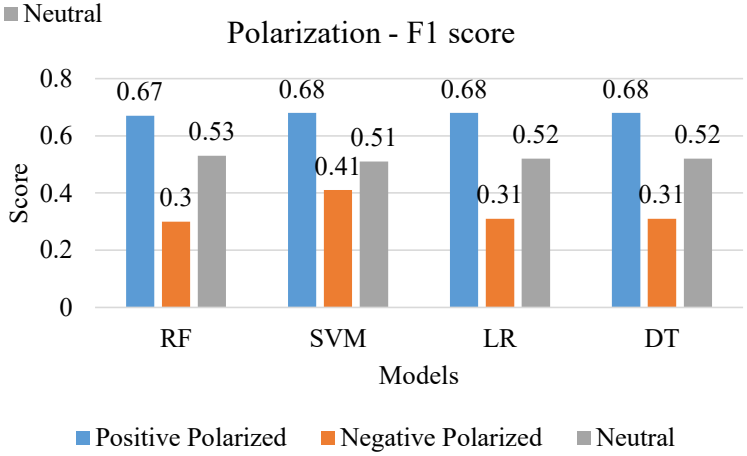


Figure 6: Precision, recall and F1 score for Polarization class.

RC2: Detection and Characterization of Political Polarization → Summary

- Developed a hybrid model that integrates the user's opinion and user stance information.
- LR and SVM model performed better for classification task.
- Most misclassifications of positive and negative polarized tweets fall into neutral categories, as neutral tweets do not show any influence.

Limitation

- Research work limited to the content analysis.

Thesis Contributions

1. Generated a text-based dataset of opinion and stance attributes to study polarization (Covers RG1, RQ1).
2. Developed a hybrid model that utilize user opinion and stance measures to quantify political polarization (Covers RG2, RQ2).
3. Developed a new multifaced features dataset to detect political polarization (Covers RG3, RQ3).
4. Developed a framework using Graph Neural Network to model using Profile, Content, and Structure of OSM Users for polarization detection (Covers RG4, RQ4).
5. Developed a dataset to understand the multiple user political emotions with machine learning and deep learning techniques (Covers RG5, RQ5).

RC3 : Multifaceted Dataset of user, content and structure features → Introduction

Research Objective

To generate a multifaceted dataset of 2019 Indian General Election that includes user profile, content and network information.

Limitation

- ❑ No Multifaceted dataset for Indian election.

RC3 : Multifaceted Dataset of user, content and structure features → Methodology

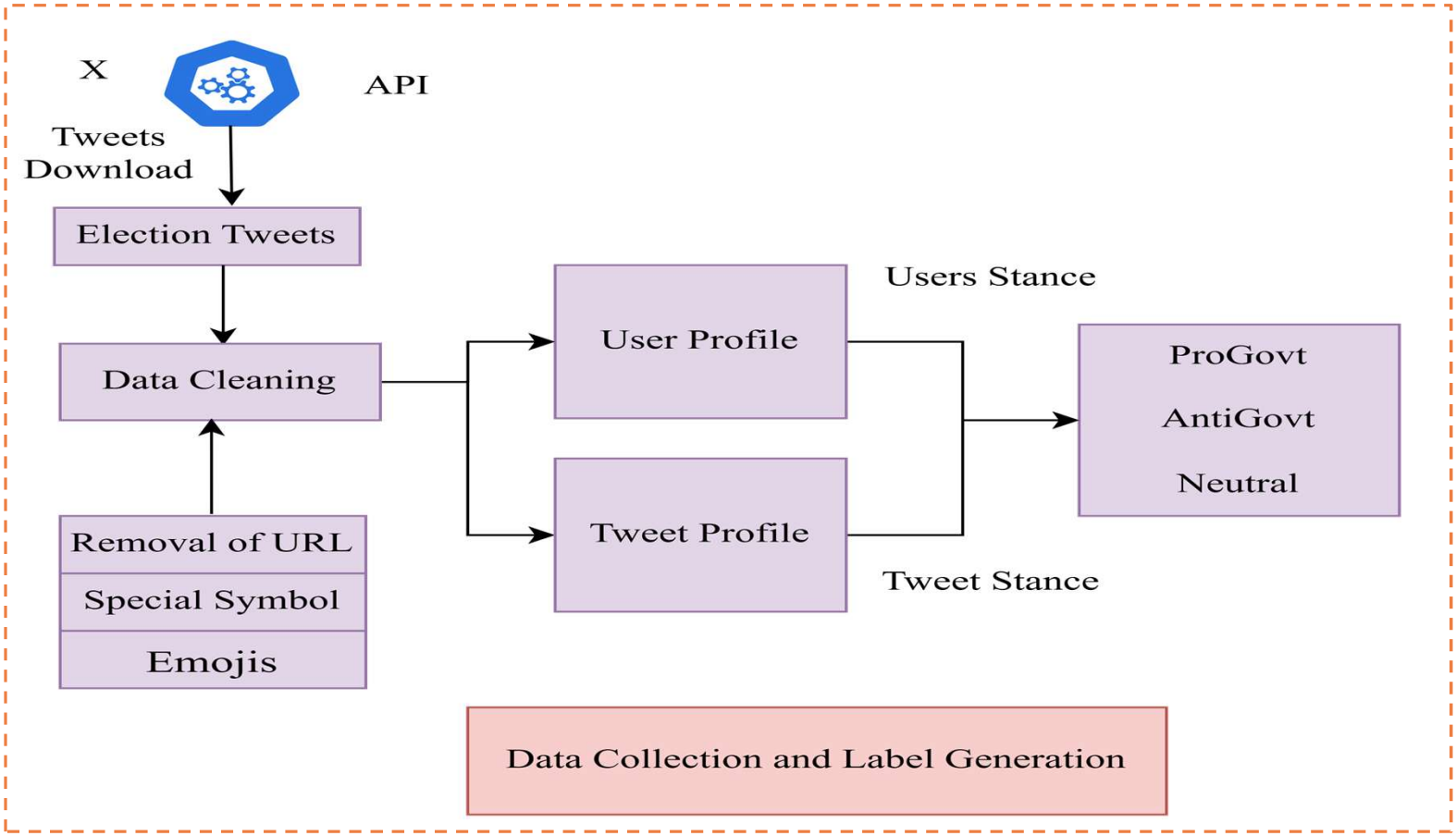


Figure 7 : Methodology for dataset generation

RC3 : Multifaceted Dataset of user, content and structure features → Methodology

Data Collection

- Precog Research Group
- Downloaded the tweets with attributes id, created_at, retweeted_status, retweet count, user_screen_name, user_description, follower_count, full_text.
- Dataset comprises with 2.5 million tweets
- Removed the non-English tweets.
- Performed threshold for minimal tweet length is the tweets with ten words.

RC3 : Multifaceted Dataset of user, content and structure features → Methodology

Tweet Sampling

- Selected tweets with minimum 10 retweets count.

User Sampling

- The first set of users is S1 = {T, 10 ⩽T < 20}, representing users who posted a minimum number of 10 tweets and a maximum of 20.
- The second set includes users S2 = {T, 20 ⩽ T < 50}.
- The third set includes the users S3 = {T, 50 ⩽ T < 80}.
- The fourth set S4 = T, 80 ⩽ T <150}.

Multi-level Stance Annotation

- User and Tweets

RC3 : Multifaceted Dataset of user, content and structure features → Snapshot of Dataset

Table 6 : Political stance of user and tweet content

S.no	User Description	Label
1.	#SPOKESPERSON & Co Head Media Dept. @XGovt4DELHI.”	ProGovt
2.	YGovt by heart, Tweets are personal	AntiGovt
3.	This election season don’t let others decide. India, Neutral Bring Your Own Vote	Neutral.
	Tweet Text	
1.	Today, for the first time I am joining a national party. I thank#XGovt. I feel fortunate that I be able to work as per their vision for the nation: #Jleader after joining XGovt, ahead of #Elections2019.https://t.co/RnoAW8f3qI	ProGovt
2.	In the last 5 years XGovt economic policies have terrorised the rural economy.MinimumIncomeGuarantee #NyayforIndia can be the game-changer to kickstart rural consumption and demand. https://t.co/NTJt3ojeMh	AntiGovt
3.	Parties who fought opposite are forming alliance post #Election2019 deceiving voters and mocking #democracy. They had no courage for prepoll tie-up. #India deserves honest, ethical leaders	Neutral

RC3 : Multifaceted Dataset of user, content and structure features → Dataset

Data Statistics

- Obtained a total of 381 users and 12,761 tweets.
- Flesis kappa as inter-annotator agreement of 0.80.

Large Dataset

- XGBoost (Extreme Gradient Boosting) model to generate the labels.
- Generated n-gram for ProGovt and AntiGovt users.

RC3 : Multifaceted Dataset of user, content and structure features → Summary

- Generated a multifaceted dataset utilizing user profile, content profile and network profile.
- Political alignment of the retweeting user is the same as that of the original user.
- Achieved seed user 381 with 12,761 tweets.
- Generated a large dataset of 4,922 users and 57,427 tweets with the accuracy of 0.94.

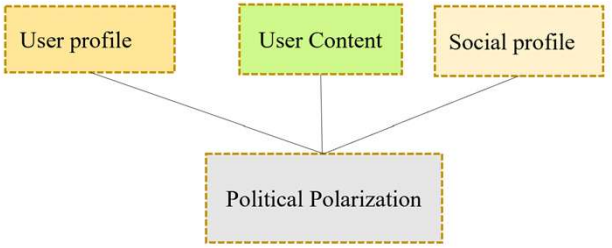
Thesis Contributions

1. Generated a text-based dataset of opinion and stance attributes to study polarization (Covers RG1, RQ1).
2. Developed a hybrid model that utilize user opinion and stance measures to quantify political polarization (Covers RG2, RQ2).
3. Developed a new multifaced features dataset to detect political polarization (Covers RG3, RQ3).
4. Developed a framework using Graph Neural Network to model using Profile, Content, and Structure of OSM Users for polarization detection (Covers RG4, RQ4).
5. Developed a dataset to understand the multiple user political emotions with machine learning and deep learning techniques (Covers RG5, RQ5).

RC4 : GCN-SBERT hybrid model with multi-level stance classification→Introduction

Research Objectives

To identify political polarization through multifaceted features.



Key Contribution

- ❑ Proposed a multi-level stance framework using graph neural network.
- ❑ Performed a temporal analysis of the user content to validate the multi-level stance analysis.

Publications

A. Surolia and S. Mehta, "Optimal Feature Selection for Retweet Prediction in Indian Election." 2023 Second International Conference on Informatics (ICI). IEEE, 2023.

A. Surolia, S. Mehta and P. Kumaraguru, “A Graph-Transformer hybrid model for Political Polarization in Indian Elections” in Journal of Transactions on Asian and Low-Resource Language Information Processing, SCI indexing and IF = 1.8 (under review)

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ Literature review

Table 7: Summary of literature survey findings based on the feature used for polarization detection.

Author	User	Content	Network	Model
Borge et. al. [12]	×	×	✓	Social network analysis
Takikawa [4]	×	×	✓	Social network analysis & NLP
Stwart et al. [28]	×	×	✓	Social network analysis
Horawalavithana [31]	×	×	✓	BERT and social network analysis
Dash et. al. [11]	×	×	✓	Clustering, social network analysis
Borah et al. [14]	×	×	✓	Social network analysis
Kamienski [18]	×	×	✓	Network attributes
Jiang et. al. [19]	✓	×	✓	RetweetBERT
lyu et. al. [8]	✓	✓	×	Graph neural network
Fang et al. [32]	×	×	✓	Polar Graph neural network
Tran et al. [33]	✓	×	✓	Social network analysis
Antonis et. al. [34]	×	×	✓	Moderation Algorithm
Tyagi et. al. [35]	×	✓	×	Classification
Multi-Level Stance Framework (Our proposed framework)	✓	✓	✓	Graph neural network

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ GCN-SBERT Hybrid Model

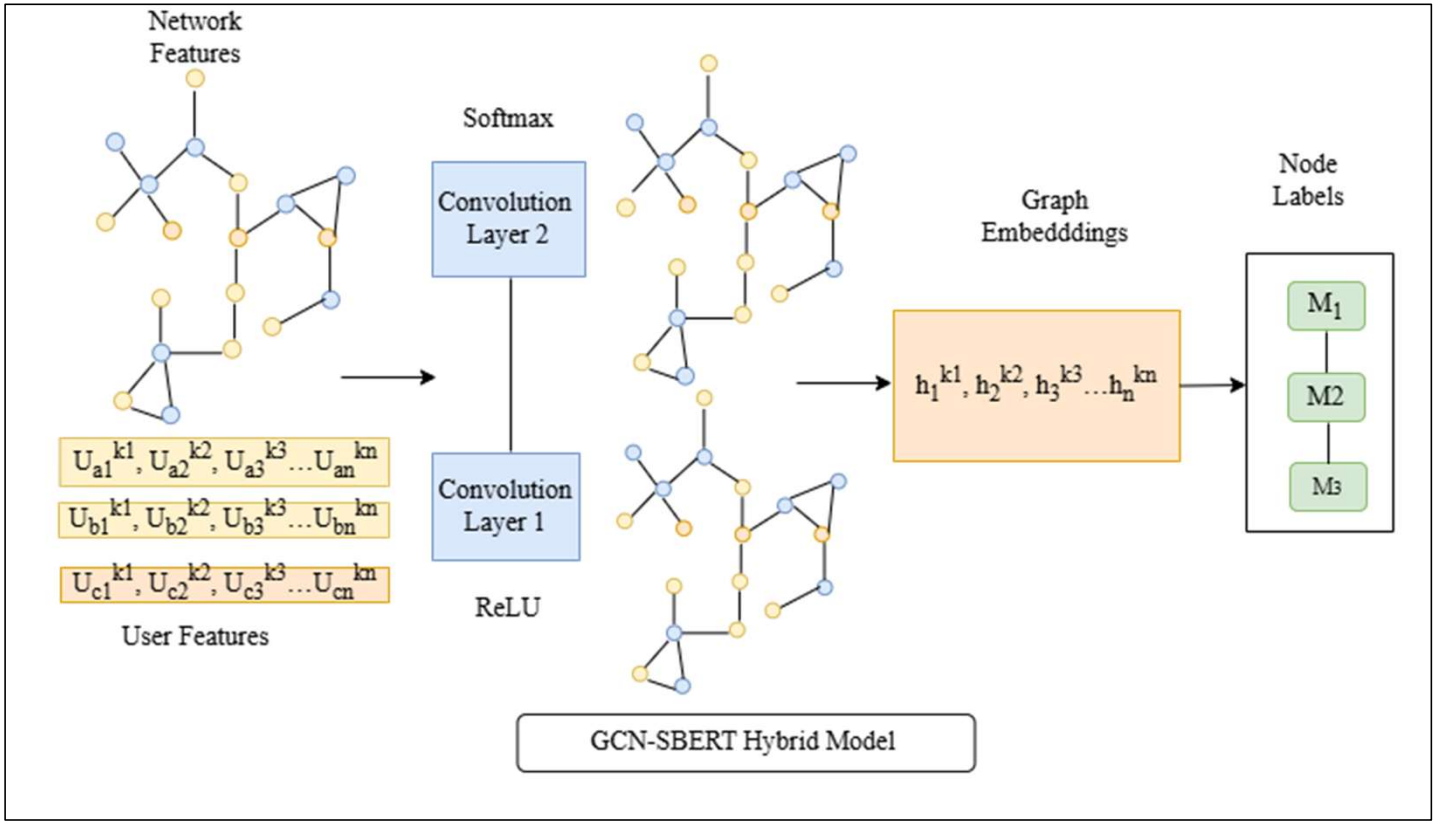


Figure 8: Methodology for GCN-SBERT model

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ Network Embedding

Network Features : Each node, vi∈ V, is connected by an edge, eij = (vi, vj)∈ E, linking vi and vj represent the retweet from node vi to node vj . Every node is assigned a feature vector xi ∈ d.

Nodes : User profile
Edge : Retweet

Attributes	Count
Number of nodes	4,922
Number of edges	9,742
Avg. Degree	256
Maximum Degree	3,254

RC4: GCN-SBERT hybrid model with multi-level stance classification→ User Embedding

Algorithm 2 : SBERT for generating user embeddings

Input: U_p =Set of User Profile , Data: model = BERTmodel(pretrained_bert_uncased), Label = {0: Neutral,1: ProGovt, 2: AntiGovt} , Output: User Embedding

Begin

1. D_i = User description for U_{pi}
2. W_i = tokenizer (D_i)
3. output= model (W_i)
4. embedding=mean_pooling(output)
5. sentence_pair = {(S_{a1}, $S_{b1)}$, (S_{a2}, S_{b2}) ..... ($S_{n1m1....}$ Sn_{2m2})}
6. fine_tune_SBERT (model, sentence_pairs, Label)
7. output=call_model (W_i)
8. embedding=mean_pooling(output)
9. similarity = cosine_similarity(embedding1, embedding2) loss = compute_loss (similarity, label)

end

ALGORITHM 4: GCN-SBERT Hybrid Model for Polarization Detection

Input: G (U, V), Data: h=hidden dimension, num_epochs=200, ρ = relu activation, μ=softmax activation, output_dim = 3; labels ={0,1,2}, A =adjacency matrix [N x N], X= feature matrix = [U x input_dim], loss function = Cross Entropy, optimizer = AdamOptimizer Output: Node Classification

Begin:

1. Call train_gcn_model(graph, labels, num_epochs)
2. Initialize the adjacency matrix of user node: A[NXN]
3. Add self-loop: A = A+ I
4. Normalize the A= A[NxN]
5. Initialize the GCN Model with input parameters.
6. model = GCNModel(input_dim=, hidden_dim, output_dim)

7. Call GCNfirstLayer with activation function ρ
8. Call GCNsecondLayer with activation function μ
9. for epoch in range(num_epochs)
10. node_predictions = model.forward(A, X) loss = loss_function(predictions, labels)
11. loss.backward() optimizer.step()
12. node_embeddings = model.forward(A, X)
13. node_prediction = softmax(node_embeddings)

end

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ User Content

User Content

Attributes of tweets

- created at
- Tweet id
- Full text
- retweet count
- user attributes

Word Embeddings

- Word2Vec
- GloVe (Global Vectors for Word Representation)
- BERT (Bidirectional Encoder Representations from Transformers)

Baseline Models

- Machine learning models - support vector machines (SVM) and random forest (RF)
- Deep learning models - long short-term memory networks (LSTMs) and bidirectional long short-term memory networks (Bi-LSTM)
- Transformer-based model - BERT

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ Experiment Design

Table 8 : Hyperparameter details of GCN, BERT, LSTM, Bi-LSTM models

Graph Model		Transformer Model		Deep Learning Model	
Hyperparameter	values	Hyperparameter	values	Hyperparameter	values
hidden_dim	32	Pre_trained	Bert-base-uncased	optimizer	adam
dropout	0.5	learning_rate	1e-5	loss	Binary cross entropy
learning_rate	0.01	dropout	0.3	dropout	0.2
batch_size	256	epoch	5	recurrent_dropout	0.2
activation	ReLU	Tokenizer_max_len	250	batch_size	128
epoch	300	batch_size	32		

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ Experiment Design

Table 9: The dataset samples employed for both train and test purposes in polarization detection and tweet stance prediction.

Classification Task	Dataset	Class	Size
User Stance	Train	ProGovt (1)	1,953
	Train	AntiGovt (2)	1,689
	Train	Neutral (0)	790
	Test	ProGovt (1)	216
	Test	AntiGovt (2)	187
	Test	Neutral (0)	87
Tweet Stance	Train	ProGovt (1)	15,024
	Train	AntiGovt (2)	14638
	Train	Neutral (0)	20,022
	Test	ProGovt (1)	1,721
	Test	AntiGovt (2)	1,683
	Test	Neutral (0)	233

Evaluation Parameter

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

RC4: GCN-SBERT hybrid model with multi-level stance classification→ Results

Table 10: Results of the different representations of user and structure embedding and models used for polarization detection.

Features	Embeddings	Accuracy	Precision	Recall	F1 Score
User Profile	Word2Vec + LSTM	0.68	0.75	0.58	0.66
	Word2Vec + Bi-LSTM	0.73	0.77	0.65	0.75
	Glove + LSTM	0.70	0.63	0.69	0.70
	Glove + Bi-LSTM	0.77	0.74	0.84	0.79
	BERT-case	0.86	0.93	0.79	0.86
User Profile + Network Profile	GCN-SBERT	**0.92**	**0.89**	**0.96**	**0.92**

RC4: GCN-SBERT hybrid model with multi-level stance classification→ Results

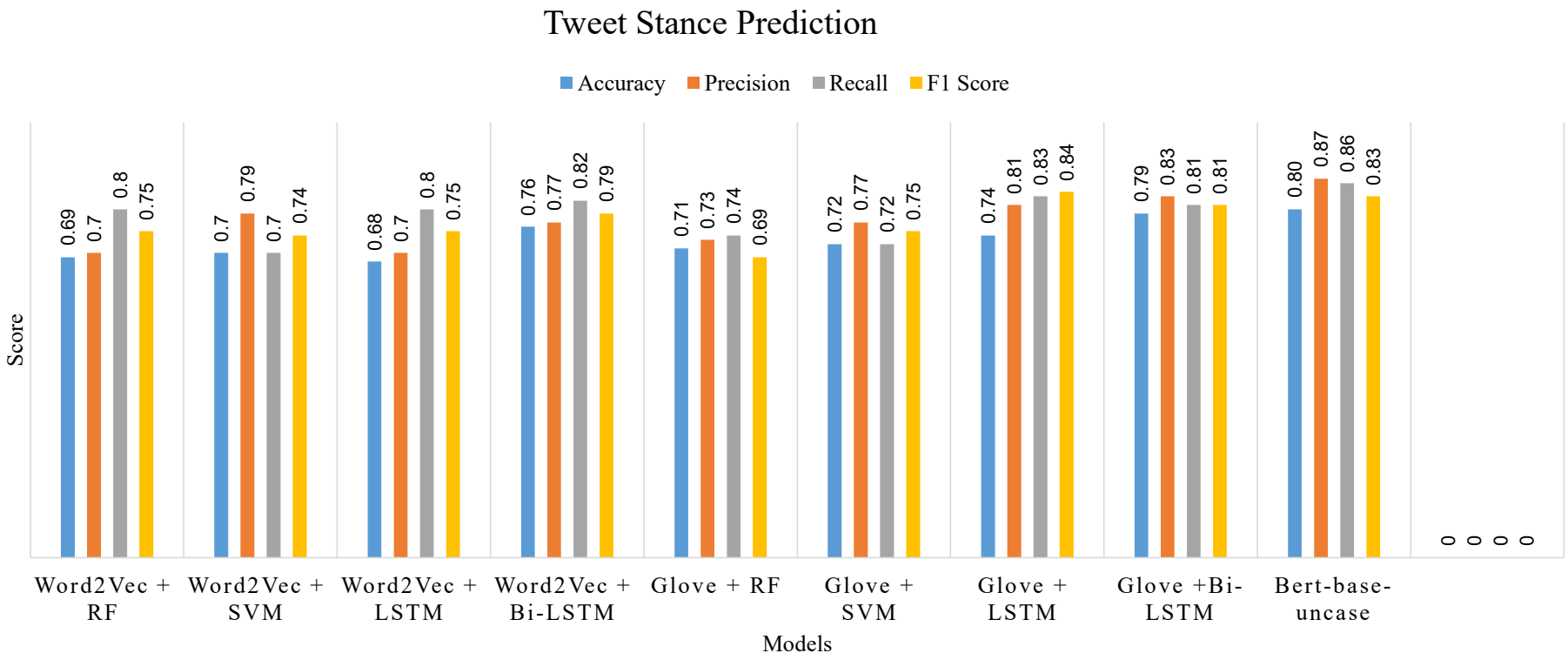


Figure 10: Represents the stance prediction of tweets using baseline models and word embeddings

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ Temporal analysis

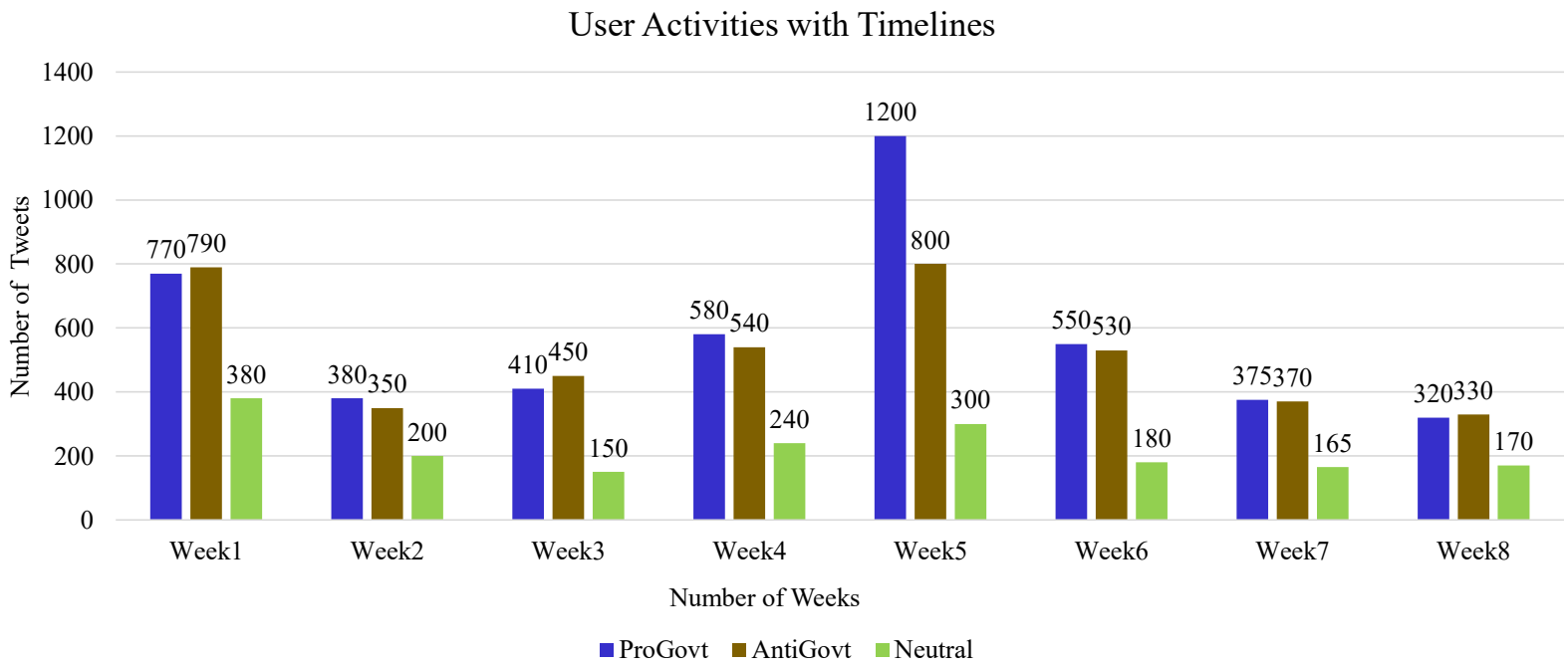


Figure 11: Graph depicts the engagement levels of ProGovt, Anti-Govt, and Neutral users over an 8-week period during the election.

RC4 : GCN-SBERT hybrid model with multi-level stance classification→ Temporal analysis

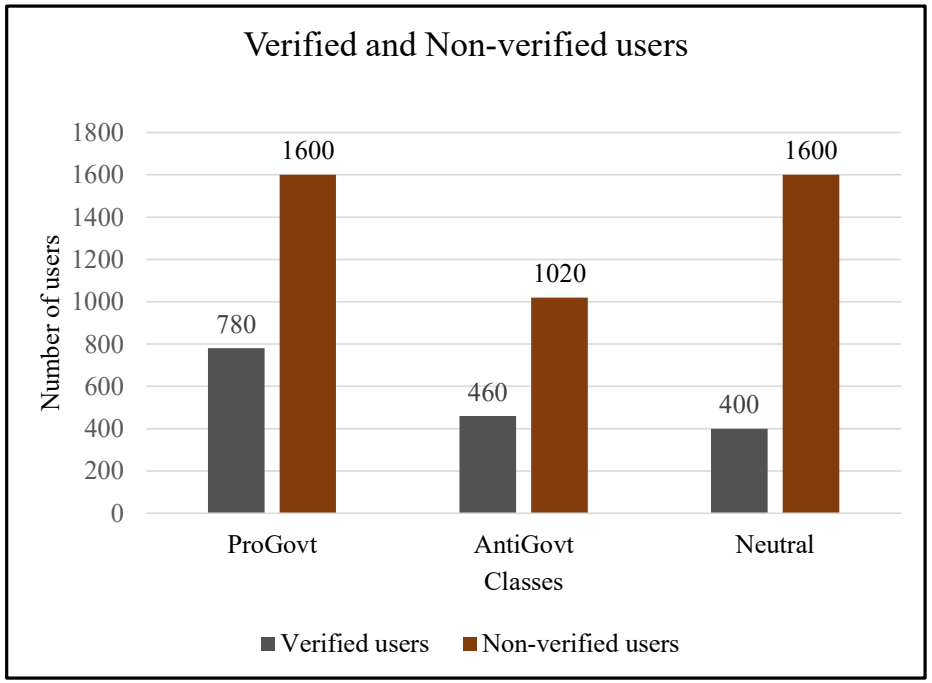


Figure 12: illustrates the number of verified and non-verified user.

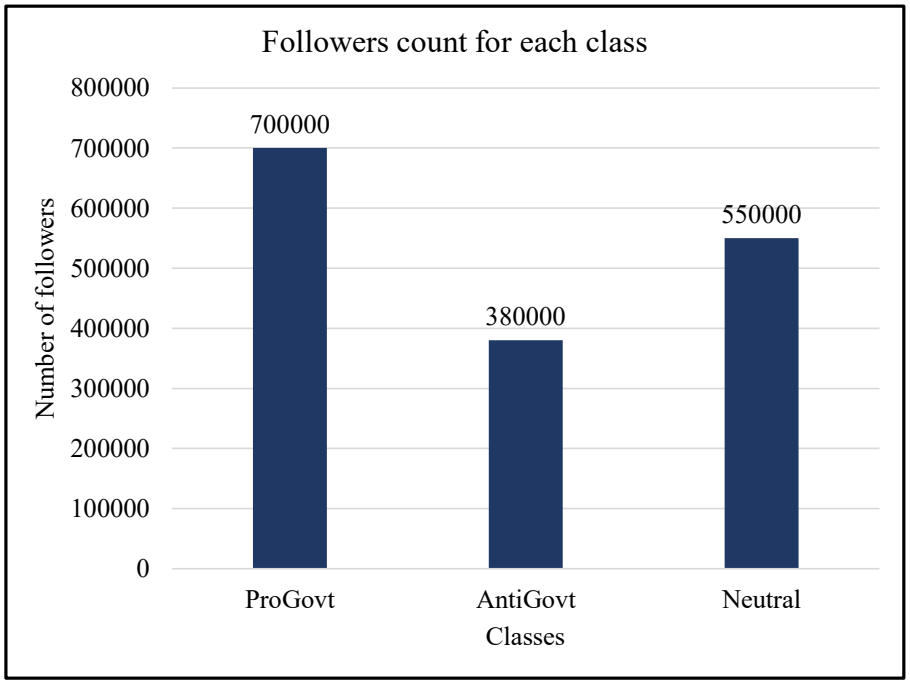


Figure 13: illustrates follower count for each class.

RC4: GCN-SBERT hybrid model with multi-level stance classification→ Temporal analysis

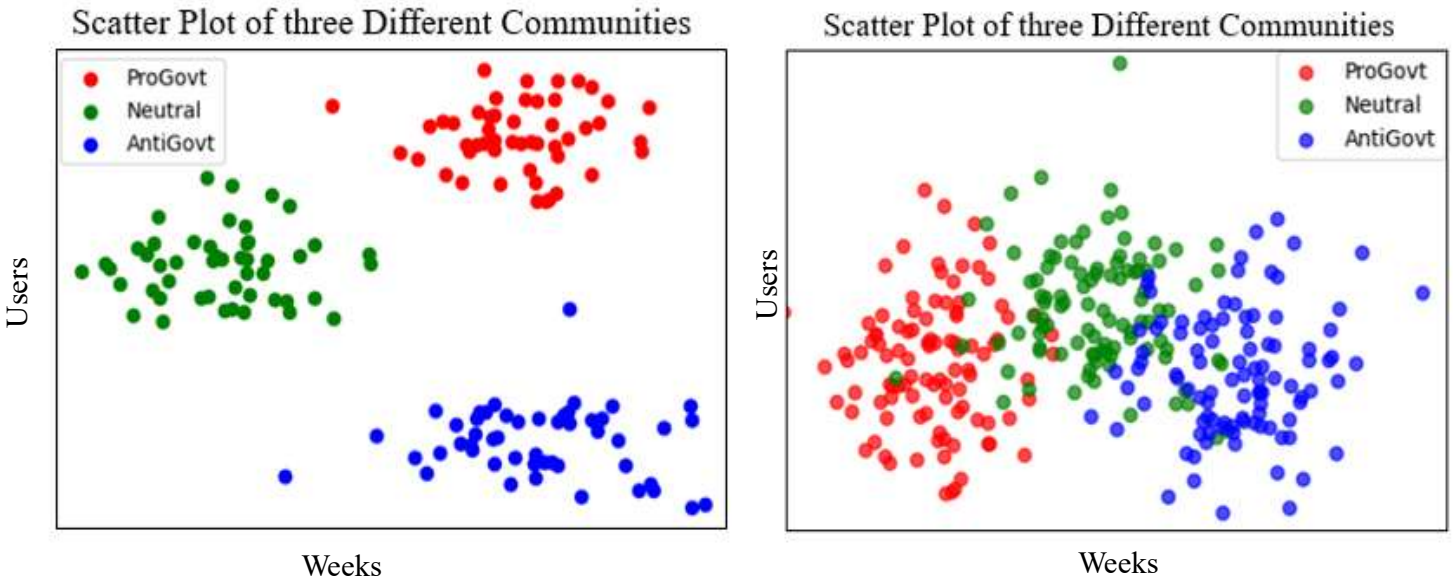


Figure 14: Different cluster for ProGovt, AntiGovt and Neutral user for first and last week.

RC4 : GCN-SBERT hybrid model with multi-level stance classification→Summary

- Proposed a GCN-SBERT hybrid model that utilize multifaceted features (user, content and structure) to perform multi-level stance analysis for polarization detection.
- GCN-SBERT model outperformed the state-of-the-art models by achieving accuracy of 0.92.
- Content stance analysis performed using BERT model with the accuracy of 0.88.
- Found ProGovt and AntiGovt users are mostly aligned with their political parties, only neutral users change their stance as per the consumption of social network data.

Thesis Contributions

1. Generated a text-based dataset of opinion and stance attributes to study polarization (Covers RG1, RQ1).
2. Developed a hybrid model that utilize user opinion and stance measures to quantify political polarization (Covers RG2, RQ2).
3. Developed a new multifaced features dataset to detect political polarization (Covers RG3, RQ3).
4. Developed a framework using Graph Neural Network to model using Profile, Content, and Structure of OSM Users for polarization detection (Covers RG4, RQ4).
5. Developed a dataset to understand the user political emotions with machine learning and deep learning techniques (Covers RG5, RQ5).

RC5: Political Emotion Multi-label classification in Indian Elections →Introduction

Research Objective

Identifying user political emotions in multi-label setup for Indian elections.

Key Contribution

- ❑ Generate a PoliEMO dataset a novel benchmark corpus of political tweets.
- ❑ Apply classification models to detect the political emotions.

Publications

A. Surolia, S. Mehta and P. Kumaraguru, “Deep Learning and Transfer learning to understand Emotions: A PoliEMO Dataset and Multi-label Classification in Indian Elections” in International Journal of Data Science and Analytics, Springer Nature Journal, Scimago, SCOPUS indexing and IF = 3.4 with H-index 31.(Published)

RC5: Political Emotion Multi-label classification in Indian Elections →Related Work

Table 11: Related work summary for emotions detection

Research	Emotion	Features	Dataset	Model	Measures
Ameer et al. [8]	Multi-label	Word and char n ram	SMS corpus (English and Roman Urdu)	Machine learning, deep learning, transformed model	Micro precision, and recall, micro avg. F1 score
Ghosh et al. [21]	Multi-label	Word embedding, GRU encoder	CEASE benchmark dataset	deep neural network model	Recall, micro avg. F1 score, error analysis
Huanget al. [22]	Multi-label	Emotion correlation	SemEval, GoEmotions	Seq2Emo, BiLSTMs	Jaccard index, hamming Loss, macro and micro avg. F1
Zhang et al. [52]	Multi-label	social contextual, temporal, textual features	benchmark Twitter dataset	graph based emotion recognition model	Micro avg. precision and recall.
Ahuja et al. [3]	Single label	afinn, subjectivity	IPL Twitter data	Clustering model	Cluster analysis, elbow method
hu et al. [22]	Single label	Vector	Stanford Twitter Sentiment and ObamaMcCain Debate	Optimization algorithm	Least squares, Lasso, MinCuts, LexRatio

RC5: Political Emotion Multi-label classification in Indian Elections →Methodology

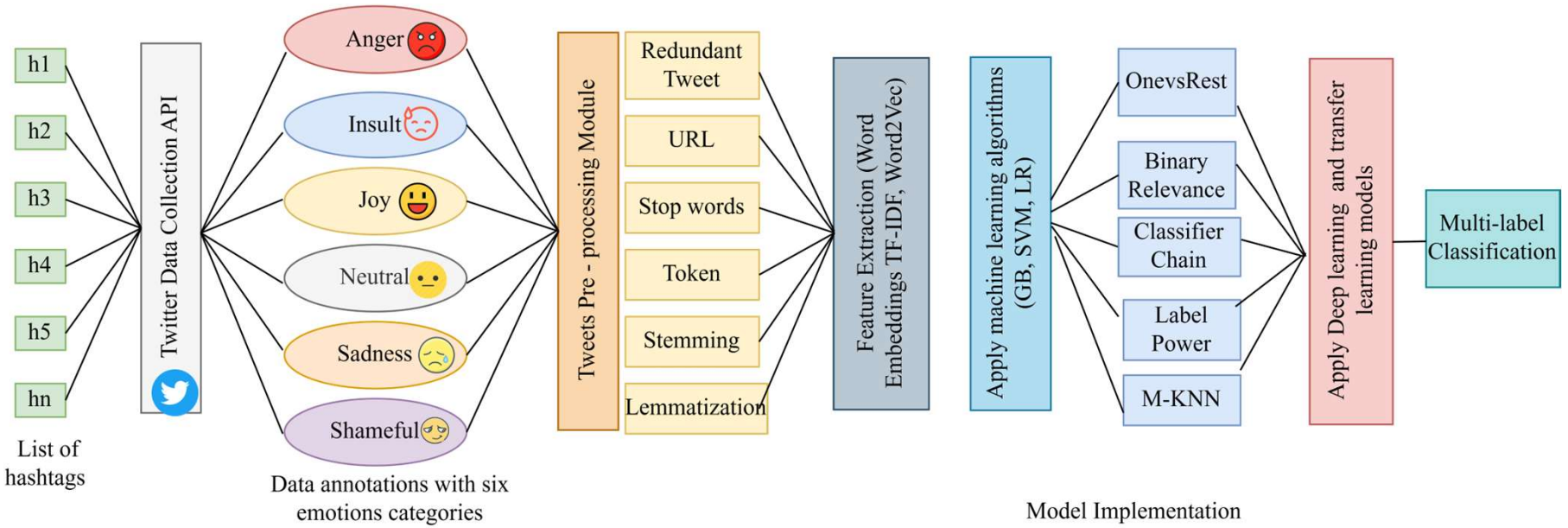


Figure 15: Methodology for multi-label emotions classification

RC5: Political Emotion Multi-label classification in Indian Elections → Snapshot of PoliEMO Dataset

Table 12: Example of emotions annotation

Tweet	Label
My heartfelt gratitude to the Govt for reposing faith in me, giving me another opportunity to serve Bathinda. I also thank the Almighty. My gratitude also goes out to my constituents for choosing to support me and my work for the past ten years. #Elections2019 #LokSabha	Joy
XGovt. accuses opposition of using the ins viraat for a family vacation. shocking if true! compare that with selfless pm. he spent over 2021cr of public money on touring in the name of foreign policy and took the whole country for a ride.	Shameful, Anger
men seen running away. The lady alleges govt men pulled my sari and told me to go back ; not vote. The man says I am asked to go back.	Insult, Shameful, Sadness
#Polling underway in the third phase of #LokSabhaElections2019 Voter turnout at 3:00 PM#Phase3 https://t.co/99K8OXSrCX	Neutral

RC5: A PoliEMO Dataset and Multi-label Classification in Indian Elections ->Dataset Finding

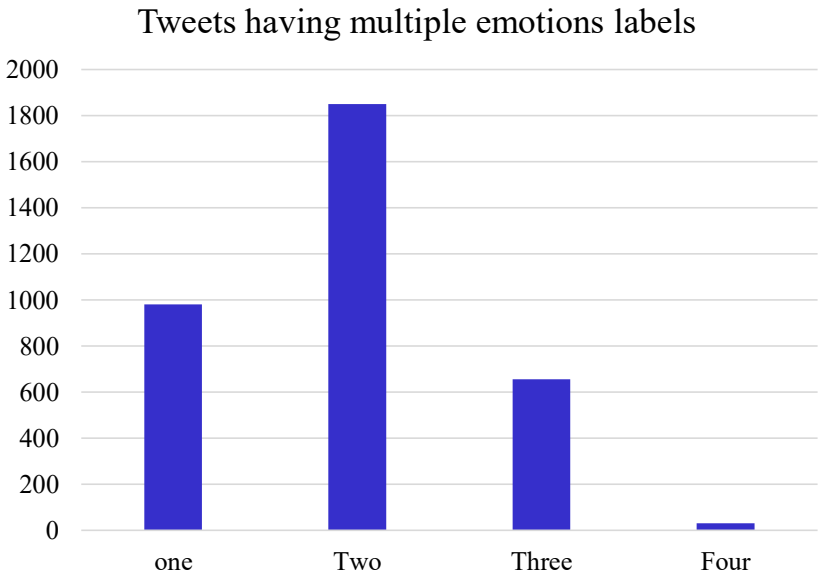


Figure 17: PoliEMO tweets count

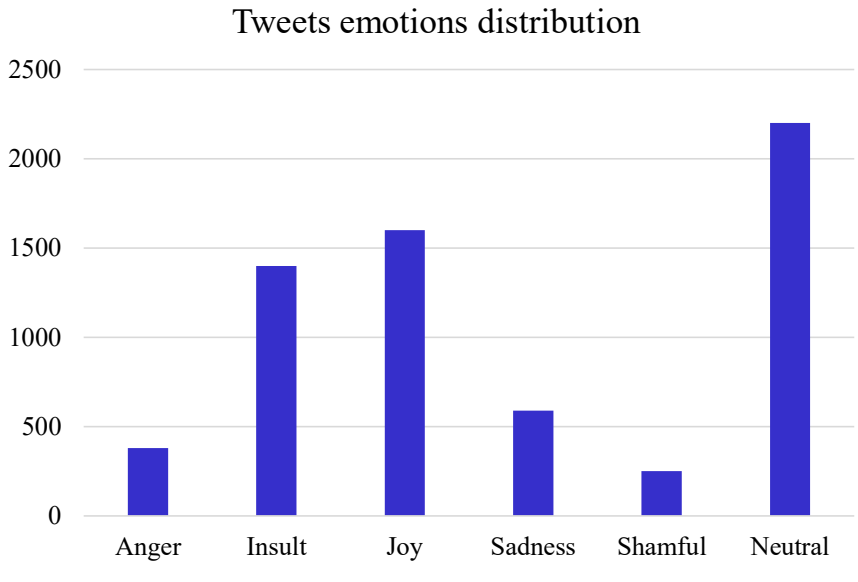


Figure 18: PoliEMO distribution of tweets

RC5: Political Emotion Multi-label classification in Indian Elections → Methodology for Multi-label Classification

Data Pre-Processing

- Removal of stop words, URL

Feature Extraction

- Term Frequency Inverse Document Frequency(TF-IDF)
- Word Embeddings (Word2vec)

Dataset: PoliEMO

- 3,512 tweets
- 6,792 emotional labels

Models for Multi-label Classification

- One-Vs-Rest
- Binary Relevance
- Classifier Chain
- Label Powerset
- Multi-label k Nearest Neighbours

Deep Learning Model

- LSTM
- Bi-LSTM

Transfer Learning Models

- BERT

Evaluation Parameter

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

RC5: A PoliEMO Dataset and Multi-label Classification in Indian Elections → Results

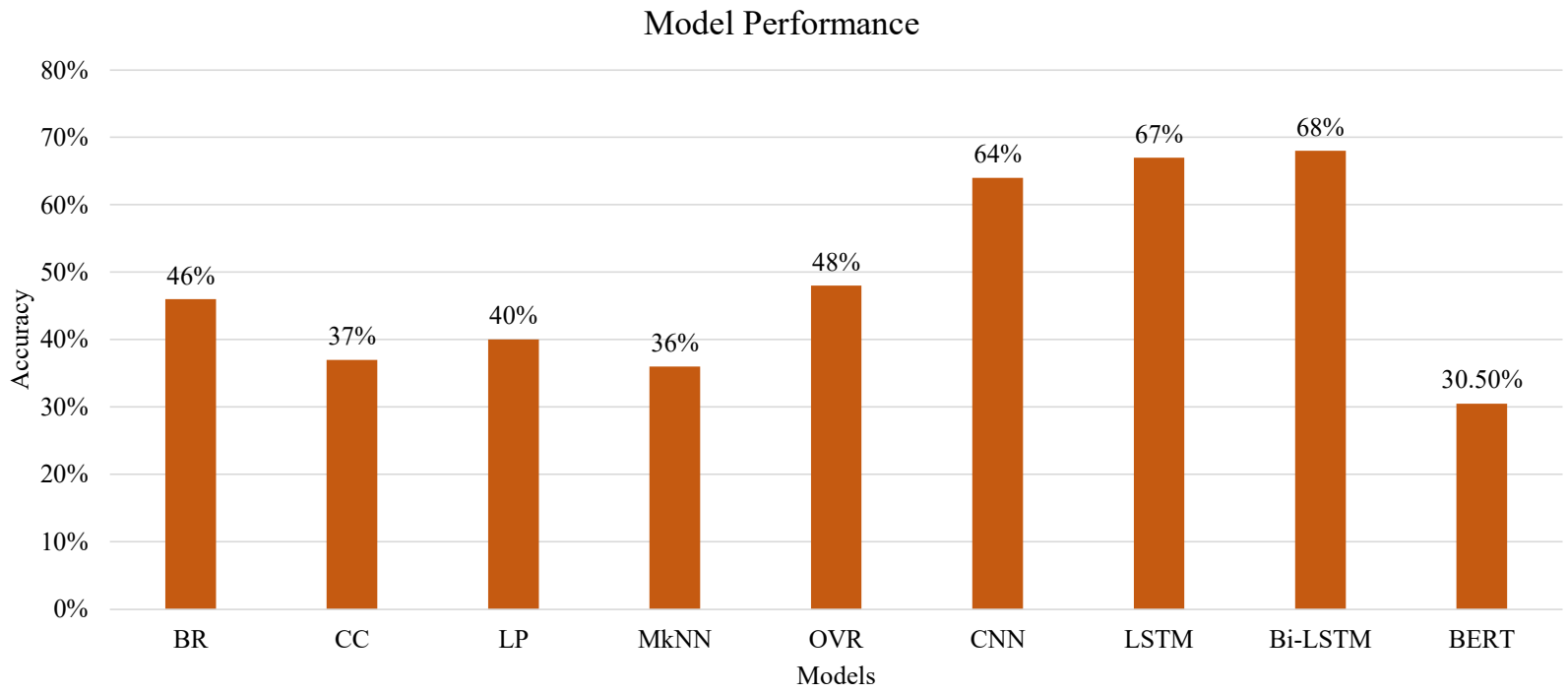


Figure 20: Model accuracy graph for multi-label emotions classification

RC5: A PoliEMO Dataset and Multi-label Classification in Indian Elections ->Multi-label classification results

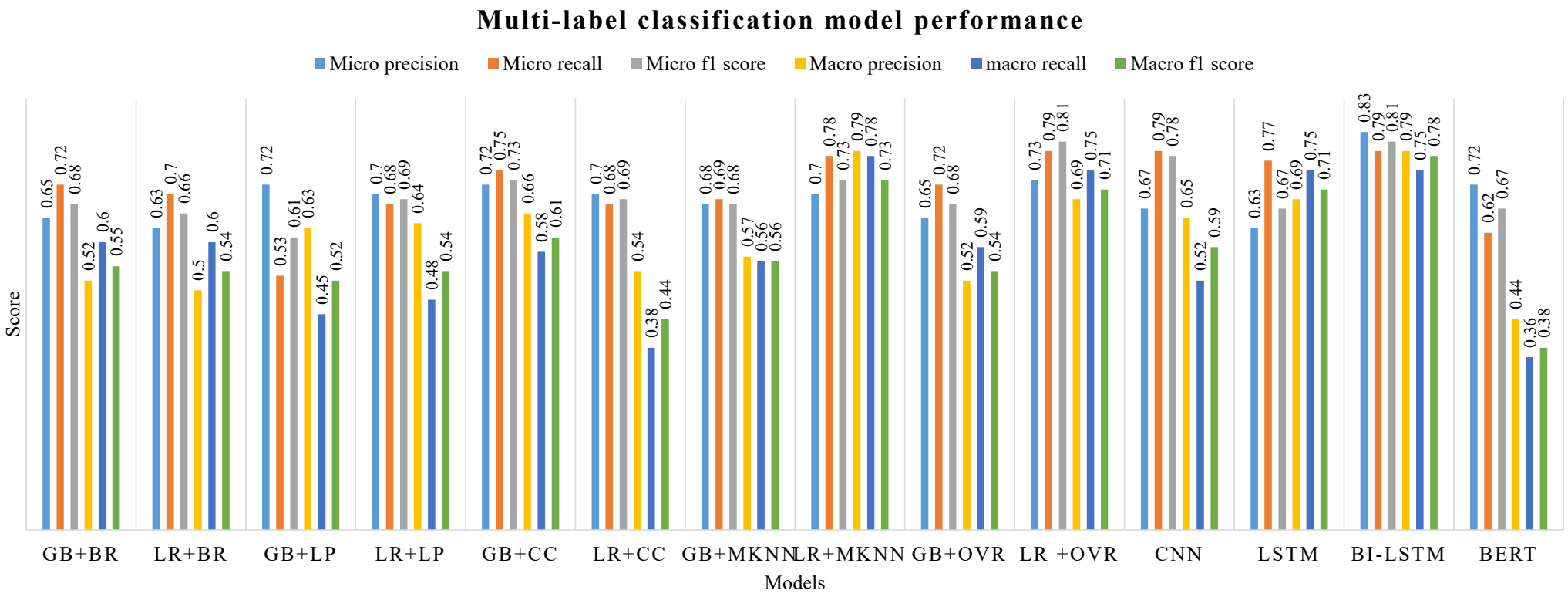


Figure 19: Performance evaluation of classification Models

RC5: A PoliEMO Dataset and Multi-label Classification in Indian Elections → Summary

- Generated a **PoliEMO**, a novel dataset in multi-label setup consisting of over **3,512 tweets** and **6,792 labels.**
- 1,850 tweets contain two emotions, 670 have three emotions, 31 tweets show the maximum of four emotions.
- Achieved 71% inter annotator agreement.
- The co-related emotions are found to be together.
- Achieved 68% accuracy with Bi-LSTM model.

Conclusion

1. Generated a **Novel-textual Dataset** for Indian General Election (IGE) of user tweet and opinion label.
2. Developed a **Opinion stance-level information (OSLI) hybrid model** that integrates both opinion and stance information to detect political polarization.
3. Generated a **multifaceted features dataset** which provides users profile, content and structure information to understand the political polarization.
4. Developed a **GCN-SBERT hybrid model** that utilize multifaceted features to perform multi-level stance analysis for polarization detection and also performed the **temporal analysis** of user activity.
5. Analyse the user political emotion and generate a **PoliEMO dataset** which provides a multi-label analysis of user emotion.

Acknowledgements

- Thanks to external examiner.
- Thanks to Internal Committee members Dr. Lakhveer Kaur & Dr. Kedar Nath Singh
- Thanks to my supervisors Prof. Shikha Mehta & Prof. Ponnurangam Kumaraguru
- Thanks to Precog Group.

List of Publications

1. A. Gupta and S. Mehta, "Automatic stance detection for twitter data." 2022 1st International Conference on Informatics (ICI). IEEE, 2022.

2. A. Surolia and S. Mehta, "Optimal Feature Selection for Retweet Prediction in Indian Election." 2023 Second International Conference on Informatics (ICI). IEEE, 2023.

3. A. Surolia, S. Mehta and P. Kumaraguru, “Deep Learning and Transfer learning to understand Emotions: A PoliEMO Dataset and Multi-label Classification in Indian Elections” in International Journal of Data Science and Analytics, Springer Nature Journal, Scimago, SCOPUS indexing and IF = 3.4 with H-index 31.

4. A. Surolia, S. Mehta and P. Kumaraguru, “Detection and characterization of political polarization using user opinion and stance features for Indian Election” to the Journal of Theoretical and Applied Information Technology, Scimago, Elsevier SCOPUS Indexing with H- index 39.

5. A. Surolia, S. Mehta and P. Kumaraguru, “A Graph-Transformer hybrid model for Political Polarization in Indian Elections” in Journal of Transactions on Asian and Low-Resource Language Information Processing, SCI indexing and IF = 1.8 (Communicated)

6. A. Surolia, and S. Mehta, “Political Polarization in Social Media”, in Transforming Digital Commerce, Accepted

References

1. McCoy, J., & Somer, M. (2022). Pernicious Polarization and Democratic Resilience. Democratic resilience: Can the United States withstand rising polarization, 61-92.
2. Negi, S., Buitelaar, P.: Suggestion mining from opinionated text. Sentiment Analysis in Social Networks, 129–139 (2017)
3. Mohammad, S. M., Sobhani, P., & Kiritchenko, S. (2017). Stance and sentiment in tweets. ACM Transactions on Internet Technology (TOIT), 17(3), 1-23
4. Morales, A.J., Borondo, J., Losada, J.C., Benito, R.M.: Measuring political polarization: Twitter shows the two sides of venezuela. Chaos: An Interdisciplinary Journal of Nonlinear Science 25(3) (2015)
5. Di Martino, E., Cinelli, M., Cerqueti, R., & Quattrociocchi, W. (2025). Quantifying Polarization: A Comparative Study of Measures and Methods. *arXiv preprint arXiv:2501.07473*.
6. Pecile, G., Di Marco, N., Cinelli, M., & Quattrociocchi, W. (2025). Mapping the global election landscape on social media in 2024. *PloS one*, *20*(2), e0316271.
7. Bor, D., Lee, B. S., & Oughton, E. J. (2023). Quantifying polarization across political groups on key policy issues using sentiment analysis. *arXiv preprint arXiv:2302.07775*.
8. Belcastro, L., Cantini, R., Marozzo, F., Talia, D., & Trunfio, P. (2020). Learning political polarization on social media using neural networks. *IEEE access*, *8*, 47177-47187.
9. López-Chau, A., Valle-Cruz, D., Sandoval-Almazan, R., & Sandoval-Almazan, R. (2019, June). Analyzing polarization through social media with artificial intelligence: The Mexican presidential election in 2018. In *Proceedings of the 20th Annual international conference on digital government research* (pp. 502-503).
10. Jiang, J., Ren, X., Ferrara, E.: Retweet-bert: political leaning detection using language features and information diffusion on social networks. In: Proceedings of the International AAAI Conference on Web and Social Media, vol. 17, pp. 459–469 (2023)
11. Dash, S., Mishra, D., Shekhawat, G., Pal, J.: Divided we rule: Influencer polarization on twitter during political crises in india. In: Proceedings of the International AAAI Conference on Web and Social Media, vol. 16, pp. 135–146 (2022)
12. Lyu, H., Luo, J.: Understanding political polarization via jointly modelling users, connections and multimodal contents on heterogeneous graphs. In:Proceedings of the 30th ACM International Conference on Multimedia, pp.4072–4082 (2022)
13. Fang, Z., Xu, L., Song, G., Long, Q., Zhang, Y.: Polarized graph neural networks. In: Proceedings of the ACM Web Conference 2022, pp. 1404–1413 (2022)
14. Tran, G.T., Nguyen, L.V., Jung, J.J., Han, J.: Understanding political polarization based on user activity: a case study in korean political youtube channels. Sage Open 12(2), 21582440221094587 (2022)

15. Horawalavithana, S., Ng, K. W., & Iamnitchi, A. (2021, June). Drivers of polarized discussions on twitter during venezuela political crisis. In *Proceedings of the 13th ACM Web science conference 2021* (pp. 205-214).

16. Fleiss, J. L. (1971). Measuring nominal scale agreement among many raters. Psychological bulletin, 76(5), 378.

17. Tyagi,A.,Field,A.,Lathwal,P.,Tsvetkov,Y.,Carley,K.M.:Acom putational analysis of polarization on Indian and Pakistani social media.In:InternationalConferenceonSocialInformatics,pp.364 379. Springer, Cham (2020)

18. Yang, J., Jiang, L., Wang, C., Xie, J.: Multi-label emotion classifi cation for tweets in weibo: method and application. In: 2014 IEEE 26th International Conference on Tools with Artificial Intelligence (ICTAI). pp. 424–428. IEEE Computer Society (2014) 58.

19. Zhang,X., Li, W., Ying, H., Li, F., Tang, S., Lu, S.: Emotion detec tioninonlinesocialnetworks:amultilabellearningapproach.IEEE Internet Things J. 7(9), 8133–8143 (2020) 59.

20. Zou, H., Wang, Z.: A semi-supervised short text sentiment classi f ication method based on improved BERT model from unlabelled data.J.ofBigData10(1), 1–19 (2023)

21. Hitesh, M., Vaibhav, V., Kalki, Y.A., Kamtam, S.H., Kumari, S.: Real-time sentiment analysis of 2019 election tweets using word2vec and random forest model. In: 2019 2nd International Conference on Intelligent Communication and Computational Techniques (ICCT), pp. 146–151 (2019). IEEE.

22. Gaikar, D., Sapare, G., Vishwakarma, A., Parkar, A.: Twitter sentimental analysis for predicting election result using lstm neural network (2019)

Khare, A., Gangwar, A., Singh, S., Prakash, S.: Sentiment analysis and sarcasm detection of Indian general election tweets. (2022)

Thank you!!!

Any Questions?