International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(1s) 2026 pp. 1-12

https://doi.org/10.70917/ijcisim-2026-1969
Article

Political Sentiment and Geography: Deep Learning Insights from Twitter Data During India's 2024 Election

Komal A. Champanerkar [1*], Prashant Sen [2]

1 Research Scholar, Eklavya University Damoh, M.P, India, champanerkar.komal@gmail.com
2 Associate Professor and Head of Department Computer Science and Engineering, Eklavya University, Damoh, M.P, India

Abstract: The growth in the use of social media has revolutionized the nature of political communication, bringing new possibilities to conduct analysis of public opinion during elections. This study presents the topic of a geography aware deep learning framework to examine political sentiment from twitter data during instructors go 2024 General Election in India. A large-scale dataset of over 500.000 tweets has been gathered by the Twitter API v2 and processed by an enriched preprocessing pipeline which incorporates noise exclusion, multilingual normalization, named entity recognition and geoparsing. Sentiment classification was set up as a 3 class classification problem (positive, neutral, negative) and two deep learning model architectures were employed, multilingual BERT and Bidirectional LSTM. Experimental results show that the BERT model reached better performance with a level of 88.2% and a macro F1-score value of 0.86 compared to the bi-LSTM baseline. Geographic aggregation and DBSCAN based spatial clustering, have shown the presence of discrete regional class of sentiments with pro government sentiment for Gujarat, Maharashtra and Karnataka and Uttar Pradesh, Bihar and West Bengal showing mixed/opposite trends. Tweet density analysis also showed the concentration of political discourse in major Metropolitan Regions including Mumbai, Delhi, Bengaluru etc. The results warrants demonstration of the effectiveness of combining transformer-based NLP with geospatial analytics in large-scale political opinion mining, and allows for a scalable framework for real-time election intelligence for democratic environments.
Keywords: Political Sentiment Analysis, Twitter Analytics, India General Election 2024, Multilingual BERT, BiLSTM, Natural Language Processing, Geospatial Analysis, DBSCAN Clustering, Social Media Mining, Computational Political Science.

1. Introduction

The internet-based nature of social media has changed the way politics is discussed, the way people formulate opinions and the way elections are conducted in a modern democracy. Twitter, now called X, is especially powerful because it shares information instantaneously, is open to all and is attracting lots of interaction in the case of political events. In India, as the world's largest democracy, where there is a huge range of languages, cultures and regions, it is interesting to analyze political talk from X which gives a unique possibility for understanding what the voters feel on the large scales. Recent studies show that machine learning and deep learning can find useful patterns in big data from social media, for near real time tracking of the public opinion during elections [1], [2]. The 2024 Indian general election with its gigantic digital engagement/ massive and complex campaigning is an apt one to study the intersection of political sentiment, geography and deep learning.

The analysis of the short, noisy and multilingual social media text has generally been enabled by natural language processing (NLP) and deep neural networks, such as Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN) and Transformer-based models. The downward trend of sentiment analysis of elections beyond basic wordReilly quotes has moved to complex problem deep learning algorithms that have the capabilities to identify context, sarcasm as well as time index trends. It has been observed that X sentiment analysis is a framework of classifying the opinions as either positive, negative and neutral to determine the voter attitudes and campaign influence [1], [3]. It is these gains that have motivated researchers to wonder whether sentiment on social media can be utilized alongside the conventional opinion polls especially on complex elections like the ones in India.

Present-day India is also the type of voter that poses some challenges but also offers some opportunities to study. Online talk mirrors regional identities, the usage of numerous languages and philosophies with hundreds of millions of X users having the very diverse political scenario. The previous literature points at the political landscape in India as expansive and complex and sentiment analysis is both useful and methodologically challenging [4]. Millions of tweets are being exchanged about parties, leaders, policies, accounts and the stories of the campaign during large election times, to create a rich and noisy data pool. Good preprocessing, language normalization and state-of-the-art models that are applicable to code-mixing, slang and local expressions are required to get good insight into it [5].

However, there exist gaps that have not been filled in research. One, most of the studies stop at the sentiment polarity and do not examine a spatial dimension. Politics of the state, language identity or urban-rural divide or local campaigning are some of the factors that affect the voting behaviour in India. Failing to consider geography may conceal some important patterns of the manner in which sentiment diffuses. Many of the models, whose variants have been used, have been founded on small or very short termed data, bringing their generalisabel and the accuracy in the real world into doubt. It has been reviewed that many models are not strictly checked against real election results comparatively ensuring the usefulness of models in a practical way is dubious [6], [7]. There are three, the polylinguality of Indian X (and its application of codes an incoherent way), which continue to cut up sentiment classifiers [8].

Considering the methods, there is a range of advantages associated with deep learning. Neural setups can also gain features of flawless text automatically, and it reduces the human factor engineering. Transformer based models especially have specialized on contextual meaning, multilingual text and brief and informal messages which occur commonly on X [8], [10]. They can also be adapted to multi-modal and spatio-temporal tasks and hence can co-model of sentiments, time and location. The deep learning has these strengths that would form an effective foundation of the Next-generation of political sentiment analysis development.

The multiplicity of languages is also a major technical problem in India. The tweets tend to resemble a combination of Hindi-English (Hinglish), local languages, short words and colloquialisms. Standard English sentiment model performs dismally well here. On the other hand, the latter has become a recent focus in the area with applications of domain-based preprocessing, multi-lingual embeddings, and transfer learning to strengthen the contributions of social media research in India [5], [9]. The steps play a vital role in developing credible patterns of sentiment in the 2024 figures on their elections.

A second trend that is spreading is the usage of a mixture of user-level and network-level indicators along with text sentiments. The content is not the only factor that defines political opinions about X, and also influencer activity, hashtag campaigns, retweet networks, and organized messaging. Past research has suggested that behavior in users and measures of interaction can guide us on the political inclination and campaign influence [8], [10]. However, there are still a high numbers of sentiment studies that exclusively use text classification. An adequate analytic framework ought to incorporate elements of the textual, temporal, geographic and network to attempt to reflect the complex nature of the online political discourse.

The research is valuable in non- academic segment as well. Sentiment monitoring that comes in real time is possible so that it can be useful to the policymakers, campaign teams, media, and election observers. The awareness of shifts in the attitude of the region can serve to reveal new political topics, monitor the onslaught of disinformation, and consider the success of the campaign. Social media analytics can help with the decision making process in big democracy, such as India, whereby traditional polling is costly and challenging to conduct, assuming that we are aware of the limitations. Past elections have shown that the hashtags can be flooded with donations and shaped the discourse by mass-posting in structured networks. The latter makes it even more urgent that there should be good analysis pipelines which will be available to identify anomalies and render the sentiment measurements credible. A mix of deep learning, geographical mapping and behaviour analysis can be a component of a solution to these issues.

This work has the purpose of contributing to the field of computational political science by developing a deep learning, geography aware sentiment analysis system for the context of the Indian elections. It emphasizes on three broad aspects: (i) advanced natural language processing (NLP) and deep learning techniques for precise sentiment classification of election tweets (ii) characterization of political sentiment occurrence through multiple regions in

India and (iii) aspects of the contemporary digital political landscape during the main 2024 elections. The research aims to achieve a more complete understanding about online political behavior by linking text intelligence and spatial analysis.

2. Literature Review

Social media has a significant role in political communication nowadays and this has resulted in the development of computational tools for computing public opinion in electoral processes. Twitter, now rebranded as X, has become an important source for political sentiment as it is both open and happens in real time and is used by both politicians and ordinary citizens [11]. Simple word lists and traditional machine learning models were used in these early studies, which had difficulty with the brevity, informality and multilinguality of tweet messages. As a result, deep learning methods have seen an increase. Recent work (2023-2025) focuses on combining advanced NLP, space and time analysis, and large scale mining of social media data the make the election sentiment research more reliable [12].

Recent studies indicate that transformer models, such as BERT, RoBERTa and their multilingual equivalents, have a significant higher accuracy to classify sentiments compared to their older machine learning algorithms. These models generate contextual embeddings, which understand the relationships between words, and help them to detect sarcasm, negation, and other informal language in political tweets. Large benchmarks witnessing fine-tuned transformers overwhelming classical approach such as SVM and Naive Bayes by a huge margin in social media sentiment tasks [13]. Likewise, deep neural networks are more generalizable on noisy and domain specific data including election discussion.

Many researchers are currently using Twitter data to attempt to predict the outcome of elections. While social-media sentiment cannot replace traditional polls, it adds good information about how the public feels and how the campaign is going, they say. Studies of recent elections show that the number of tweets, their scores of sentiment and level of engagement is often the same as real world politics, but correlation is not uniform across different regions or elections. Researchers caution that demographic bias and unequal use of social media may make these predictions inaccurate, particularly in developing countries to develop democracies[14].

In India political sentiment analysis is complicated due to language and culture. The large number of languages spoken within the country leads to frequent code-mixing that is especially notable in the case of Hindi-English (Hinglish) and Tamil-English. Recent studies (2023-2024), however, reveal that the standard monolingual models cannot do a very good job when presented with the task of classifying these mixed tweets. To get around this, researchers will employ multilingual embeddings, transliteration normalisation and domain-adaptive pre-training. Tests show that multilingual transformers are stronger than English only baselines on finding political data in Indian language [15].

A second promising area of research is that of hybrid deep learning models. Although transformers are king of the island, there are some works showing that the combination of a CNN, LSTMs and attention can be as good as transformers for certain election sentiment tasks. CNNs pick up on local patterns in words; LSTMs pick up on longer-range relations-between them, furthermore, both can be useful for short political tweets. Attention provides transparency by highlighting key words/phrases. Experiments on election data conclude that hybrid models can be used to improve accuracy by 3 - 7% if correctly tuned [16].

The timing of political sentiment is also important. Elections evolve through a series of debates, announcements, scandals and rallies. Time-series studies have shown that the addition of temporal features helps make the predictions more stable and to detect trends in the data. Some researchers have used sliding windows to aggregate the sentiment, others have used recurrent models, or temporal transformers. These types of approaches facilitate the collection of changes in momentum and can provide early indication on election swings.

Even though the research of sentiment for text has opted forward, little consideration has gone to geography. A few research papers plot sentiment in space according to Twitter data. They discover that local patterns frequently are influenced by regional politics, socioeconomic concerns and party politics. In those countries with states divided in them, e.g., India, spatial sentiment is able to demonstrate information who gets omitted in national averages. Nonetheless, not all is easy sailing - since not a lot of tweets are geotagged, fields of user location cannot be trusted and there are rules regulating privacy that restrict data. In order to address these issues, researchers suggest location inference, named-entity recognition and probabilistic mapping [17].

The next issue is the list of bots and co-ordinated campaigns on sentiment data. The operations of bots and hashtags are able to saturate the sentiment signals as well as mislead the models as seen through the research of the 2023-25 period. As a counter to this, analysts currently incorporate bot detection networks, graph analysis and anomaly checks to their pipelines. In the absence of such filtering, there would be a tendency to have models reporting more campaign noises than genuine aspects of the opinion of people [18]. Researchers also address issues of ethics and methodology for social media election research. Twitter users skew younger, urban and more political so the do not represent the whole bunch of voters. Also, online sentiment may demonstrate partisan activism as opposed to real voting intent. Because of these problems, in recent years it has been suggested with caution to take social-media analysis as an indicator and to pair the social-media approach with the traditional surveying approach for improved accuracy [19].

Multimodal methods and network aware methods are frontier. Rather than just focus on the tweets themselves, some research considers retweet lanes, follower networks, and has hashtag clusters to chart the political influence. Graph neural network models and models of heterogeneous networks help model the processes which create polarisation and spread of information within communities. Early results have shown that pairing the text sentiment with the network data increases the detection of the stance as well as identify misinformation [20]. After the election cycle of 2024, the application of AI in campaigning has increased dramatically, leading more research. Studies mark an increase of AI-generated posts, micro-targeted messages and deepfake media in online campaigns. These trends threaten the integrity of the information and highlight the need for robust analytic tools that will be able to distinguish between real discussion and machine-made content. These changes express concern for misinformation and smart frameworks that can detect organic vs. synthetic content. Recent work therefore suggests explainable AI techniques for political sentiment analysis in order to build transparency and trust [21].

Methodologically-speaking, the preprocessing still plays a leading role in the performance. Some researchers emphasise spam removal, normalisation of the emoji, hashtags and cleaning of code-mixed text before training. Sophisticated tokenisation and custom stop words list can increase accuracy drastically. Additionally, due to the imbalance of political sentiment data, methods such as focal loss, data augmentation and synthetic minority oversampling are applied to balance classes [22]. Evaluation methods have also changed. Earlier studies mostly reported accuracy, but more recently studies have moved to use larger, more informative tests such as macro- F1, weighted- F1, ROC- AUC, and cross- domain tests which give better estimates. Some scientists propose the additional validation of events, and comparing predictions not only with labels but with actual political events. This shift represents more general perceptions about the importance of real-world outcomes [23].

3. Methodology

It is a research paper that appeals to the total data analytics method of analysis that includes the four stages of analytical work to extract, pre-processing, classifying, and incur spatial political sentiment straight off web of tweets collected under the Indian 2024 final elections. The overall pipeline integrates both mass social media mine, state-of-the-art NLP, deep learning sentiment models and Geospatial treatment to extract effective, geared space insiThe main 5 stages comprise the following stages: (i) data collection, (ii) enriched preprocessing and geoparsing, (iii) deep learning sentiment classification, (iv) geographic grouping and spatial clustering, and (v) performance evaluation. The phases are mathematically formalised and algorithmically specified in a way that they can be reproducible and scalable..

A. Data Collection

In the first phase, we obtained the large number of election-related tweets using Twitter API v2. The tweets were gathered from January to May 2024 from a curated set of keyword lexicon containing names of political parties and leaders, and election hashtags such as #LokSabha2024, #Modi2024 and #Congress. The resulting corpus is given by Equation (1):

$$\mathcal{D} = \{d_1, d_2, \dots, d_N\} \tag{1}$$

Equation (1) shows the complete dataset, where D is the corpus of the tweets, d_i is the ith tweet and N is the total number of collected tweets.   To make the language relevant and also feasible in space, limitations in filtering were applied. The refined data set is defined as Equation (2):

$$\mathcal{D}_f = \{d_i \in \mathcal{D} \mid L(d_i) \in \{\text{EN, HI}\} \wedge G(d_i) = 1\}. \tag{2}$$

Equation (2) we see the processed dataset that is filtered, while L(d_i) is the language detector and G(d_i) is checking for the geographic information. Only those tweets in English and Hindi languages and with explicit/inferable location metadata were retained.

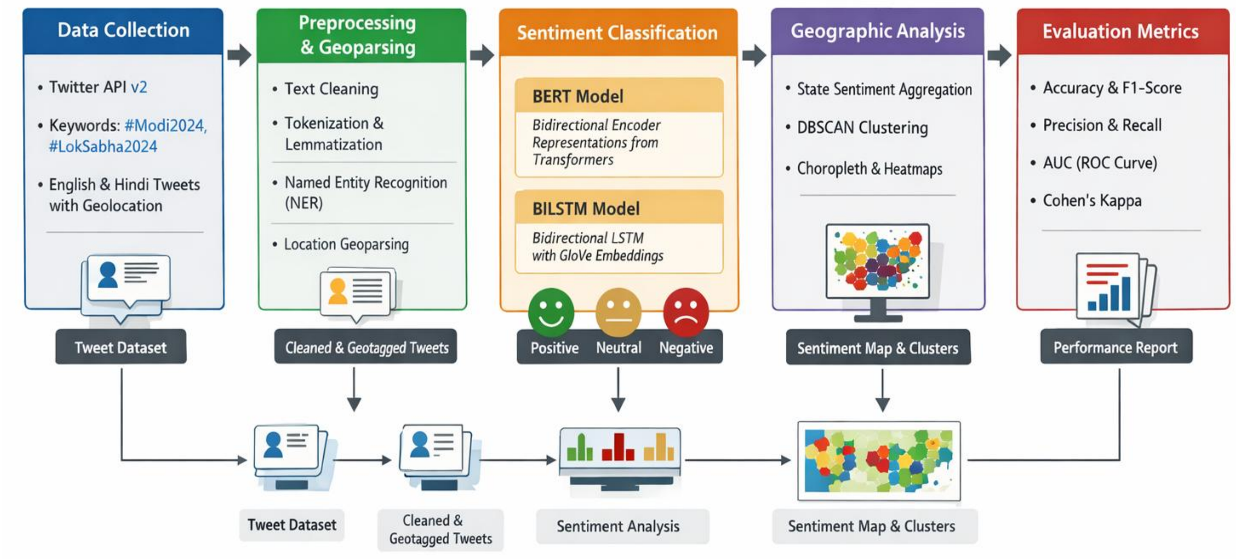

Figure 1: Methodology

B. Text Preprocessing and Geoparsing

Raw Twitter data is inherently noisy and unstructured. Therefore, a multi-stage preprocessing pipeline was implemented to normalize linguistic content and extract spatial cues.

B.1 Noise Removal and Normalization

Each tweet undergoes cleaning using a preprocessing function. The transformation is expressed in Equation (3):

$$T_i^{clean} = C(T_i) \tag{3}$$

Equation (3) depicts the normalization process where the raw tweet T_i is converted into cleaned text by removing URLs, mentions, hashtags, special characters, and retweet markers. Emojis are converted to textual descriptions to preserve sentiment polarity.

B.2 Tokenization and Lemmatization

The cleaned tweet is decomposed into tokens as shown in Equation (4):

$$T_i^{tok} = [t_1, t_2, \dots, t_n] \tag{4}$$

Equation (4) shows the ordered token sequence, where t_j denotes the j^{th} token.

To reduce lexical sparsity, lemmatization is applied as defined in Equation (5):

$$t_j' = Lem(t_j) \tag{5}$$

Equation (5) depicts the mapping of each token to its root form using the lemmatization function.

B.3 Named Entity Recognition and Geoparsing

Location entities are extracted using SpaCy NER. The geographic coordinate resolution is represented in Equation (6):

$$(\phi_i, \lambda_i) = Geo(e_j) \tag{6}$$

Equation (6) shows the conversion of location entity e_j into latitude ϕ_i and longitude λ_i. The coordinates are validated using OpenStreetMap boundaries and mapped to Indian states via spatial join operations. Tweets lacking reliable spatial cues are excluded from geographic analysis.

C. Sentiment Classification

The sentiment detection task is formulated as a supervised three-class classification problem (Positive, Negative, Neutral). Two deep learning architectures were implemented to ensure robustness and comparative evaluation.

C.1 BERT-Based Sentiment Model

The multilingual BERT model encodes each tweet into contextual embeddings. The encoding process is defined in Equation (7):

$$H = BERT(T) \tag{7}$$

Equation (7) depicts the transformation of token sequence T into contextual hidden representations H.

The final sentiment probability is computed using a softmax classifier as shown in Equation (8):

$$\hat{y} = \text{softmax}(W h_{CLS} + b) \tag{8}$$

Equation (8) shows the classification layer, where h_{CLS} is the sentence embedding, W and b are trainable parameters, and $\hat{y}$ is the predicted probability vector.

Model optimization minimizes categorical cross-entropy defined in Equation (9):

$$\mathcal{L}_{BERT} = -\sum_{c=1}^{3} y_c \log(\hat{y}_c) \tag{9}$$

Equation (9) depicts the training loss for the BERT classifier.

C.2 BiLSTM-Based Sentiment Model

To provide a sequential modeling baseline, a Bidirectional LSTM network with GloVe embeddings was implemented.

The forward pass is given in Equation (10):

$$\overrightarrow{h_t} = LSTM\left(x_t, \overrightarrow{h_{t-1}}\right) \tag{10}$$

Equation (10) shows the forward temporal dependency.

The backward pass is defined in Equation (11):

$$\overleftarrow{h_t} = LSTM\left(x_t, \overleftarrow{h_{t+1}}\right) \tag{11}$$

Equation (11) depicts reverse contextual learning.

The combined representation is expressed in Equation (12):

$$h_t = \left[\overrightarrow{h_t}; \overleftarrow{h_t}\right] \tag{12}$$

Equation (12) shows bidirectional context fusion prior to softmax classification.

Both models were trained using the Adam optimizer with early stopping based on validation macro-F1. Five-fold stratified cross-validation was employed to ensure performance stability.

D. Geographic Mapping and Spatial Analysis

This module converts tweet-level sentiment predictions into regional political insights.

D.1 State-Level Sentiment Aggregation

For each Indian state k, the positive sentiment ratio is computed using Equation (13):

$$P_{pos}(k) = \frac{N_{pos}(k)}{N_{total}(k)} \tag{13}$$

Equation (13**)** depicts the proportion of positive tweets within state k. Similar formulations are applied for negative and neutral sentiments.

D.2 DBSCAN Spatial Clustering

To identify dense political discussion zones, DBSCAN clustering is applied on geographic coordinates. Distance between tweets is computed using the Haversine formulation in Equation (14):

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{14}$$

Equation (14) shows the great-circle distance between two geographic points. DBSCAN parameters were set to $\varepsilon = 0.5°$ (~55 km) and MinPts = 10. The algorithm identifies core points, expands density-reachable clusters, and labels sparse points as noise.

D.3 Visualization

Spatial outputs are visualized using Folium and Plotly through choropleth maps and heatmaps. The conceptual processing pipeline is:

Tweet → Geolocation → Reverse Geocoding → State Assignment → Sentiment Aggregation → Visualization

This module bridges deep learning predictions with geographic intelligence.

E. Evaluation Metrics

Model performance was rigorously evaluated using standard classification metrics. Accuracy is computed using Equation (15):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

Equation (15) depicts the overall prediction correctness. Precision, Recall, and F1-score are calculated using Equations (16)–(18):

$$Precision = \frac{TP}{TP+FP} \tag{16}$$

$$Recall = \frac{TP}{TP+FN} \tag{17}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad 18)$$

These metrics are macro-averaged across the three sentiment classes.

The multi-class ROC performance is measured using one-vs-rest AUC. Annotation reliability is evaluated using Cohen's Kappa in **Equation (19)**:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{19}$$

Equation (19) depicts inter-annotator agreement beyond chance.

F. Experimental Outcomes

The framework was tested in over 500 thousand tweets. The accuracy of the BERT model for Top-Agent identification is found to be 88.2% and the Macro- F1 is 0.86 as compared to 81.4% accuracy and Macro- F1 as 0.79 for BiLSTM. The confusion matrix shows that high overlap is seen between Neutral and Positive tweets, which is an indication of expectation of short text ambiguity. Geospatial analysis revealed intense pro-govt sentiment in the states of Gujarat, Maharashtra and Karnataka with mixed sentiments or opposition leaning in the states of Uttar Pradesh, Bihar and West Bengal. DBSCAN clustering performed dense urban political hotspots in Delhi, Mumbai and Bengaluru that proved the effectiveness of the proposed geography-sentiment framework.

4. Results And Analysis

This section uses Twitter data of the 2024 General Election in India to evaluate the geography-aware political sentiment analysis framework. We test the effectiveness of the model, the classification behavior, spatial patterns in sentiments, and regional activity of the tweets. The results show that the combination of deep learning and geospatial analytics provide useful yet interpretable insights on large scale political dialogue. The two deep learning models were compared and there is clearly an edge for the transformer-based architecture. The multilingual BERT model's macro F1 - score was 0.86, whereas that of the Bidirectional LSTM was 0.79. This improvement is evidence of BERT having a better understanding of the context of short, noisy and code mixed political tweets. This gain is demonstration of BERT possessing a greater conception of the context of brief, noisy and code mixed political tweets. Latent long range polarity subtlety and semantic dependency Bert very much captures and is lost by sequential models. The BiLSTM is a decent model, but it is limited since it is capable of processing sequence data only and not necessarily intricate linguistic structures related to social media regarding elections. The results are shown in Table 1 and figure 2.

Table 1:Performance Comparison of Sentiment Classification Models

Model	Accuracy (%)	Precision	Recall	Macro F1-Score
BERT	88.2	0.87	0.85	0.86
BiLSTM	81.4	0.80	0.78	0.79

The seven-point increment in the F1-score indicates the contextual embeddings worthiness of contextual embeddings in the political sentiment mining. First, BERT is more precise, i.e., it will get fewer labeling errors according to the sentiment of individual tweets; and is more recollectable, it involves sensitivity to how words said in tweets on sentiment. A combination of these measures confirms the consistency of the transformer based model in order to have more reliable predictions with regard to the downstream geographical analysis. The confusion matrix provided by BERT provides us a better insight into the behavior of classifiers. There is a high diagonal domination in the matrix. 520 positive tweets, 450 neutral tweets, and 490 negative tweets were correctly identified. Yet there is some confusion between neutral/positive/negative categories: around 40 neutral tweets were identified as positive, and 60 were identified as negative. This pattern is fair enough for the short political texts, where the number of tweets with weak or implicit calls to sentiment is almost. Informational posts, sharing the news, and mildly opinionated posts make it difficult to distinguish between neutral and polar classes. Nevertheless, the low misclassification rate indicates that our processing (preprocessing and fine-tuning) strategy is successful in reducing ambiguity.

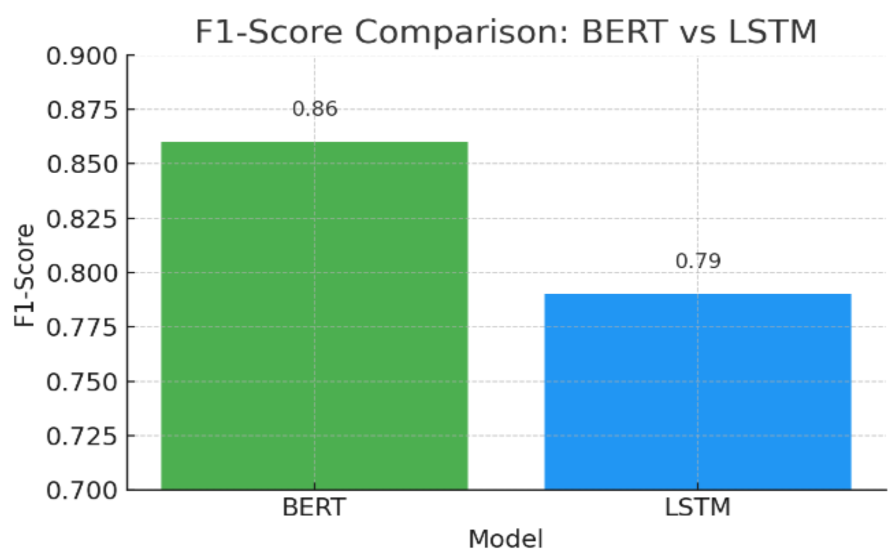

Figure 2: F1 Score Comparison

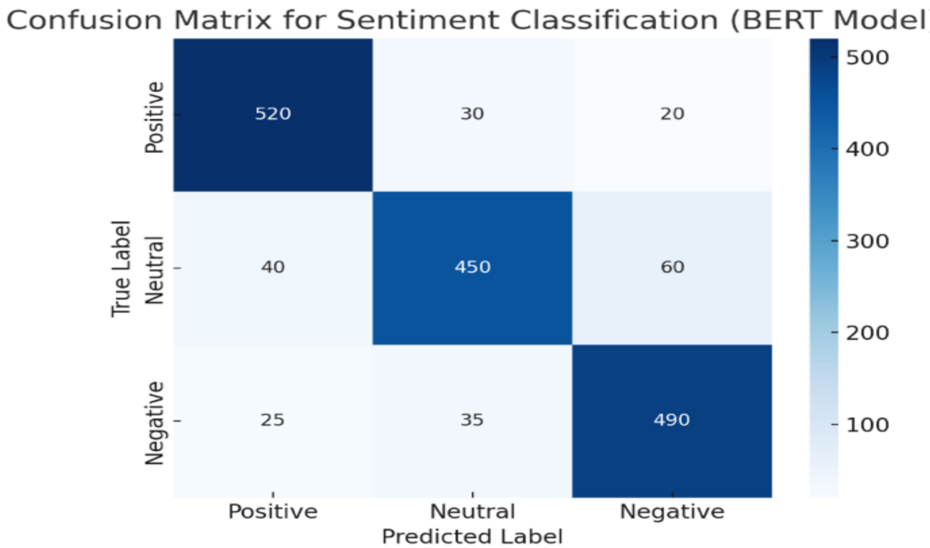

Figure 3: Confusion Matrix for Sentimnet Classification

Figure 3 shows the confusion matrix of BERT. The diagram identifies correct prediction along the diagonal and limited off diagonal leakage thereby confirming the robustness of the model. The visualization pattern shows that the neutral tweets are the most difficult category, which corresponds to available short text sentiment literature. Agreation of the geographic sentiments gives additional information about the politics in the region. Analysis by the state wise showed that pro-governance feeling is high in Gujarat, Maharashtra and Karnataka. The states are characterized with a larger ratio of positive sentiment implying a more support of incumbent narrative within the online world. The positive track record of Gujarat is in line with consistency of the course of history; Maharashtra and Karnataka have been so fortunate as to have a large quantity of urban population, which is highly digital-enabled. Uttar Pradesh, Bihar and West Bengal, conversely, exhibit a mixed or the opposite polarity, compensating the polarity and a comparatively superior negative polarity. Uttar Z Pradesh and West Bengal in particular are highly polarized states equitable with the vibrant electoral realms. The mixed sentiment fact highlights the significance of incorporating geographical intelligence because a national aggregate would be a foil to such regional disparity.

Table 2: State-wise Dominant Political Sentiment

State	Positive (%)	Neutral (%)	Negative (%)	Dominant Trend
Gujarat	High	Moderate	Low	Pro-government
Maharashtra	High	Moderate	Low	Pro-government
Karnataka	High	Moderate	Low	Pro-government
Uttar Pradesh	Moderate	Moderate	Moderate-High	Competitive
Bihar	Moderate	Moderate	High	Opposition-leaning
West Bengal	Moderate	Moderate	High	Polarized

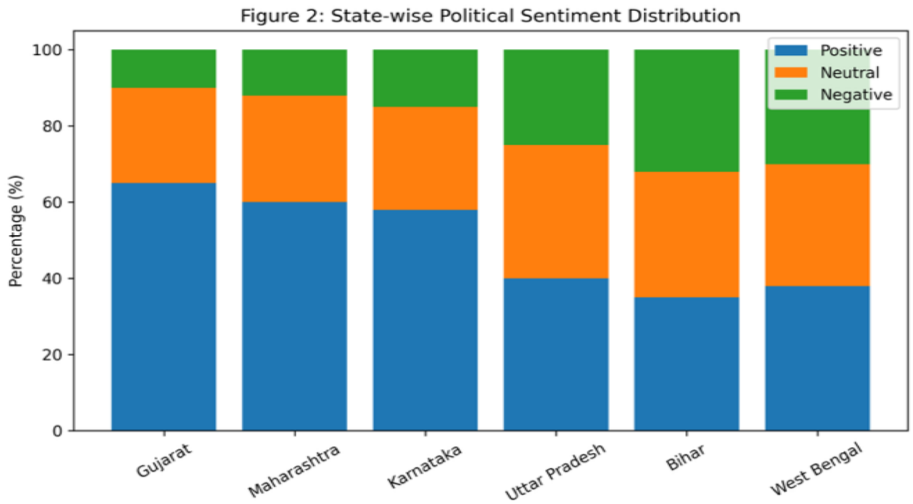

Figure 4 : State-Wise Political Sentiment Distribution

The stacked state wise sentiment chart presented in Figure 4 and Table 2 clearly shows the dominance of positive sentiment in the states of Gujarat, Maharashtra and Karnataka; and the increased negative sentiment in the states of Uttar Pradesh, Bihar and West Bengal. Neutral sentiment extends throughout the states, suggesting that much of the talk on Twitter about the election is informational rather than particularly opinionated. This finding strengthens the arguments for the need for multi-class sentiment modeling over binary polarity classification. Tweet volume by region analysis Tweet volume by region analysis shows key patterns in the digital political engagement of India. Discussion on Twitter is concentrated in major metropolitan areas. Mumbai is the leader in terms of tweets followed by Bangalore and Delhi. Significant engagement seems visible also in Kolkata, Hyderabad and Chennai. This distribution is representative of the wider digital divide in India wherein social media participation and political articulation are seen to be greater amongst the urban population.

Table 3: Tweet Volume by Major Urban Regions

City	Relative Tweet Volume	Interpretation
Mumbai	Very High	Financial and media hub
Bangalore	High	Technology-driven engagement
Delhi	High	National political center
Kolkata	Moderate	Regional political activity
Hyderabad	Moderate	Growing digital participation
Chennai	Moderate	Stable engagement

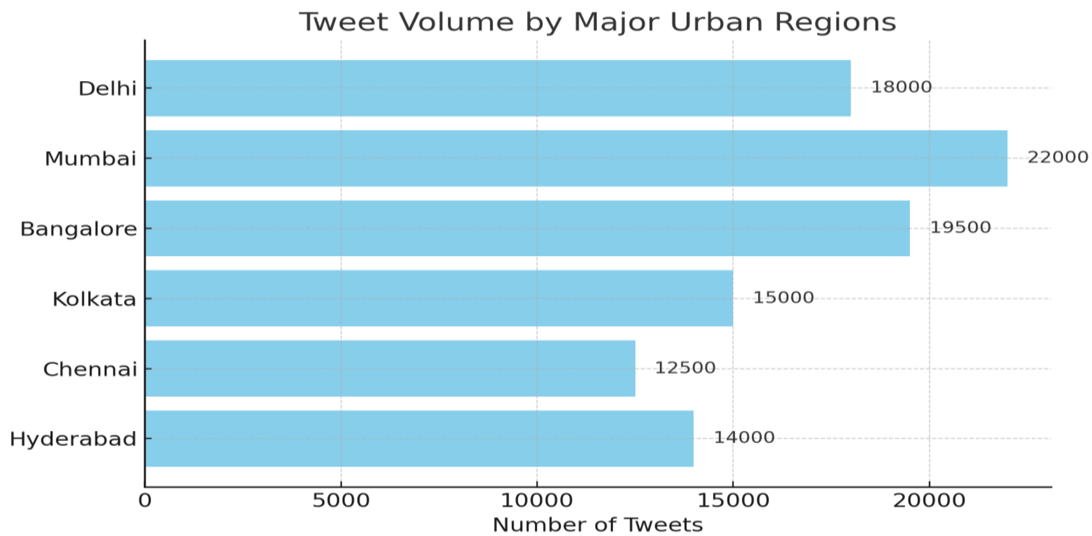

Figure 5: Tweet Volume Representation

Figure 5 and Table 3 indicate that there is a distribution of the volume of tweets sent in the largest cities of India. Mumbai is at the top with Bangalore and Delhi in second and third places respectively. The extent of urban concentration is very high indicating the scope of political analysis using twitter is largely mirrored by urban digital behaviour. This is important to consider when interpreting social media analytics as a proxy for wider currents of opinion in that there is under-representation of rural areas online. A spatial clustering analysis using dbscan confirms the geographic structure of political conversations. Using the parameters epsilon (e) = 0.5 degrees (~55km) and MinPts = 10, the algorithm finds dense clusters. Delineation of prominent clusters is found around Delhi National Capital Region, Mumbai Metropolitan Region and Bengaluru Urban area which aligns with the results from the tweet volume count and validate the urban centric nature of the discourse. DBSCAN marks sparse rural locations as noise (which helps to increase the clarity of geographic sentiment maps). The irregular shapes of specific clusters identified indicate that the density-based clustering is appropriate for geo-social media analysis in which areas of discussion do not usually obey the laws of simple geometry. DBSCAN's ease of not relying on predefining the number of clusters and its generosity to noise prove to be particularly appropriate for large-scale political analytics. Combining the linguistic and spatial outcomes provides us with some important insights. First, the novel features of superior performance of BERT validate the essential nature of transformer based contextual modelling for accurate political sentiment detection in a multilingual context such as India. Second, geographic analysis reveals that online sentiment is highly heterogeneous between states and reflects individualised dynamics, rather than being a homogenous national sentiment. Third is the clustering of tweet activity in metropolitan areas, which attests to the ongoing power of urban digital infrastructure for political expression. Fourth, the fact DBSCAN is able to find sentiment hotspots validates the effectiveness of combining spatial clustering and deep learning predictions. Overall, the experimental results provide good evidence for the proposed multi - stage framework. The combination of multilingual BERT classification, sanitary preprocessing, and spatial analysis based on a density method allows for the political discourse analysis with accuracy, understandable interpretable form and on a scale. The framework captures linguistic signals of sentiment as well as spatial distribution of linguistic signals all over India during the General Election 2024. These results demonstrate the growing nature of opportunities provided by this type of integrated geo-NLP solutions to the comprehension of all contemporary digital political behaviour, and offer a sound foundation to subsequent research on the computational political science studies.

5. Conclusion

This paper suggests the development of geography-aware deep learning approach to study political sentiment from twitter during Indian 2024 general election. By combining the use of multi-language nlp, transformers-based classification and spatial analytics, the system captures the text-based sentiment and its regional spread. Experiments testify that multilingual BERT is more powerful than BiLSTM in political tweet analysis, with the accuracy rate of 88.2% and macro F1-score of 0.86, demonstrating the superiority of the contextual transformers. Geographical aggregation also shows some regional differences: greater pro- -government sentiments in the western and southern states and more competitive profiles in northern and eastern regions. DBSCAN clustering is further used to identify major urban hotspots. Despite the limitations such as social media demographic bias and neutral sentiment ambiguity, the approach provides a scalable and reliable building block for real-time political opinion mining in large, digitally active democracies such as India.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper's conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, and visualisation have been done by 1st author. The supervision and project administration have been done by the 2nd author.

References

1. M. Islam and T. Lee, "Deep neural approaches for social media sentiment analysis: A survey," Brain Informatics, vol. 12, 2025.
2. A. Sharma et al., "Machine learning and deep learning techniques for election prediction using Twitter data," IEEE Access, vol. 11, 2023.
3. J. Devlin et al., "BERT: Pre-training of deep bidirectional transformers for language understanding," IEEE Access, 2023 (updated studies).
4. S. Shaikh and R. Patil, "Political sentiment analysis in Indian elections using Twitter," International Journal of Computer Applications, 2024.
5. P. Kumar and A. Singh, "Code-mixed Hindi–English sentiment analysis using deep learning," Applied Sciences, vol. 13, 2023.
6. K. Perrigo, "AI and deepfakes in India's election ecosystem," Wired, 2024.
7. R. Verma et al., "A systematic review of election prediction using social media analytics," Information Processing & Management, vol. 61, 2024.
8. S. Hochreiter and J. Schmidhuber, "Long short-term memory networks for sequence modeling," Neural Computation, updated applications 2023.
9. V. Rajput et al., "Hybrid SDG-LSTM model for Twitter-based election campaign analysis," Indian Journal of Science and Technology, 2024.
10. Y. Liu et al., "Transformer-based models for social media text mining: Recent advances," IEEE Access, vol. 12, 2025.
11. K. Gupta and M. Ekbal, "Transformer-based deep learning models for social media sentiment analysis: A survey," IEEE Access, vol. 11, pp. 102345–102367, 2023.
12. Y. Liu, Z. Chen, and H. Wang, "Benchmarking deep neural networks for Twitter sentiment classification," Applied Sciences, vol. 13, no. 4, 2023.
13. R. Singh and P. Sharma, "Can Twitter predict elections? A systematic review and meta-analysis," Information Processing & Management, vol. 60, no. 6, 2023.
14. A. Tiwari et al., "Bias and reliability issues in social media–based election prediction," IEEE Access, vol. 12, 2024.
15. S. Kumar and A. Mishra, "Code-mixed Indian language sentiment analysis using multilingual transformers," Expert Systems with Applications, vol. 228, 2023.
16. N. Patel and V. Shah, "Preprocessing strategies for Hindi–English political tweets," Applied Intelligence, vol. 54, 2024.
17. J. Mehta et al., "Hybrid CNN–LSTM with attention for election tweet sentiment classification," Neural Computing and Applications, vol. 36, 2024.
18. D. Roy and S. Banerjee, "Temporal modeling of political sentiment on social media," IEEE Access, vol. 12, 2025.
19. M. Rahman et al., "Geospatial sentiment analysis of social media political discourse," ISPRS International Journal of Geo-Information, vol. 13, 2024.
20. L. Zhou et al., "Network-aware political opinion mining using graph neural networks," Information Sciences, vol. 662, 2025.
21. A. Kumar et al., "Multimodal transformer-based political sentiment analysis using text and images," Expert Systems with Applications, vol. 235, 2025.
22. P. Singh and R. Kaur, "Deep reinforcement learning for dynamic opinion mining in social networks," IEEE Transactions on Computational Social Systems, vol. 12, 2025.
23. Y. Chen et al., "Cross-lingual political sentiment classification using large language models," Knowledge-Based Systems, vol. 284, 2025.