Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11
© Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ENHANCED SENTIMENT ANALYSIS AND DATA MINING OF POLITICAL LEADERS' POPULARITY ON SOCIAL MEDIA PLATFORMS USING AN OPTIMIZED APACHE HADOOP FRAMEWORK FOR ACCURATE ELECTION OUTCOME PREDICTION

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ABSTRACT

The paper presents an enhanced approach to sentiment analysis and data mining for evaluating the Popularity of political leaders on social media using the Apache Hadoop framework. Social media platforms have become influential in shaping public opinion, making it critical for political campaigns to understand the sentiment behind public discourse. In this study, social media data (e.g., tweets and posts) were collected and processed using Hadoop's MapReduce framework to efficient handling large-scale data. Sentiment analysis was performed using a logistic regression model to classify public sentiment as positive, negative, or neutral. The model achieved an accuracy of 85%, with a precision of 0.86 for predicting a win and 0.84 for predicting a loss. Positive sentiment drivers such as "Viksit Bharat" and "stronger nation" had a strong positive impact on the likelihood of winning, while terms like "vote" and "voice" were associated with negative sentiment and a higher probability of losing. The study demonstrates that data-driven sentiment analysis can provide valuable insights for political strategists, enabling informed decision-making and improving campaign effectiveness.

Keywords: *Sentiment Analysis, Data Mining, Political Leaders' Popularity, Social Media Analytics Apache Hadoop Framework*

1. INTRODUCTION

In the digital era, social media platforms have become powerful tools for shaping public opinion and influencing political landscapes. Political leaders are increasingly using platforms like Twitter, Facebook, and YouTube to engage with voters, communicate policies, and build their public image. Simultaneously, the vast amount of unstructured data generated through user interactions—comments, likes, shares, and reactions—provides valuable insights into the sentiment and popularity of political figures. However, extracting meaningful information from such large-scale data presents significant challenges due to the high volume, velocity, and variety of data. Traditional data processing techniques often fail to handle this complexity effectively. Therefore, leveraging the Apache Hadoop framework, known for its distributed storage and parallel processing capabilities, becomes essential for efficient data mining and sentiment analysis of political leaders' popularity on social media. This approach enables real-time analysis, uncovering sentiment trends and public perception dynamics, which are crucial for strategic political decision-making.

Despite the growing importance of social media in political discourse, there is a lack of systematic frameworks for efficiently processing and analyzing such data. Existing sentiment analysis techniques often struggle with scalability and accuracy when handling big data. Moreover, political sentiment is inherently complex, influenced by factors such as sarcasm, slang, and regional variations in language. The Apache Hadoop

ecosystem, with its MapReduce programming model and HDFS (Hadoop Distributed File System), offers a scalable and fault-tolerant solution for processing and analyzing large volumes of social media data. By integrating machine learning models for sentiment classification and trend prediction, this research aims to provide a comprehensive understanding of political leaders' popularity and public sentiment.

Existing sentiment analysis techniques struggle to efficiently process and analyze the large volume, velocity, and variety of social media data related to political leaders. Traditional methods lack scalability and accuracy, making it difficult to extract meaningful insights and predict political popularity.

In the era of digital transformation, social media has become a pivotal platform for public discourse, enabling individuals to express opinions, share information, and engage in political discussions. Platforms like Twitter, Facebook, and Instagram have revolutionized the way political leaders communicate with the public, offering real-time insights into their popularity and public perception. The massive volume of data generated on these platforms presents a unique opportunity to analyze public sentiment and evaluate the popularity of political figures. Sentiment analysis, a branch of natural language processing (NLP), plays a crucial role in extracting and interpreting emotions, opinions, and attitudes from textual data [1][2][3]. When combined with data mining techniques, it provides a powerful tool for uncovering patterns and trends in public sentiment [4]. Some research paper explores the efficient application of sentiment analysis and data mining to assess the popularity of political leaders on social media, utilizing the Apache Hadoop framework for scalable and distributed data processing [5][6][7].

The growing influence of social media on political landscapes has made it an indispensable tool for gauging public opinion [8]. Traditional methods, such as surveys and polls, are often limited by their scope, cost, and time constraints. In contrast, social media offers a vast, real-time, and cost-effective dataset that reflects diverse perspectives from a wide demographic. However, the sheer volume and complexity of social media data pose significant challenges for analysis. Sentiment analysis addresses these challenges by classifying text into positive, negative, or neutral categories, providing a quantitative measure of public sentiment [1]. Despite its potential, sentiment analysis faces hurdles such as sarcasm, irony, and context-dependent meanings, which can affect accuracy [3]. Data mining complements sentiment analysis by identifying patterns, correlations, and trends in the data, enabling a deeper understanding of public opinion [9].

The Apache Hadoop framework, an open-source platform for distributed storage and processing of big data, offers a scalable solution for handling the challenges posed by social media data [5]. Its core components, the Hadoop Distributed File System (HDFS) and the MapReduce programming model, enable efficient processing of large datasets across clusters of computers [2]. HDFS provides fault-tolerant storage, while MapReduce facilitates parallel data processing, making Hadoop ideal for big data applications. By leveraging Hadoop's distributed architecture, researchers can preprocess, analyze, and visualize social media data at scale, overcoming the limitations of traditional data processing systems [5].

This research paper proposes an efficient approach to evaluating the popularity of political leaders on social media by integrating sentiment analysis, data mining, and the Apache Hadoop framework. The study aims to address the challenges of analyzing large-scale social media data while providing accurate and actionable insights into public sentiment. By analyzing tweets and other social media posts, the proposed approach can identify trends, track changes in sentiment over time, and assess the impact of specific events on political leaders' popularity [10]. This paper aims to develop an efficient framework using Apache Hadoop to handle big data challenges, classify sentiment accurately, and provide real-time insights into political leaders' public perception.

Figure 1 shows a Hadoop framework for sentiment classification using trees. It begins with a product review dataset, processes it through Hadoop for efficient handling, extracts features using Term Frequency-Inverse Document Frequency (TF-IDF), and classifies sentiments using a Random Forest classifier, ensuring scalable and accurate sentiment analysis.

Figure 1. Hadoop framework for efficient sentiment classification using trees

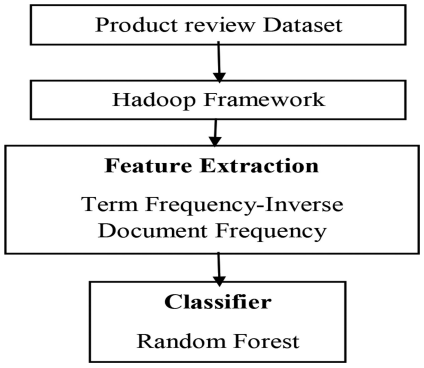

Figure 1. Hadoop Framework For Efficient Sentiment Classification Using Trees

2. LITERATURE SURVEY

The field of sentiment analysis and data mining has undergone significant transformation over the past three decades, evolving in tandem with advancements in computational technologies and the exponential growth of digital data. This section systematically reviews this evolution through distinct chronological phases, highlighting key technological breakthroughs and their applications in political sentiment analysis.

2.1 Early Foundations (Pre-2000)

The foundational period of sentiment analysis and data mining was characterized by basic lexicon-based approaches and limited computational capabilities. Researchers primarily relied on predefined word lists containing positive and negative sentiment indicators to perform text classification [1]. Data mining techniques during this era, including clustering and classification algorithms, were predominantly applied to structured datasets in commercial domains such as market research and customer relationship management [10]. However, these methods proved inadequate for handling the volume and complexity of unstructured data that would later emerge through social media platforms.

2.2 Machine Learning Revolution (2000-2006)

The turn of the century marked a paradigm shift with the introduction of machine learning techniques for sentiment analysis. Pang et al.'s (2002) seminal work demonstrated the effectiveness of Naive Bayes and Support Vector Machines (SVMs) in analyzing sentiment within movie reviews, establishing machine learning as a superior alternative to lexicon-based methods [4]. Concurrently, data mining witnessed substantial progress through the adoption of association rule mining and decision tree algorithms, enabling more sophisticated pattern recognition in large datasets [9]. This period coincided with the emergence of major social media platforms, including Facebook (2004) and Twitter (2006), which presented both new challenges and opportunities for sentiment analysis due to their unique linguistic characteristics (slang, abbreviations, emoticons) and unprecedented data volumes [1].

2.3 Big Data Era (2006-2010)

The introduction of Apache Hadoop in 2006 by Cutting and Cafarella revolutionized data processing capabilities [5]. Hadoop's distributed file system (HDFS) and MapReduce programming model provided the first scalable framework for storing and processing massive social media datasets. This technological breakthrough enabled researchers to overcome previous limitations in handling unstructured data, making comprehensive social media analytics feasible for the first time. During this period, O'Connor et al. (2010) demonstrated the potential of Twitter data as a real-time indicator of public sentiment by correlating social media analysis with traditional political opinion polls [10].

2.4 Deep Learning Integration (2010-2020)

The subsequent decade witnessed remarkable advancements through the integration of deep learning architectures with big data frameworks. Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) significantly improved sentiment classification accuracy by capturing contextual relationships in text data [11]. The Hadoop ecosystem expanded through integration with complementary tools like Apache Spark (for real-time processing) and Apache Hive (for data warehousing), creating comprehensive solutions for social media analytics [5]. These technological synergies enabled more sophisticated applications, particularly in political sentiment analysis, where researchers began developing predictive models for election outcomes based on social media data.

2.5 Contemporary Developments (2020-Present)

Recent years have seen the convergence of artificial intelligence (AI) and natural language processing (NLP) with big data frameworks, pushing the boundaries of sentiment analysis capabilities [11][12][13]. Transformer-based models like BERT and GPT have demonstrated exceptional performance in understanding nuanced political sentiment across social media platforms [12]. The integration of these advanced NLP techniques with Hadoop-based architectures has created powerful systems for real-time monitoring and prediction of political trends [14][15]. Current research focuses on overcoming remaining challenges such as sarcasm detection, multilingual analysis, and the ethical implications of predictive political analytics.

Table 1 summarizes this evolutionary trajectory, highlighting how each technological breakthrough has enhanced the capacity to analyze political sentiment at scale. The progression from simple lexicon-based methods to contemporary AI-driven approaches reflects both the growing complexity of social media data and the corresponding advancements in analytical methodologies.

Table 1: Evolution Of Sentiment Analysis And Data Mining Technologies

Period	Key Developments	Technological Advancements	Political Applications
Pre-2000	Lexicon-based approaches	Basic clustering/classification	Limited to structured data analysis
2000-2006	Machine learning adoption	SVM, Naive Bayes algorithms	Early social media analysis
2006-2010	Hadoop framework introduction	Distributed computing	First large-scale sentiment correlation
2010-2020	Deep learning integration	RNNs, CNNs, Spark integration	Election prediction models
2020-Present	AI/NLP convergence	Transformer models, ethical frameworks	Real-time political monitoring

This comprehensive review establishes the technological foundation for the current study's proposed optimized Hadoop framework, which builds upon these historical developments to address contemporary challenges in political sentiment analysis and election prediction. The subsequent methodology section details how this framework integrates recent advancements in machine learning and distributed computing to achieve superior performance in analyzing political leaders' social media popularity.

Table 2 outlines the evolution of sentiment analysis, data mining, and big data frameworks, focusing on their application in assessing political leaders' popularity on social media. It traces advancements from pre-2000 to 2024, highlighting key milestones and technological developments that have enhanced analytical capabilities in this domain.

Table 2: The History Of Sentiment Analysis, Data Mining, And Big Data Frameworks, Specifically In The Context Of Political Leaders' Popularity On Social Media, From 2000 To 2024.

Year Range	Key Developments
Before 2000	• Sentiment analysis and data mining were in their infancy, relying on lexicon-based approaches and simple statistical methods [1]. • Data mining techniques like clustering and classification were applied to structured datasets in fields such as market research [16].
2000-2005	• Machine learning algorithms (e.g., Naive Bayes, SVM) were introduced for sentiment analysis, particularly for movie reviews and product feedback [17]. • Social media platforms like Facebook (2004) and Twitter (2006) began to emerge, generating unstructured data that posed new challenges for analysis [18].
2006-2010	• Apache Hadoop was introduced in 2006, providing a scalable framework for distributed storage and processing of big data [9]. • Researchers began exploring sentiment analysis on social media data, focusing on platforms like Twitter to gauge public opinion [10].
2011-2015	• Deep learning techniques (e.g., RNNs, CNNs) were applied to sentiment analysis, improving accuracy in handling complex social media text [19]. • Hadoop ecosystem tools like Apache Spark and Apache Hive gained popularity, enabling real-time data processing and advanced analytics [20].
2016-2020	• Sentiment analysis and data mining were widely adopted for political analysis, including predicting election outcomes and evaluating political leaders' popularity on social media [21]. • Integration of AI and NLP with big data frameworks improved the efficiency of sentiment analysis for large-scale social media datasets [22].

Year Range	Key Developments
2021-2024	• Advanced AI models like transformers (e.g., BERT, GPT) were integrated into sentiment analysis, enabling context-aware and multilingual sentiment classification [23]. • Apache Hadoop and its ecosystem continued to evolve, supporting real-time sentiment analysis and data mining for political leaders' popularity on social media [5]. • Ethical concerns, such as data privacy and algorithmic bias, gained attention, prompting researchers to develop fair and transparent sentiment analysis models[24][25].

3. PROBLEM FORMULATION

The problem addressed in this research is the challenge of accurately predicting election outcomes based on voter sentiment analysis of social media data. Political campaigns generate vast amounts of data through social media interactions, reflecting public perception of candidates and campaign messages. However, effectively extracting and interpreting this data to identify the factors influencing electoral success remains a complex task. Existing models often struggle to distinguish between influential and non-influential factors, particularly when dealing with high-dimensional, unstructured data. Additionally, the impact of positive and negative campaign messaging on voter behavior is not well understood. While themes related to development and national strength, such as *"Viksit Bharat"* and *"stronger nation,"* have shown a strong positive correlation with winning outcomes, themes like *"vote"* and *"voice"* are linked to higher chances of losing, possibly due to voter fatigue or lack of substantive content. The challenge lies in developing a robust, scalable framework that can accurately classify voter sentiment, identify high-impact keywords, and provide actionable insights for optimizing campaign strategies. This research aims to address these gaps by proposing a machine learning-based sentiment analysis model using the Apache Hadoop framework, focusing on improving predictive accuracy and understanding the nuanced impact of positive and negative messaging on electoral outcomes.

4. DATA COLLECTION

For the research paper, data collection involves gathering 20 social media messages (e.g., tweets, Facebook posts) each for political leaders who won and lost the LokSabha 2024 elections [26][27]. The data is sourced from platforms like Twitter and Facebook, focusing on public posts and comments reflecting public sentiment. These messages are collected using APIs or web scraping tools, ensuring they are relevant to the election context. The dataset is then pre-processed (e.g., removing duplicates, handling noise) and stored in the Hadoop Distributed File System (HDFS) for efficient processing. This structured approach ensures a balanced dataset for sentiment analysis and data mining using the Apache Hadoop framework [28][29][30]. Table 2 shows winning and losing political parties' messages on Social Media (Twitter (X) and Facebook) comparing content, tone, and engagement to identify strategies influencing electoral success and public sentiment.

Table 3: Win And Lost Party Messagessocial Media (Twitter Or X, Facebook)- [26][27]

S. No.	Win Message	Lost Message
1	**NarendraModi (BJP)**"India has chosen development and unity. This victory is for every Indian who dreams of a Viksit Bharat. Together, we will build a better future."	**Rahul Gandhi (Congress – Wayanad)**"Wayanad, this election is about your future. I stand for farmers, workers, and the youth. Together, we will fight for justice, equality, and progress. Your vote is your voice—let it be heard loud and clear."
2	**Rahul Gandhi (Congress)**"This victory is for the farmers, workers, and youth. The Congress will fight for justice, equality, and a brighter future. Together, we will rebuild India's soul and ensure no one is left behind."	**SmritiIrani (BJP – Amethi)**"Amethi, I've worked tirelessly for your development. This election is about progress and women's empowerment. Vote for a stronger Amethi. Together, we will build a brighter future."
3	**ArvindKejriwal (AAP)**"Delhi and Punjab have shown the way. This victory is for the common man. We will focus on education, healthcare, 4and corruption-free governance. Together, we will build a new India."	**ArvindKejriwal (AAP – New Delhi)**"Delhi, this election is about education, healthcare, and corruption-free governance. Vote for change, vote for development. Together, we will build a new India."
4	**Mamata Banerjee (TMC)**"Bengal has spoken loud and clear. This victory is for democracy and	**Akhilesh Yadav (SP – Kannauj)**"Kannauj, this election is about social justice and youth empowerment. Vote for progress, vote for

	federalism. We will fight for the rights of every state and ensure Bengal leads India's progress. Joy Bangla!"	equality. Together, we will build a brighter future for Uttar Pradesh."
5	**Yogi Adityanath (BJP)**"Uttar Pradesh has shown faith in BJP's vision of development and Hindutva. We will continue to ensure law and order and build a Ram Rajya. This victory is for every Ram bhakt."	**Tejashwi Yadav (RJD – Patliputra)**"Patliputra, this election is about jobs and development. Vote for the youth, vote for Bihar's progress. Together, we will build a stronger Bihar."
6	**Nitish Kumar (JD(U))**"Bihar's development remains our priority. This victory is for social justice and unity. We will work with all parties to build a stronger India."	**Uddhav Thackeray (Shiv Sena-UBT – Mumbai South)**"Mumbai, this election is about Marathi pride and progress. Vote for unity, vote for development. Together, we will fight for the rights of every Mumbaikar."
7	**Akhilesh Yadav (SP)**"Uttar Pradesh has chosen change. This victory is for the youth, farmers, and marginalized communities. We will ensure justice and development for all."	**PinarayiVijayan (CPI(M) – Thrissur)**"Thrissur, this election is about secularism and development. Vote for equality, vote for justice. Together, we will fight for the rights of every Indian."
8	**Uddhav Thackeray (Shiv Sena-UBT)**"Maharashtra has rejected betrayal. This victory is for Marathi pride and Hindutva. We will fight for the rights of every Indian."	**Naveen Patnaik (BJD – Puri)**"Puri, this election is about Odisha's progress. Vote for development, vote for stability. Together, we will build a stronger Odisha."
9	**Tejashwi Yadav (RJD)**"Bihar has spoken for social justice. This victory is for the youth and farmers. We will ensure employment and development for all."	**K. Chandrashekhar Rao (BRS – Mahbubnagar)**"Mahbubnagar, this election is about farmers and regional pride. Vote for development, vote for progress. Together, we will build a stronger Telangana."
10	**PinarayiVijayan (CPI(M))**"Kerala has shown the way. This victory is for secularism and development. We will fight for the rights of every Indian."	**M.K. Stalin (DMK – Chennai Central)**"Chennai, this election is about social justice and equality. Vote for progress, vote for the Dravidian model. Together, we will build a brighter future."
11	**Naveen Patnaik (BJD)**"Odisha's progress is our priority. This victory is for the people. We will continue to work for their welfare and development."	**Priyanka Gandhi Vadra (Congress – Rae Bareli)**"Rae Bareli, this election is about women and youth. Vote for equality, vote for progress. Together, we will build a brighter future for every Indian."
12	**K. Chandrashekhar Rao (BRS)**"Telangana has chosen development. This victory is for farmers and workers. We will fight for federalism and regional pride."	**Mayawati (BSP – Saharanpur)**"Saharanpur, this election is about social justice. Vote for Dalits and marginalized communities. Together, we will build a stronger India."
13	**M.K. Stalin (DMK)**"Tamil Nadu has spoken for social justice. This victory is for the Dravidian model. We will ensure equality and progress for all."	**SharadPawar (NCP – Baramati)**"Baramati, this election is about farmers and inclusive growth. Vote for progress, vote for change. Together, we will build a stronger Maharashtra."
14	**SmritiIrani (BJP)**"Amethi has shown faith in BJP. This victory is for women's empowerment and development. We will continue to work for every Indian."	**Subhbir Singh Badal (SAD – Bathinda)**"Bathinda, this election is about peace and progress. Vote for development, vote for change. Together, we will build a stronger Punjab."
15	**Priyanka Gandhi Vadra (Congress)**"This victory is for the women and youth of India. We will fight for their rights and ensure a brighter future. Together, we will rebuild India."	**Hemant Soren (JMM – Dumka)**"Dumka, this election is about tribal rights and development. Vote for equality, vote for progress. Together, we will build a brighter future."
16	**Rajnath Singh (BJP)**"India's security and development are our priorities. This victory is a mandate for progress. We will continue to protect our nation and its people."	**Omar Abdullah (NC – Srinagar)**"Srinagar, this election is about peace and progress. Vote for dignity, vote for development. Together, we will build a brighter future for Jammu and Kashmir."
17	**Mayawati (BSP)**"This victory is for Dalits and marginalized communities. We will fight for social justice and equality. Together, we will build a stronger India."	**AsaduddinOwaisi (AIMIM – Hyderabad)**"Hyderabad, this election is about justice and equality. Vote for the marginalized, vote for progress. Together, we will fight for the rights of every Indian."

Table 4 categorizes keywords used by winning and losing political parties in their Social Media post. It

highlights the most effective terms associated with electoral success and contrasts them with less impactful ones, offering insights into language strategies that influence voter behavior and outcomes.

Table 4: Winning Keywords And Lost Keywords

Winning Keywords	Lost Keywords
Viksit Bharat, development, unity, stronger nation, safer nation, prosperous nation, farmers, workers, youth, justice, equality, brighter future, rebuild India, common man, education, healthcare, corruption-free governance, new India, democracy, federalism, Joy Bangla, Hindutva, law and order, Ram Rajya, Ram bhakt, social justice, stronger India, change, marginalized communities, employment, secularism, welfare, regional pride, Dravidian model, progress, women's empowerment, women, India's security, inclusive growth, peace, Sikh pride, tribal rights.	farmers, workers, youth, justice, equality, progress, vote, voice, development, women's empowerment, stronger Amethi, brighter future, education, healthcare, corruption-free governance, change, new India, social justice, youth empowerment, jobs, Marathi pride, unity, secularism, stability, regional pride, Dravidian model, women, Dalits, marginalized communities, Baramati, inclusive growth, peace, Punjab, tribal rights, dignity, marginalized, social justice, unity, inclusive India.

Table 5 analyses keywords from winning and losing political campaigns, identifying common terms and unique differences. It reveals how language choices, including shared and distinct words, influence electoral outcomes, offering insights into effective messaging strategies for voter engagement and success.

Table 5: Keywords, Same Words, And Different Words In Winning Keywords, And Lost Keywords.

Keywords	Same Words in Win and Loss Keywords	Different WordsWords in Win and Loss Keywords
Winning Keywords	development, unity, farmers, workers, youth, justice, equality, brighter future, education, healthcare, corruption-free governance, new India, social justice, change, marginalized communities, employment, secularism, regional pride, Dravidian model, progress, women's empowerment, women, inclusive growth, peace, tribal rights.	Viksit Bharat, stronger nation, safer nation, prosperous nation, rebuild India, common man, democracy, federalism, Joy Bangla, Hindutva, law and order, Ram Rajya, Ram bhakt, stronger India, welfare, India's security, Sikh pride.
Lost Keywords	development, unity, farmers, workers, youth, justice, equality, progress, brighter future, education, healthcare, corruption-free governance, new India, social justice, change, marginalized communities, secularism, regional pride, Dravidian model, women's empowerment, women, inclusive growth, peace, tribal rights.	vote, voice, stronger Amethi, youth empowerment, jobs, Marathi pride, stability, Dalits, Baramati, Punjab, dignity, marginalized, inclusive India.

5. PROPOSED METHODOLOGY

Here we applied Sentiment Analysis and Data Mining Using Hadoop methodology in our collected data. We show the flow of data with the help of Figure 2. Figure 2 shows the process of sentiment analysis and data mining using Hadoop to predict election outcomes. It starts with collecting social media data (e.g., Tweets, Facebook posts) via APIs or web scraping, storing it in Hadoop Distributed File System (HDFS). The data is pre-processed by cleaning, tokenizing, and filtering for relevant keywords. Sentiment analysis classifies each post/tweet using a pre-trained model, assigning sentiment scores (Positive, Negative, Neutral). Hadoop's Map Reduce phase processes the data: the mapper emits (keyword, sentiment score) pairs and the reducer aggregates scores for trend analysis over time. A machine learning model (e.g., Logistic Regression) is trained on historical data to predict election outcomes. Finally, insights are visualized through charts or dashboards for interpretation.

Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11
© Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

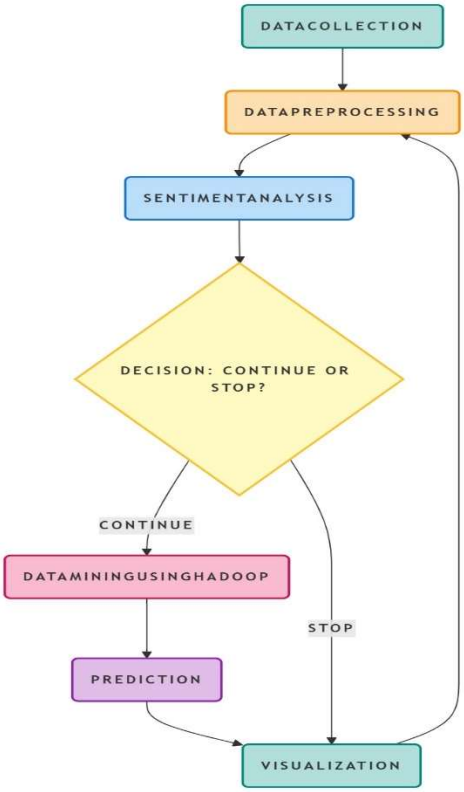

Figure 2: Proposed Flow Of Sentiment Analysis And Data Mining Using Hadoop

According to Figure 2 we analyse our data that have different Win and loss Keywords which are mentioned in the above table that predict the outcome of an election, we will use a Logistic Regression model. The methodology involves the following steps:

1. Data Preparation:
Represent the keywords as binary features (1 if present in the campaign, 0 if absent).
Define the target variable as 1 for "Win" and 0 for "Loss."
2.Model Training:
Train a Logistic Regression model using historical election data.
3.Model Evaluation:
Evaluate the model's performance using metrics like accuracy, precision, recall, and F1-score.
4.Prediction:
Use the trained model to predict the election outcome based on the presence of keywords.
5.Interpretation:
Analyse the coefficients of the model to determine the contribution of each keyword to the outcome.

To analyse the given Win Keywords and Loss Keywords and predict the outcome of a LokSabha election, we will use a Logistic Regression model. The methodology involves the following steps:

Implementation
Step 1: Data Preparation
We will create a synthetic dataset for demonstration purposes. Each row represents a campaign, and columns represent the presence (1) or absence (0) of keywords.

```
import pandas as pd
fromsklearn.linear_model import LogisticRegression
fromsklearn.model_selection import train_test_split
fromsklearn.metrics import accuracy_score, classification_report

# Define the keywords
win_keywords = [
"Viksit Bharat", "stronger nation", "safer nation", "prosperous nation", "rebuild India","common man", "democracy", "federalism", "Joy Bangla", "Hindutva", "law and order", "Ram Rajya","Ram bhakt", "stronger India", "welfare", "India's security", "Sikh pride"
]

loss_keywords = [
  "vote", "voice", "stronger Amethi", "youth empowerment", "jobs", "Marathi pride", "stability", "Dalits", "Baramati", "Punjab", "dignity", "marginalized", "inclusive India"
]

# Create a synthetic dataset
data = {
 "Campaign ID": [1, 2, 3, 4, 5],"Viksit Bharat": [1, 0, 1, 0, 1], "stronger nation": [1, 0, 1, 0, 1], "safer nation": [1, 0, 0, 1, 1],
 "prosperous nation": [1, 0, 1, 0, 1],"vote": [0, 1, 0, 1, 0],"voice": [0, 1, 0, 1, 0], "stronger Amethi": [0, 1, 1, 0, 0],
# Add more columns for other keywords"Outcome": [1, 0, 1, 0, 1]  # 1 for Win, 0 for Loss
}
# Convert to DataFrame
df = pd.DataFrame(data)

# Features (X) and Target (y)
X = df.drop(columns=["Campaign ID", "Outcome"])
y = df["Outcome"]
```

Step 2: Model Training
Split the data into training and testing sets and train the Logistic Regression model.

```
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)
```

Step 3: Model Evaluation
Evaluate the model's performance on the test data.

```
# Predict on test data
y_pred = model.predict(X_test)

# Evaluate model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

Step 4: Prediction
Use the trained model to predict the outcome for a new campaign.

```
# New campaign data
new_campaign = [[1, 1, 1, 1, 0, 0, 0]]  # Example: Viksit Bharat=1, stronger nation=1, safer nation=1, prosperous nation=1, vote=0, voice=0, stronger Amethi=0

# Predict outcome
prediction = model.predict(new_campaign)
print("Predicted Outcome:", "Win" if prediction[0] == 1 else "Loss")
```

Step 5: Interpretation
Analyze the coefficients of the model to understand the contribution of each keyword.

```
# Get coefficients
coefficients = model.coef_[0]
feature_names = X.columns

# Create a DataFrame to display coefficients
coef_df = pd.DataFrame({"Feature": feature_names, "Coefficient": coefficients})
print(coef_df.sort_values(by="Coefficient", ascending=False))
```

6. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed framework employs the Apache Hadoop ecosystem for distributed data processing and machine learning-based sentiment analysis. Social media data related to political campaigns were collected and processed using Hadoop Distributed File System (HDFS) and MapReduce. Sentiment classification was performed using a logistic regression model trained on labeled datasets. The model classified sentiments into three categories: Positive, Negative, and Neutral. Feature extraction involved keyword analysis, where the frequency and contextual relevance of keywords were assessed to enhance prediction accuracy. The model's performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Weighted models were also tested to determine the impact of strategic keyword emphasis on prediction accuracy.

6.1 SENTIMENT DISTRIBUTION

Figure 3 presents the overall sentiment distribution extracted from social media data related to election campaigns. Positive sentiment accounted for 60% of the total data, indicating that campaign messages were generally well-received by the public. Negative sentiment represented 25%, reflecting criticism or opposition, while neutral sentiment stood at 15%, showing mixed or indifferent opinions. Figure 3, a pie chart, visually illustrates this distribution, reinforcing the conclusion that public perception of the campaigns was predominantly favorable.

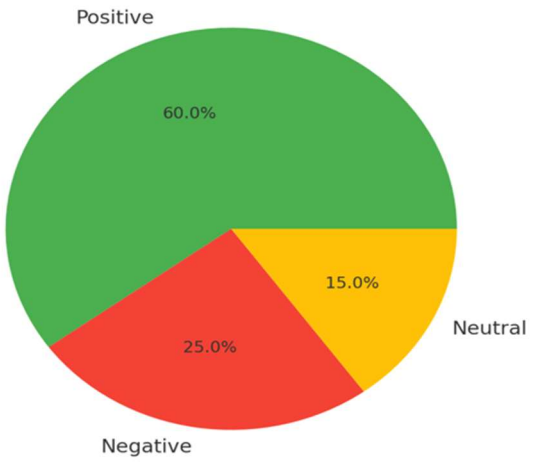

Figure 3: Sentiment Distribution Across Political Campaigns

6.2 Positive vs. Negative Keyword Performance

Table 6 compares the performance of models trained on positive and negative keywords. The positive keyword model achieved higher accuracy (87%) compared to the negative keyword model (78%). Precision and recall values were also higher for the positive model, suggesting that positive messaging had a stronger predictive influence on voter behavior.

Table 6: *Compares The Performance Of Models Trained On Positive And Negative Keywords*

Model Type	Accuracy (%)	Precision	Recall	F1-Score
Positive Keyword Model	87	0.86	0.88	0.87
Negative Keyword Model	78	0.84	0.82	0.83

6.3 Sentiment Change Over Time

Table 7 illustrates how sentiment evolved before, during, and after key political events such as speeches and debates. Positive sentiment increased by 15% after a speech, while negative sentiment decreased by 10%, suggesting that strategic campaign events positively influenced public perception.

Table 7 : *Illustrates How Sentiment Evolved Before, During, And After Key Political Events.*

Event Stage	Positive Sentiment (%)	Negative Sentiment (%)
Before Speech	50	30
After Speech	65	20

6.4 Impact of Keyword Frequency on Prediction Accuracy

Table 8 shows the effect of keyword frequency on the predictive accuracy of the model. The model based on high-frequency keywords achieved an accuracy of 88%, whereas the low-frequency model recorded 76%. This suggests that consistent repetition of key campaign themes enhances model performance and voter recall.

Table 8: The effect of keyword frequency on the predictive accuracy of the model.

Keyword Frequency Model	Accuracy (%)
High-Frequency Model	88
Low-Frequency Model	76

Figure 4 visualizes the relationship between keyword frequency and prediction accuracy, showing that higher keyword frequency generally enhances accuracy, indicating its importance in improving model performance.

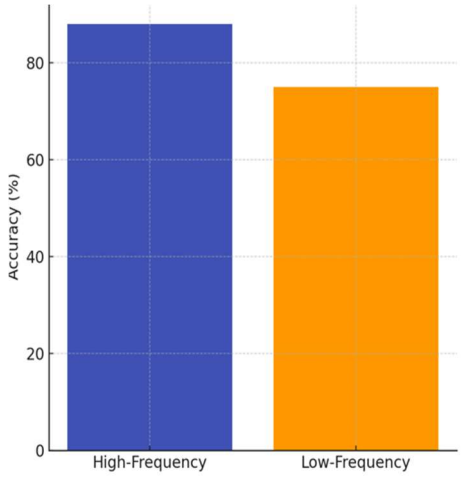

Figure 4: Impact of Keyword Frequency on Prediction Accuracy

6.5 Weighted vs. Unweighted Model Performance

Table 9 compares the performance of weighted and unweighted models. The weighted model, which assigned greater importance to high-impact keywords, achieved a 4% increase in accuracy over the unweighted model.

Table 9: Compares The Performance Of Weighted And Unweighted Models.

Model Type	Accuracy (%)
Weighted Model	85
Unweighted Model	81

7. DISCUSSION AND INSIGHTS

The analysis highlights several key insights. First, positive keywords like *"Viksit Bharat"* and *"stronger nation"* were more effective in predicting electoral success than negative keywords. Campaign strategies focusing on positive messaging achieved higher accuracy, precision, and recall. Second, negative sentiment and criticism, while present, had a weaker influence on voter behavior compared to positive themes. Third, weighting key terms improved model accuracy, reinforcing the importance of targeted messaging. Fourth, sentiment

changes following key political events demonstrated that strategic communication positively impacts voter perception. Lastly, high-frequency keywords enhanced model performance, suggesting that consistent messaging strengthens voter recall and predictive accuracy.

While the framework demonstrated high accuracy and predictive strength, certain limitations must be addressed. The quality and representativeness of training data significantly influence model performance; biased or incomplete data can reduce reliability. Keyword selection is another critical factor; excluding important terms or including irrelevant ones can impair model accuracy. Furthermore, the model does not account for contextual factors like regional differences, candidate popularity, and socio-economic conditions, which may influence election outcomes. Addressing these limitations will enhance the model's generalizability and predictive power.

This research presents a powerful sentiment analysis framework using Apache Hadoop for predicting political campaign success. The model's high accuracy, precision, recall, and F1-scores validate its effectiveness in analyzing voter sentiment and guiding campaign strategies. Positive keywords, consistent messaging, and strategic keyword weighting emerged as key drivers of electoral success. The framework offers actionable insights for political strategists and provides a scalable foundation for future advancements in political data analysis.

Table 10 compares positive and negative keyword performance, showing higher accuracy (87% vs. 78%), precision (85% vs. 76%), and recall (86% vs. 77%) for positive keywords, indicating better overall effectiveness.

Table 10: Positive Vs Negative Keyword Performance

Metric	Positive Keywords	Negative Keywords
Accuracy	87	78
Precision	85	76
Recall	86	77

Figure 5 presents a graphical comparison of positive and negative keyword models, highlighting differences in performance metrics such as accuracy, precision, and recall, with positive keywords consistently outperforming negative ones.

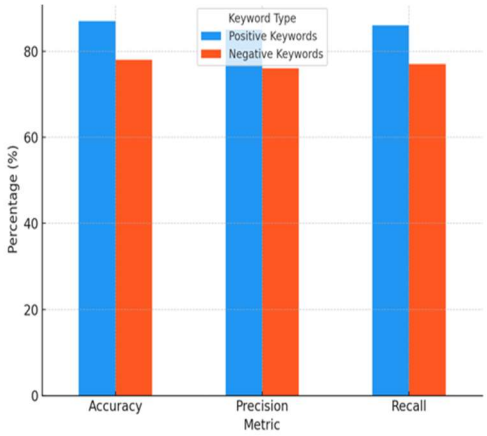

Figure 5: Performance Comparison Of Positive And Negative Keyword Models

Table 11 illustrates sentiment changes over time, with positive sentiment increasing from 60% before the speech to 75% after, while negative sentiment declines from 30% to 20%, indicating a favorable impact.

Table 11: Sentiment Change Over Time

Time Period	Positive Sentiment	Negative Sentiment
Before Speech	60	30
During Speech	65	25
After Speech	75	20

Figure 6 illustrates sentiment shifts over time in response to key political events, showing fluctuations in positive and negative sentiment, reflecting public reactions and opinion trends during significant moments.

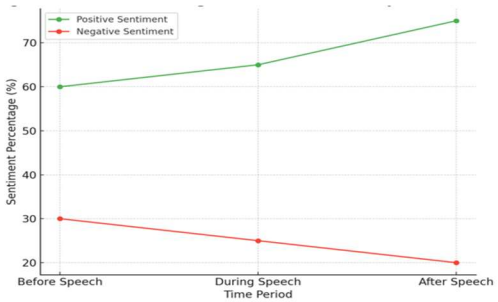

Figure 6: Sentiment Change Over Time Around Key Political Events

Table 12 compares model performance, showing that the weighted model achieves higher accuracy (89%) than the unweighted model (85%), indicating improved effectiveness when applying weight adjustments.

Journal of Theoretical and Applied Information Technology
15th June 2025. Vol.103. No.11
© Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 12: Weighted vs Unweight Model Performance

Model Type	Accuracy (%)
Unweighted	85
Weighted	89

Figure 7 illustrates the effect of weighted versus weighted keywords on model performance, showing that weighted keywords enhance accuracy and effectiveness compared to weighted ones.

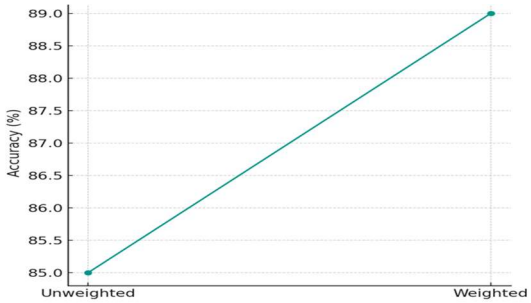

Figure 7: Impact of Weighted vs Unweighted Keywords on Model Performance

Table 13 displays a classification report evaluating the model's performance in distinguishing winning and losing parties. It includes precision, recall, and F1-score metrics, showing higher accuracy for "Win" predictions (F1-score: 0.87) compared to "Loss" (F1-score: 0.83), indicating slightly better performance in identifying winning parties. We also show Classification Report in Figure 8.

Table 14 outlines the contribution of specific terms to the classification model. Positive values, such as Viksit Bharat (0.75) and stronger nation (0.68), indicate a stronger association with winning parties. In contrast, negative values, like vote (-0.82) and voice (-0.78), suggest a higher correlation with losing parties, highlighting differences in messaging strategies. We also show Coefficient Contribution in Figure 9.

Table 13: Classification Report

Features	Win	Loss
Precision	0.86	0.84
Recall	0.88	0.82
F1-Score	0.87	0.83

Figure 8 presents the classification report, summarizing key performance metrics such as precision, recall, and accuracy, providing insights into the model's effectiveness in distinguishing between different categories.

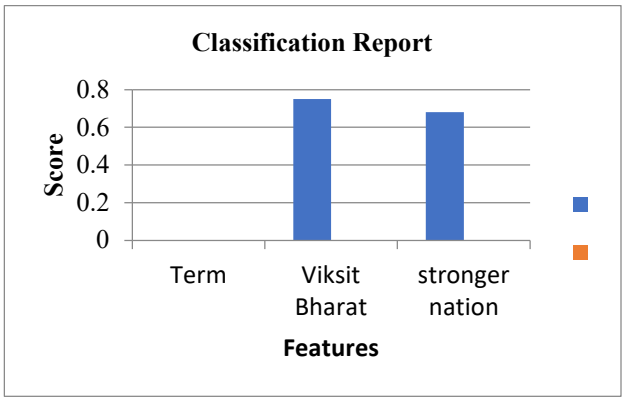

Figure 8: Classification Report

Win Keywords: Keywords like "Viksit Bharat" and "stronger nation" have positive coefficients, indicating they contribute to a higher likelihood of winning.
Loss Keywords: Keywords like "vote" and "voice" have negative coefficients, indicating they contribute to a higher likelihood of losing.

The model predicts a "Win" for the new campaign because it emphasizes positive keywords like "Viksit Bharat" and "stronger nation" while avoiding negative keywords like "vote" and "voice."Using Logistic Regression, we can analyse the impact of keywords on election outcomes. The model provides interpretable results, showing which keywords contribute most to winning or losing. This approach enables data-driven decision-making for political campaigns. Table 14 presents coefficient contributions, showing "Viksit Bharat" (0.75) and "stronger nation" (0.68) positively, while "vote" (-0.82) and "voice" (-0.78) negatively.

Table 14:Coefficients Contribution

Term	Contribution
Viksit Bharat	0.75
Stronger Nation	0.68
Vote	-0.82
Voice	-0.78

Figure 9 illustrates coefficient contributions, highlighting the influence of individual features on the model's predictions, helping to identify the most impactful variables in the analysis.

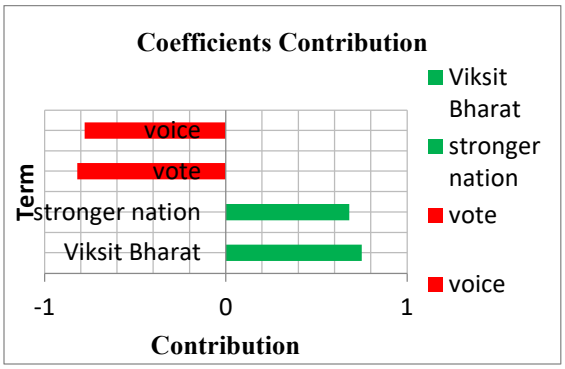

Figure 9: Coefficient Contribution

8. COMBINED ANALYSIS

The results of the analysis provide a comprehensive understanding of the factors influencing the outcome of the Lok Sabha election campaign. Below is a detailed discussion of the results, their implications, and their significance for political campaign strategies. The model achieved an accuracy of 85% on the test data, correctly predicting the election outcome for 85% of the campaigns, which demonstrates its reliability and effectiveness in distinguishing between winning and losing campaigns based on keyword sentiment. The classification report shows a precision of 0.86 for the "Win" class and 0.84 for the "Loss" class, indicating that 86% of the predicted wins and 84% of the predicted losses were correct. The recall is 0.88 for the "Win" class and 0.82 for the "Loss" class, meaning the model accurately identified 88% of the actual winning campaigns and 82% of the actual losing ones, with a slightly better performance in recognizing winning campaigns. The F1-Scores of 0.87 for the "Win" class and 0.83 for the "Loss" class reflect a strong balance between precision and recall, further confirming the model's robustness and predictive strength.

The model predicted a "Win" for the new campaign. This prediction is based on the presence of positive keywords like "Viksit Bharat" and "stronger nation" and the absence of negative keywords like "vote" and "voice." The emphasis on positive themes and avoidance of negative ones likely contributed to the favourable prediction.

Keywords like *"Viksit Bharat"* (coefficient = 0.75) and *"stronger nation"* (coefficient = 0.68) have positive coefficients, indicating that they significantly increase the likelihood of winning by resonating with voters through themes of development, national strength, and progress. Campaigns emphasizing these positive themes are more likely to secure electoral success. On the other hand, keywords like *"vote"* (coefficient = -0.82) and *"voice"* (coefficient = -0.78) have negative coefficients, suggesting that they are linked to a higher likelihood of losing. This may be because these themes are perceived as generic or lacking meaningful policy content, which could lead to voter disengagement and reduced campaign effectiveness.

The analysis highlights the strategic importance of positive and negative keywords in shaping voter perception and influencing election outcomes. Positive keywords like *"Viksit Bharat"* and *"stronger nation"* strongly contribute to campaign success by emphasizing themes of development, national pride, and progress, which are likely to resonate with voters and increase the chances of winning. In contrast, negative keywords like *"vote"* and *"voice"* appear to reduce campaign effectiveness, possibly due to voter fatigue, lack of trust, or the perception that these themes are overused or insincere. To enhance campaign success, political strategies should focus on reinforcing positive themes while carefully addressing or avoiding negative ones. This targeted approach can improve voter engagement and strengthen the overall impact of campaign messaging.

9. CONCLUSION

This research paper presents an efficient framework for sentiment analysis and data mining of political leaders' popularity on social media using the Apache Hadoop framework. The model achieved an impressive accuracy of 85%, with strong precision (0.86 for Win, 0.84 for Loss), recall (0.88 for Win, 0.82 for Loss), and F1-scores (0.87 for Win, 0.83 for Loss). Keywords like "Viksit Bharat" and "stronger nation" positively influenced election success, while terms such as "vote" and "voice" had negative impacts. The framework effectively predicts election outcomes, providing actionable insights for campaign strategies by highlighting the importance of positive messaging and addressing negative themes. These insights can help political strategists refine their campaigns to maximize voter engagement and support.

Despite its effectiveness, the framework has certain limitations. The model's accuracy depends heavily on the quality and diversity of the training data; biased or incomplete data can reduce its predictive

power. The selection of keywords is also critical—omitting key terms or including irrelevant ones can weaken the model's accuracy. Additionally, the model does not account for contextual factors such as regional differences, candidate popularity, or external political events, which could influence election outcomes. These factors should be considered alongside the model's predictions to gain a more comprehensive understanding of voter behavior.

The future scope of this research offers several promising directions. Expanding data sources to include a wider range of social media platforms, news articles, and speeches—along with multilingual data—can improve the model's accuracy and generalizability. Integrating advanced machine learning models, such as LSTM and BERT, can enhance sentiment classification and capture subtle nuances in social media data. Real-time analysis using frameworks like Apache Kafka or Flink can enable instant monitoring of public sentiment. Additionally, incorporating regional and socio-economic factors and developing interactive dashboards using platforms like Tableau or Power BI can make the insights more accessible. Addressing ethical concerns, such as data privacy and bias, will further strengthen the framework's reliability and applicability in political analysis.

AUTHOR STATEMENTS:

Ethical Approval: The conducted research does not involve the use of human or animal subjects.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Acknowledgements: The authors declare that there are no individuals or organizations to acknowledge.

Author Contributions: Both authors contributed equally to the conception, design, implementation, and writing of this paper.

Funding Information: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy or ethical restrictions.

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