Sentiment Analysis of Indian Political Tweets: A Comparative Study with LSTM and RNN Model

Swati V. Bhat, Vidhi R. Patel, Om R. Muddapur, Chandanagouda H., Uday Kulkarni and Sunil Gurlahosur

School of Computer Science and Engineering, KLE Technological University, Hubli, India

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Abstract: Sentiment analysis has emerged as one of the prime focuses in machine learning, particularly with the rise of social media platforms such as X (formerly Twitter), Reddit, Instagram, and Facebook. These platforms are now central to public conversations, including discussions on politics, generating massive amounts of data through tweets and comments. The study focuses on applying existing deep learning models to the underexplored domain of sentiment analysis of Indian political tweets. The objective is to determine whether models such as LSTM and RNN are applicable to the analysis of Indian political sentiment. The study uses advanced natural language processing techniques, such as Term Frequency-Inverse Document Frequency (TF-IDF) and Word2Vec, for feature extraction to represent tweet text. The research is testing these models on a new and unique dataset of Indian political tweets to find out which model and feature combination best suits this specific context. Experimental results show that TF-IDF embeddings, along with LSTM and RNN models, significantly outperform Word2Vec in sentiment classification with accuracy rates of 83.02% and 81.06%, respectively. These findings demonstrate the potential of LSTM with TF-IDF to effectively analyze political discourse on social media and suggest insights into the suitability of existing models for Indian political sentiment analysis.

1 INTRODUCTION

The explosive growth of social media platforms such as Twitter, Reddit, Instagram and Facebook has fundamentally changed how people communicate, exchange information, and express their views(Duncombe, 2019). These platforms have become integral to global conversations, enabling users to engage in real-time discussions on a wide range of topics (Madakam and Tripathi, 2021). Among them, Twitter stands out as a platform of choice for dynamic public discourse. Its simplicity, and accessibility allow users to express thoughts and opinions on various matters, including politics, a subject that consistently evokes strong reactions and vibrant debates (Park, 2013).

Politics has always been a major topic in society. On X (formerly Twitter), people regularly discuss current affairs, express their opinions about policies, and assess the deeds and choices of political figures. This enormous number of conversations is a gold mine of public opinion, providing priceless insights into the opinions, worries, and goals of the population (Research, 2021). These insights can be used by analysts, researchers, and policymakers to better understand public sentiment, guide choices, develop governance plans, and even promote cross-border cooperation.

The problem lies in the current limitations of sentiment analysis research on social media platforms like Twitter. Most studies focus on specific events or use basic methods that classify opinions simply as positive or negative, missing the finer emotional details, layered trends, and complexities of public discussions. Additionally, many existing approaches fail to use advanced computational techniques to capture the context and subtleties of text data. This creates a gap in understanding the full spectrum of public sentiment, especially in the diverse and fast-evolving political landscape of India, where refined insights are crucial for informed decision-making and meaningful participation.

The paper addresses the challenge of analyzing Indian political sentiment by evaluating the suitabil-

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ity of existing deep learning models such as LSTM and RNN. It aims to test whether these models can effectively capture the complexity of public sentiment in India's rapidly evolving political landscape. This study extracts meaningful features from textual data by using advanced text representation techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) (Qaiser and Ali, 2018b) , (Liu et al., 2018) and Word2Vec (Jatnika et al., 2019). These models are then applied to analyze contextual aspects of political tweets.Providing valuable insights for future research in Indian political sentiment analysis.

The paper is structured to comprehensively address the objectives of the study, with Section 2 providing a detailed background study that reviews existing sentiment analysis techniques such as TF-IDF, Word2Vec (Lei, 2020), LSTM and RNN. This section also explores their applications in social media analysis, with a focus on prior research in political sentiment analysis, emphasizing the strengths and limitations of current approaches,highlighting the description of existing models.Then in section 3 the proposed methodology is outlined, detailing the use of advanced text representation and deep learning techniques, such as TF-IDF for feature extraction, Word2Vec for contextual word embedding, and LSTM and RNN models for sequential data analysis. It also describes the process of data cleaning, preprocessing, and model training, ensuring accuracy and efficiency. And in section 4 the experimental results are discussed in-depth, including a comparative analysis of the proposed methods using metrics like accuracy, recall, precision, and F1-score, accompanied by visualizations that provide insights into sentiment distribution and polarity trends. Then in the final section 5 the paper concludes with a summary of the key findings and their implications for understanding public sentiment in Indian politics,along with a discussion on potential future research directions, such as expanding the methods to other domains or exploring advanced sentiment analysis.

2 BACKGROUND STUDY

Several techniques have been developed for sentiment analysis, particularly machine learning approaches, which are useful for improving the accuracy of sentiment classification across various domains, including politics, finance, and social media.

Machine learning approaches have been extensively explored. (Gangwar and Mehta, 2022) investigates Israeli political tweets, addressing challenges

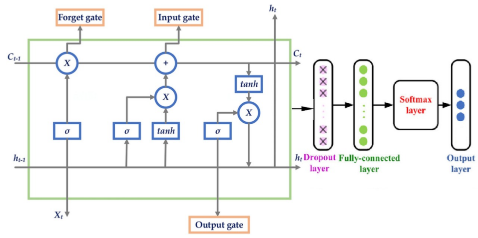

Figure 1: The internal structure of a single hidden unit in an LSTM, visualizing the computation of h_t and C_t using an input x_t, the hidden state value of the previous unit h_{t-1}, and the cell state unit value of the preceding unit C_{t-1}.

such as regional dialects and linguistic biases. Similarly, (Hicham et al., 2023) emphasizes the effectiveness of TF-IDF for sparse data, as elaborated in (Qaiser and Ali, 2018a). Word2Vec, another feature representation, captures semantic relationships between words, enhancing deep learning models like LSTM networks and RNNs, as demonstrated in (Jatnika and Setiawan, 2020).

Advanced neural network models, such as LSTM and RNN, have proven to be very effective for the analysis of sequential data. LSTMs have an excellent capability of capturing long-term dependencies and are very effective for tasks like sentiment analysis on long-form text. For instance, (Paduri et al., 2022) illustrates how LSTM can model temporal patterns, while (Murthy et al., 2020) has demonstrated its ability in analyzing the sentiment within complex text structures. The architecture of an LSTM network, as described in (Darji, 2021), is presented in Figure 1. It depicts the internal structure of a single LSTM cell, including its gating mechanisms, namely the input, forget, and output gates, which control the flow of instructions.

RNNs, on the other hand, are well-suited for tasks involving shorter or fragmented text, such as tweets or reviews, due to their ability to model sequential dependencies. Studies like (Kurniasari and Setyanto, 2020) and (Thomas and C A, 2018) emphasize the utility of RNNs in sentiment classification. The architecture of RNNs, as visualized in (Stier et al., 2021), is depicted in Figure 2. It highlights their sequential processing structure, where hidden states are passed from one time step to the next, enabling RNNs to capture temporal patterns effectively.

Despite the advancement in sentiment analysis, the Indian political tweets are still not well explored. Models like LSTM and RNN have been promising, but their performance on Indian political tweets has not been fully tested. Techniques like TF-IDF and Word2Vec work well for feature extraction, but it is unknown how effective they are when combined with these deep learning models. This gap can be filled by

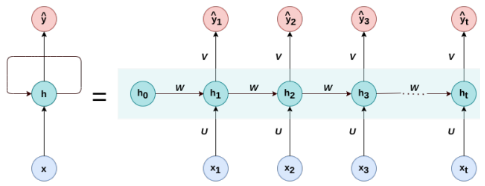

Figure 2: A simple Recurrent Neural Network unfolded over t time steps, where U represents input-to-hidden weights, W represents hidden-to-hidden weights, and V represents hidden-to-output weights.

using LSTM and RNN models with these text representation techniques to analyze the unique sentiment in Indian political tweets.

3 PROPOSED WORK

To understand the sentiment behind political tweets in the Indian context, we need a thoughtful and structured approach. This section highlights the strategies and methods used to analyze and make sense of these sentiments effectively.Figure 3 illustrates the end-to-end workflow applied for sentiment analysis of Indian political tweets.

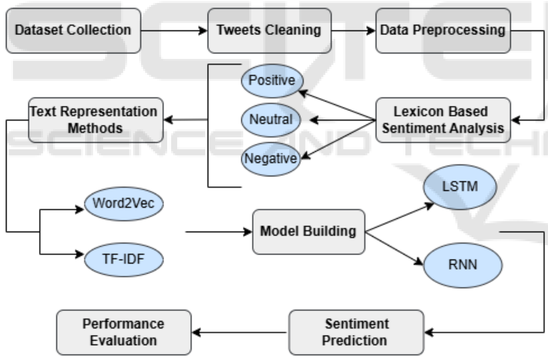

Figure 3: Workflow: Step-by-step process for sentiment analysis of political tweets.

3.1 Methodology and Implementation

This section provides a detailed overview of the models, methodologies, and their implementation strategies employed for analyzing sentiment in Indian political tweets. By delving into the computational techniques and tools used it aims to offer a comprehensive understanding of how sentiment analysis was conducted. The focus is on outlining the approaches used to process and interpret the vast amount of textual data, providing information about how these techniques were applied to extract meaningful insights from the public discourse on Indian politics.

3.1.1 Data Preprocessing

The dataset has been refined to enhance its suitability for analysis. This involved preparing plain text versions of the tweets by removing stopwords, extra whitespaces, usernames, and punctuation. Additionally, case folding was applied, duplicate entries were eliminated, and rows without tweets were removed. Irrelevant columns such as date and user details have been dropped to come up with a cleaner version of the dataset. The Natural Language Toolkit (NLTK) pre-trained 'punkt' English tokenizer was used to split longer tweets into individual words.

3.1.2 Lexicon Based Sentiment Analysis

The dataset was unlabeled, which consisted only of tweets without classification into positive, negative, or neutral categories. Sentiment analysis was performed to compute the sentiment in terms of the semantic orientation of words or phrases in the tweets.This was achieved using the python package TextBlob, which returns the polarity of the text. The polarity values range from -1 to 1, with negative sentiment at -1, neutral at 0, and positive at +1.

3.1.3 Text representation methods

In this subsection, we take a closer look at the techniques used to create word embeddings and evaluate the importance of words in a tweet.The methods include:

a) Word2Vec : In analyzing Indian political tweets, Word2Vec helps to represent a text in a way that captures the context and meaning of words, making it easier to identify subtle sentiments and topics in political discussions. Its ability to preserve the relationships between words allows machine learning models to perform better by utilizing the created word embeddings.

Figure 4 shows the Word2Vec architecture(Zhang, 2019) applied to political tweets on the sample tweet "should we laugh or cry who is calling whom corrupt jokers of Indian politics." The tweet is tokenized and the Skip-gram approach is used to learn word embeddings by predicting the context of a target word. Each word is represented as a vector, capturing semantic relationships to reflect the meaning and context in political discourse.

b) TF-IDF : It is use to measure the importance of words in each tweet relative to the entire dataset. TF calculates how often a word appears in a tweet, using methods like raw frequency or logarithmic nor-

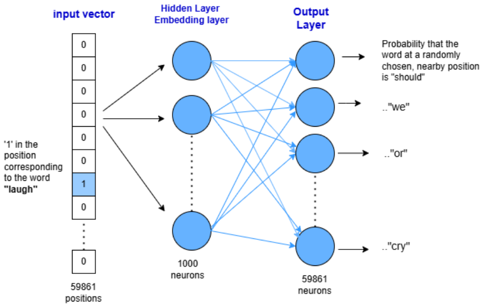

Figure 4: Word2Vec Neural Network Architecture: Illustration of the model used to convert words into vector representations for semantic analysis.

malization. IDF identifies significant terms by reducing the weight of commonly used words (stop words) and emphasizing unique or less frequent words across tweets. This helps highlight key terms like political names and topics, enabling effective feature extraction for sentiment classification.

The TF-IDF weight of a term x in tweet y is:

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right) \quad (1)$$

where, $tf_{x,y}$ is the frequency of term x in tweet y, df_x is the number of tweets containing term x, N is the total number of tweets.

3.1.4 Model Building

The dataset is divided into two sets training set (80%) and testing set (20%). The training set is used to train the LSTM and RNN models, thus enabling them to learn from the data.

Both models take word embeddings as input. These word embeddings are generated using Word2Vec or TF-IDF. Each word in a tweet is represented as a vector, and the sequence of these word embeddings is passed through the RNN and LSTM models for sentiment analysis.

Data: Input sequence $\{x_t\}_{t=1}^{T}$
Result: Predicted output sequence $\{\hat{y}_t\}_{t=1}^{T}$
Initialize hidden state h_0;
for $t \leftarrow 1$ **to** T **do**
  Compute hidden state:
   $z_t \leftarrow Ux_t + Wh_{t-1} + b_h$;
  Apply activation function: $h_t \leftarrow \tanh(z_t)$;
  Compute output: $o_t \leftarrow Vh_t + b_o$;
  Predict output: $\hat{y}_t \leftarrow \text{softmax}(o_t)$;
end
return $\{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_T\}$;

Algorithm 1: RNN Model for Sequential Data Prediction.

Algorithm 1 describes the working of the RNN model, where each word is processed sequentially over time steps $t = 1$ to T. At each step, the hidden state h_t is updated using the current word embedding x_t, the previous hidden state h_{t-1}, and a bias term with an activation function (tanh). The output o_t is computed from h_t using a weight matrix and bias, and the sentiment prediction $\hat{y}_t$ is obtained by applying the softmax function.

Data: Input sequence $\{x_t\}_{t=1}^{T}$
Result: Predicted output y_{pred}
Initialize parameters
 $W_i, W_f, W_o, W_g, b_i, b_f, b_o, b_g, W_{fc}, b_{fc}$;
Initialize cell state c_0 and hidden state h_0;
for $t \leftarrow 1$ **to** T **do**
  Compute input gate:
   $i_t \leftarrow \sigma(W_i[h_{t-1}, x_t] + b_i)$;
  Compute forget gate:
   $f_t \leftarrow \sigma(W_f[h_{t-1}, x_t] + b_f)$;
  Compute output gate:
   $o_t \leftarrow \sigma(W_o[h_{t-1}, x_t] + b_o)$;
  Compute candidate values:
   $\tilde{c}_t \leftarrow \tanh(W_g[h_{t-1}, x_t] + b_g)$;
  Update cell state: $c_t \leftarrow f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$;
  Update hidden state: $h_t \leftarrow o_t \odot \tanh(c_t)$;
end
Compute final output: $y \leftarrow W_{fc} \cdot h_T^{\text{drop}} + b_{fc}$;
Predict with softmax: $y_{\text{pred}} \leftarrow \text{softmax}(y)$;
return y_{pred};

Algorithm 2: LSTM Model for Sequence-to-Output Prediction.

Algorithm 2 describes the working of LSTM model, where at each time step t, the input tweet is processed by updating the input gate i_t, forget gate f_t and output gate o_t. The candidate values $\tilde{c}_t$ are used to update the cell state c_t, while the hidden state h_t is updated to capture relevant context. The final prediction y_{pred} is made by feeding the hidden state through a fully connected layer followed by the softmax function.

After training the models for 10 epochs, predictions are made using the unseen testing data based on the patterns learned. Both models use the same hyperparameters with an embedding dimension of 1000, a hidden dimension of 128, and a learning rate of 0.001.

4 EXPERIMENTAL RESULTS AND ANALYSIS

The dataset for the analysis of Indian political tweets in the study was obtained from Kaggle (Adritpal08, 2024). It contains 50,000 tweets along with information like posting date, user details, and engagement metrics such as likes and retweets. Figure 5 illustrates the distribution of polarity across the dataset after preprocessing, showcasing the sentiment breakdown of the tweets.

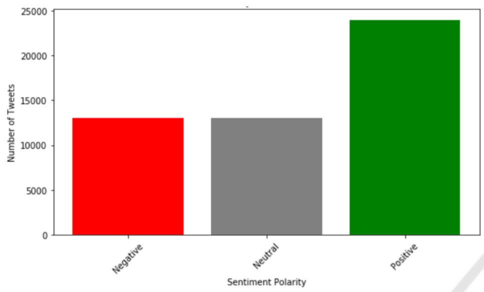

Figure 5: Sentiment polarity vs Number of Tweets.

The final training dataset includes about 24,000 positive tweets, 15,000 neutral tweets, and 13,000 negative tweets, which indicates most of the tweets are positive, followed by neutral and then negative.

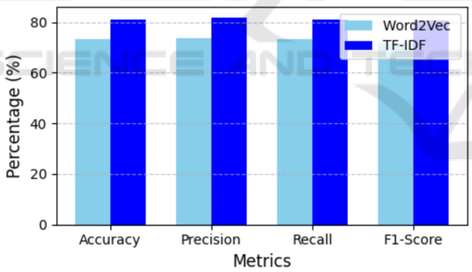

Figure 6: Performance matrics of LSTM in %.

Figure 6 shows how the LSTM model performs using TF-IDF and Word2Vec representations across different metrics. It is clear that the LSTM with TF-IDF performs much better. This suggests that TF-IDF captures the important features of the Indian political dataset more effectively. On the other hand, Word2Vec which creates distributed word representations, may not fully capture the specific details and context of this dataset.

In Figure 7, the performance metrics indicate that the RNN model achieves better results with TF-IDF compared to Word2Vec across all evaluated metrics. This observation implies that, for the Indian political tweets dataset, TF-IDF serves as a more effective feature representation for sentiment analysis. The superior performance with TF-IDF can be attributed to its ability to highlight important terms, enabling the RNN model to focus on relevant features, a benefit that may not be as pronounced when using Word2Vec. Consequently, TF-IDF emerges as the more suitable choice for this task.

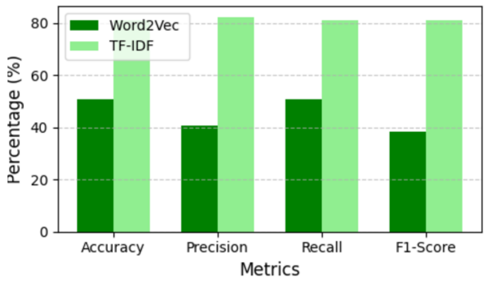

Figure 7: Performance matrics of RNN in %.

Table 1: Testing Accuracy of models with different techniques.

Models	Accuracy (%)	
	Word2Vec	TF-IDF
LSTM	73.08	83.02
RNN	50.7	81.06

As observed in Table 1, the LSTM model with TF-IDF outperforms the same model with Word2Vec, achieving better performance across various metrics. This indicates that TF-IDF offers more effective feature representations for the Indian political tweets dataset when used with LSTM, highlighting its superiority over Word2Vec embeddings for this task. The enhanced performance of LSTM can be attributed to its ability to capture long-range dependencies in the text, which is essential for understanding the contextual and nuanced nature of political sentiments. Unlike RNNs, LSTMs are better equipped to retain important information across long sequences, making them more suitable for task like sentiment analysis of political tweets.

5 CONCLUSION AND FUTURE WORK

This study compares the performance of LSTM and RNN models for sentiment analysis of Indian political tweets, filling the gap in the underexplored area of Indian political sentiment analysis. The results show that LSTM combined with TF-IDF delivers the highest accuracy of 83.02%, outperforming other combinations such as Word2Vec (73.08%) and RNN with either TF-IDF (81.06%) or Word2Vec (50.7%).These results show that the combination of LSTM with TF-IDF is particularly effective in identifying key contextual features in political discourse, which shows the strength of LSTM in capturing sequential patterns. The study emphasizes the suitability of integrating existing deep learning models with text representation techniques for sentiment analysis, providing valuable insights into how these methods can be applied to the domain of Indian political tweets.

In the future, the results of this study can be further improved by refining feature extraction techniques and exploring more advanced model architectures. Additionally, scaling the analysis to larger and more diverse datasets could enhance the robustness and generalizability of the findings. These advancements would provide deeper and more reliable insights into public sentiment, making this research even more impactful for understanding political discourse.

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