Beyond_Tech@DravidianLangTech 2025: Political Multiclass Sentiment Analysis using Machine Learning and Neural Network

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Abstract

Research on political feeling is essential for comprehending public opinion in the digital age, as social media and news platforms are often the sites of discussions. To categorize political remarks into sentiments like positive, negative, neutral, opinionated, substantiated, and sarcastic, this study offers a multiclass sentiment analysis approach. We trained models, such as Random Forest and a Feedforward Neural Network, after preprocessing and feature extraction from a large dataset of political texts using Natural Language Processing approaches. The Random Forest model, which was great at identifying more complex attitudes like sarcasm and opinionated utterances, had the greatest accuracy of 84%, followed closely by the Feedforward Neural Network model, which had 83%. These results highlight how well political discourse can be analyzed by combining deep learning and traditional machine learning techniques. There is also room for improvement by adding external metadata and using sophisticated models like BERT for better sentiment classification.

1 Introduction

Political sentiment analysis is crucial for understanding public opinions on political topics, particularly in today's digital age where political discussions have largely moved to online platforms like social media. These discussions generate vast amounts of textual data, but political sentiment is complex, ranging from neutral and supportive to oppositional and sarcastic, making analysis challenging.

In this study Chakravarthi et al. (2025), we propose a multiclass sentiment analysis method for political text, categorizing sentiments into positive, negative, neutral, substantiated, opinionated, and sarcastic. Using NLP techniques such as tokenization, lemmatization, and TF-IDF for feature extraction, we compare the performance of machine learning models, including Random Forest and Neural Networks. Neural Networks performed better, particularly in identifying subtle emotions like sarcasm. Our results show that combining traditional machine learning with deep learning improves sentiment analysis accuracy in political discourse, despite ongoing challenges with sarcasm detection.

2 Related Works

The paper Ma'Aly et al. (2024) examined the multi-label sentiment categorization of YouTube comments from the 2024 Indonesian presidential election using CNN, Bi-LSTM, and hybrid CNN-BiLSTM models. The model that captured long-term dependencies, the Bi-LSTM, had the best accuracy of 98% and the highest AUC of 0.92. In order to address class imbalance, preprocessing techniques included normalization, stopword removal, text augmentation, and class weights. Tun and Khaing (2023) development of superior sentiment lexicons for political tweets is the main subject of this work, which investigates Twitter's function in political discourse and sentiment analysis. In sentiment classification, the Linear SVC model achieved 98% accuracy, outperforming the Multinomial Naive Bayes (MNB) and Decision Tree (DT) models.To enhance tweet quality, the study (Saranya and Usha, 2023) suggests a sentiment analysis technique utilizing TF-IDF and Intelligent WordNet lemmatization. Emotion detection using a Random Forest network outperforms current multiclass sentiment classification methods with an accuracy of 90%. The method goes beyond merely detecting emotions and places a strong emphasis on closely examining tweets that are positive or negative.

Mu et al. (2024) presented a model for multimodal sentiment analysis of government comments

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using a unique cross-attention fusion network and contrastive learning, which achieves 96.80% accuracy. Policymakers benefit from improved emotion polarity recognition thanks to the model's 10.21% accuracy gain over the CLIP model. Diqi et al. (2024) used the Multinomial Naive Bayes algorithm to analyze sentiment in digital election campaign ads with 96% accuracy. It highlights the necessity of customized approaches and suggests that future research investigate cutting-edge NLP methods using real-time social media data. Innork et al. (2023) investigated a number of machine learning techniques for sentiment analysis, such as Random Forest, K-Nearest Neighbors, Support Vector Machine, Multinomial Naive Bayes, and an ensemble method. According to the study, when it comes to categorizing hotel evaluations, the ensemble approach works better than the others.

Kowsik et al. (2024) used sentiment analysis to classify political leanings in Twitter data, the study "Sentiment Analysis of Twitter Data to Detect and Predict Political Leniency Using Natural Language Processing" achieves a 99% confidence level in identifying the political biases of user profiles .In order to forecast the results of legislative debates, Salah (2014) investigates sentiment analysis techniques based on classification and vocabulary. It presents the Debate Graph Extraction framework and suggests domain-specific sentiment lexicons to display and examine the sentiment and structure of disputes. Liebeskind et al. (2017) examined 5.3 million Facebook comments about politicians and evaluates nine machine learning techniques for sentiment analysis. Classifying generic attitudes against content-specific attitudes revealed differences, with n-gram representation being the most successful and logistic regression achieving the best accuracy.

Sumathy and Muthukumari (2018) focused on sentiment analysis of social media reviews using machine learning. A Support Vector Machine (SVM) was used to classify reviews as positive or negative, outperforming Naive Bayes in terms of accuracy. The SVM model was optimized with a multi-class kernel and hyperparameter tuning.

3 Problem Description

Sentiment analysis of Tamil political debates is difficult because of the language's complexity, cultural quirks, and emotions like positive, negative, neutral, opinionated, substantiated, and ironic. Classifier development is made more challenging by the absence of annotated datasets, and traditional binary sentiment analysis is insufficient. This work creates a multiclass sentiment analysis model for Tamil political literature in order to handle problems such as inconsistent data, language normalization, and the intricacy of political speech. Prediction, model training, feature extraction, and data preparation for multiclass sentiment classification are all included in the system. The dataset used is provided by the codalab Chakravarthi et al. (2025).Our system performed competitively, placing 16th Rank among 153 participants in this shared task.

3.1 Data Preprocessing

In sentiment analysis, preprocessing is essential, especially when using a regional language like Tamil. Several processes are used to clean and normalize the raw textual data:

- Normalization of Unicode Characters: To guarantee consistent text representation, unwanted Unicode characters are eliminated.
- Elimination of Non-Tamil Characters: Only the pertinent script is kept after all non-Tamil characters, special symbols, and numerical values are filtered out.
- Handling Spoken Variants: The approach normalizes vowels and diphthongs to their regular written forms to accommodate typical spoken variants in Tamil.
- Tokenization: Stanza is used to tokenize the preprocessed text, which aids in breaking it into discrete words or tokens.
- The consistency and cleanliness of the textual data are guaranteed by this pre-processing pipeline, preparing it for feature extraction.

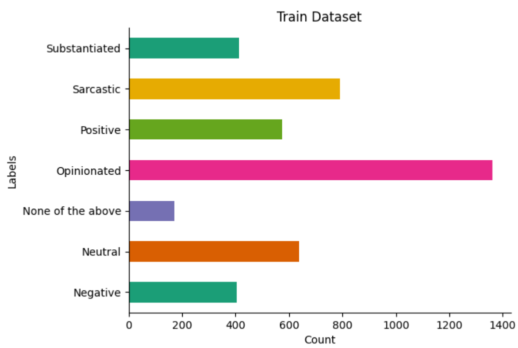

Figure 1: Train dataset Labels and it's count

3.2 Feature Extraction

Following preprocessing, we use the TF-IDF (Term Frequency-Inverse Document Frequency) approach to extract features from the text. Each word's significance in relation to the overall dataset is captured by TF-IDF, which transforms the text into numerical vectors. The model is able to concentrate on important phrases that are essential for differentiating various feelings thanks to this modification.

3.3 Balancing the Dataset

Sentiment classification datasets frequently have unequal class representation, with certain sentiment categories (like neutral) being overrepresented and others (like sarcasm) being underrepresented. The system uses to upsampling for the minority classes in order to lessen this problem. In order to guarantee that the dataset is balanced and that every sentiment class is equally represented throughout training, this technique creates extra samples for the underrepresented classes.

4 Methodology

In this study, two machine learning algorithms are used to categorize Tamil political literature into six different sentiment categories: sarcastic, opinionated, substantiated, neutral, positive, and negative.

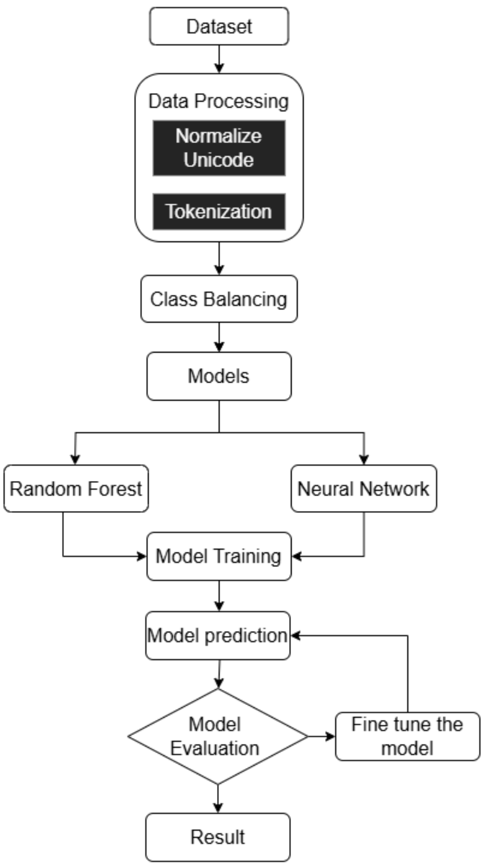

Figure 2: Proposed System Workflow

The models were trained to predict these sentiment classes after the data was preprocessed using Natural Language Processing (NLP) techniques and features were extracted using TF-IDF.

4.1 Random Forest Classifier

An ensemble learning method called the Random Forest algorithm creates several decision trees during training and averages their predictions to increase classification accuracy. This approach is reliable because it uses the combined output of multiple independent trees to minimize overfitting.

- Model Input: The TF-IDF feature vectors produced from the preprocessed Tamil text data were used to train the Random Forest model. The significance of each word in the text is represented by these vectors.
- Model Configuration: We set up 100 decision trees (n_estimators=100) in the Random Forest classifier. A random selection of characteristics was used to train each tree, and hyperparameters like each tree's depth were adjusted to balance the effectiveness and performance of the model.
- **Performance:** Random Forest achieved 95% accuracy on training data and 84% on test data. It performed well in classifying positive, neutral, and negative sentiments. However, it struggled with nuanced emotions like sarcasm and well-supported claims.

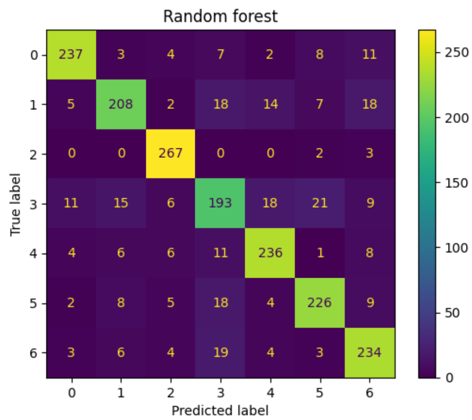

Figure 3: Confusion Matrix for Random Forest

Metric	Precision	Recall	F1-Score
Accuracy	0.84	-	-
Macro avg	0.84	0.84	0.84
Weighted avg	0.84	0.84	0.84

Table 1: Classification Report for Random Forest Model

4.2 Feedforward Neural Network

The Random Forest model might not be able to properly handle the deeper and more complex patterns in the text, so a Feedforward Neural Network model was used. Because of their superior ability to learn non-linear correlations, neural networks are well-suited for the complex task of classifying political mood.

1. Architecture for the Model: Several layers made up the neural network architecture:

    - Input Layer: The TF-IDF vectorized text data was sent to the input layer.
    - Four thick hidden layers of 512, 256, 128 and 64 neurons each were included in the model. To add non-linearity and enable the model to learn intricate correlations between features, each hidden layer employed the ReLU activation function.
    - Dropout Layers: By randomly deactivating neurons during training, dropout layers were added to minimize overfitting.
    - Output Layer: Using a softmax activation function, the output layer categorized the text into six sentiment categories: sarcastic, opinionated, substantiated, neutral, positive, and negative.

2. Model Training: The Adam optimizer with a sparse categorical cross-entropy loss function was used to train the neural network. With a batch size of 128 and 30 epochs, the model was trained with the goal of maximizing classification accuracy while minimizing loss.

3. Performance: Training with neural network the accuracy was 94% and test data accuracy was 83%. It was marginally less successful than the Random Forest model in categorizing neutral sentiments, but it did well in detecting subtle sentiments like sarcasm and opinionated utterances.

Metric	Precision	Recall	F1-Score
Accuracy	0.84	-	-
Macro avg	0.83	0.84	0.83
Weighted avg	0.83	0.84	0.83

Table 2: Classification Report for Neural Network Model

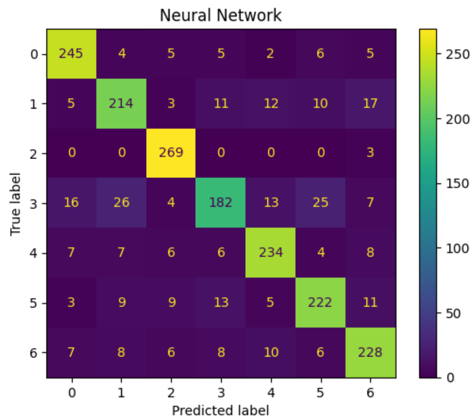

Figure 4: Confusion Matrix for Neural Network model

5 Conclusion

In this experiment Sanjai (2025), we engineered and tested two machine learning classifiers: Random Forest and a Neural Network, toward multi-class sentiment analysis of the Tamil political corpus, with six classes: sarcasm, opinion, substantiation, neutral, positive, and negative. Aims were: to analyze these complex emotional varieties in political talk, which normally involve subtle nuances such as irony and opinions sustained by evidence. It is found that the Random Forest model has an accuracy of 84% and did well with the simpler sentiments, such as positive and neutral but failed to recognize more subtle sentiments like sarcasm and substantiated claims. The Neural Network performed better even though it exhibited a slightly lower overall accuracy of about 83% but picked up more of these intricate patterns and complex sentiments better on account of its deep learning architecture capturing latent features in text. That being said, the complementarity between these models suggests that a hybrid approach that utilizes traditional machine learning techniques along with deep learning might offer a more robust solution for political sentiment analysis. In the future, further studies may concern more sophisticated models, such as BERT, using context-aware representations with even greater improvement in sentiment classification accuracy, especially in capturing subtle emotional cues in political discussions. This can contribute toward better analysis of political texts and understanding of the nuances involved in public sentiments, ultimately contributing toward better political strategies and decision making.

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