Time-Aware Political Sentiment and Narrative Dynamics in Bangla Online Discourse Using Machine Learning

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***Abstract*—The evolution of public political discourse in online environments reflects collective opinion dynamics in digitally mediated societies. This paper presents a time-aware analysis of Bangla political discourse using supervised sentiment classification and unsupervised topic modeling. Classical machine learning models with TF–IDF features are evaluated on a labeled Bangla political sentiment dataset, and the best-performing models are applied to a large timestamped Bangla media comment corpus. Latent Dirichlet Allocation is used to extract dominant narrative themes, and temporal aggregation is performed at yearly and monthly resolutions to capture long-term sentiment shifts and short-term volatility. The results demonstrate robust sentiment classification performance, a dominance of negative sentiment in large-scale discourse, narrative fragmentation across multiple topics, and measurable temporal changes in sentiment polarity.**

***Index Terms*—Political sentiment analysis, Bangla language, TF–IDF, Logistic Regression, Topic Modeling, Temporal Analysis**

I. Introduction

Online political discourse has become a primary medium through which public opinion is expressed, contested, and reshaped. Advances in natural language processing enable large-scale quantitative analysis of such discourse, offering insights into sentiment polarity, narrative structure, and temporal dynamics. However, computational studies of Bangla political discourse remain relatively limited.

This paper proposes a reproducible machine learning pipeline to analyze sentiment and narrative evolution in Bangla political texts. The contributions of this study are threefold:

- Evaluation of classical machine learning models for Bangla political sentiment classification.
- Large-scale sentiment inference and narrative extraction from timestamped Bangla media comments.
- Time-aware analysis of sentiment dynamics at multiple temporal resolutions.

II. Datasets

Two datasets are employed to decouple model training from discourse-level inference.

A. Labeled Political Sentiment Dataset

This dataset consists of Bangla political texts annotated with sentiment labels: negative, neutral, and positive. It is used exclusively for supervised model training and evaluation.

B. BanglaMedia Dataset

The BanglaMedia dataset contains timestamped Bangla media comments with associated metadata. This dataset represents naturally occurring political discourse and is used for large-scale sentiment inference and topic modeling.

III. Methodology

A. Text Representation

Documents are represented using Term Frequency–Inverse Document Frequency (TF–IDF):

$$\text{TF–IDF}(t, d) = \text{TF}(t, d) \log\left(\frac{N}{\text{DF}(t)}\right), \tag{1}$$

where t denotes a term, d a document, N the total number of documents, and DF(t) the document frequency of term t. Unigrams and bigrams are included.

B. Sentiment Classification

Four classifiers are evaluated:

- Logistic Regression (LogReg)
- Linear Support Vector Classifier (LinearSVC)
- Multinomial Naïve Bayes (MNB)
- SGD-based Logistic Regression (SGD_Log)

For Logistic Regression, class probabilities are modeled as:

$$P(y = k|x) = \frac{\exp(w_k^\top x)}{\sum_j \exp(w_j^\top x)}. \tag{2}$$

Performance is assessed using Accuracy and Macro-F1, with emphasis on Macro-F1 due to class imbalance.

C. Topic Modeling

Latent Dirichlet Allocation (LDA) is used to identify latent narrative topics. Each document is modeled as a mixture of topics:

$$P(w|d) = \sum_{k=1}^{K} P(w|z_k)P(z_k|d), \tag{3}$$

where $K = 10$ topics are selected for interpretability.

D. Temporal Sentiment Analysis

Predicted sentiment labels are aggregated over time. Two temporal views are considered:

- Yearly sentiment proportion
- Monthly net sentiment index (negative=-1, neutral=0, positive=+1)

IV. Experimental Results

A. Model Comparison

Table I summarizes the classification performance. LinearSVC and SGD_Log achieve the highest Macro-F1 scores, while Logistic Regression offers competitive performance with strong interpretability.

TABLE I
Sentiment classification performance comparison.

Model	Accuracy	Macro-F1
LogReg	0.8556	0.8396
LinearSVC	0.8602	0.8480
MultinomialNB	0.8283	0.7824
SGD_Log	0.8632	0.8483

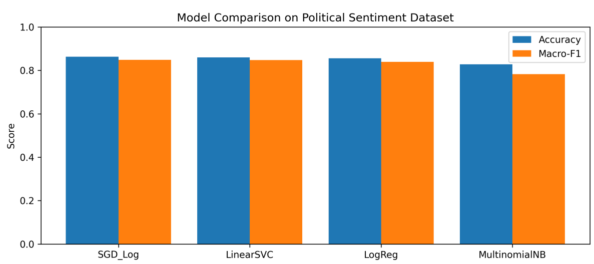
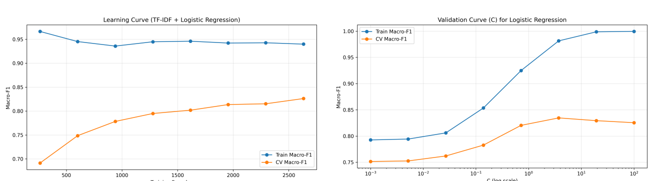


Fig. 1. Accuracy and Macro-F1 comparison across models.

B. Learning and Validation Curves

Learning curves indicate stable generalization as training size increases, while validation curves show that model performance is robust across a broad range of regularization strengths.

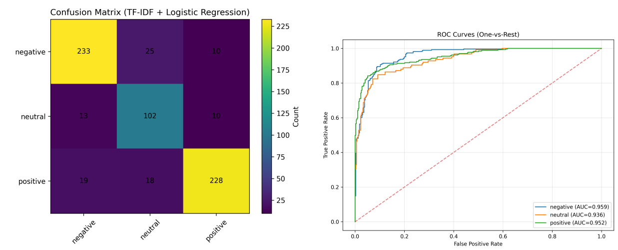


(a) Learning Curve (b) Validation Curve

Fig. 2. Training size and hyperparameter sensitivity analysis.

C. Error and Discrimination Analysis

Confusion matrix and ROC curves reveal strong separation between negative and positive sentiment, with most ambiguity occurring in the neutral class.

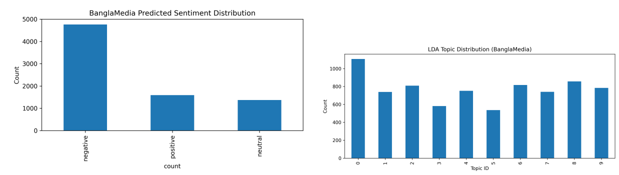


(a) Confusion Matrix (b) ROC Curves

Fig. 3. Error structure and classification discrimination.

D. Discourse-Level Sentiment and Topics

Negative sentiment dominates the BanglaMedia discourse corpus, while topic modeling reveals multiple narrative clusters with sentiment-specific concentrations.



(a) Sentiment Distribution (b) Topic Distribution

Fig. 4. Overall discourse sentiment and topic prevalence.

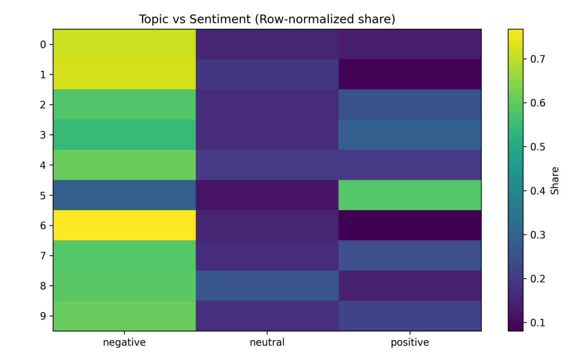
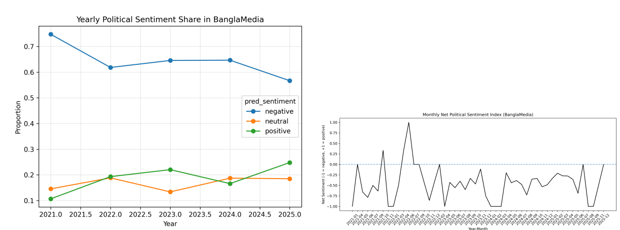


Fig. 5. Topic-wise sentiment distribution (row-normalized).

E. Temporal Sentiment Dynamics

Temporal analysis reveals both long-term shifts and short-term volatility in sentiment polarity.



(a) Yearly Trend (b) Monthly Net Sentiment

Fig. 6. Time-aware evolution of sentiment in Bangla discourse.

V. Discussion

The results demonstrate that classical machine learning models with TF–IDF features are effective for Bangla political sentiment classification. The dominance of negative sentiment, combined with narrative fragmentation and temporal volatility, suggests systematic changes in online political discourse. Importantly, the analysis characterizes aggregate discourse patterns rather than individual beliefs.

VI. Limitations and Ethics

This study analyzes publicly observable discourse and does not infer private political attitudes or voting behavior. Platform-specific biases, coordinated activity, and sampling effects may influence results. Ethical interpretation requires caution when drawing societal conclusions from online data.

VII. Conclusion

This paper presents a reproducible framework for time-aware sentiment and narrative analysis of Bangla political discourse. The findings highlight robust model performance, dominant negative sentiment, and meaningful temporal dynamics. Future work may incorporate transformer-based representations and change-point detection methods.

References

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