Enhancing Political Sentiment Analysis through Transformer-Based Temporal Sentiment and Topic Modeling of the Bangladesh Quota Movement Using a Novel ShadheenBangla Dataset

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***Abstract*—In an era of rapidly evolving political climates, especially within digitally active societies, there is a growing demand for high-quality datasets and methodologies that enable robust political sentiment analysis. This paper presents ShadheenBangla, a novel English-language social media dataset and analytical framework developed to examine public sentiment during the 2024 Bangladesh Quota Reform Movement. The dataset consists of Facebook and Twitter posts across three critical phases: before the movement (pre-July), during the quota reform protests (July 1–16), and during the subsequent anti-government escalation (July 17–August 5). Using transformer-based models, specifically BERT for sentiment classification and BERTopic for topic modeling, we analyze how public discourse evolved temporally across these phases. Our findings reveal a distinct shift in sentiment and narrative — from neutral or reform-focused commentary to increasingly polarized and politically charged expressions. This study not only introduces a context-rich dataset but also demonstrates a scalable methodology for political sentiment analysis in low-resource, movement-driven environments. The ShadheenBangla corpus and analytical pipeline aim to support future research in computational social science, digital activism, and political discourse analysis.**

***Index Terms*—Political Sentiment Analysis, Topic Modeling, BERT, BERTopic, ShadheenBangla**

I. Introduction

Sentiment analysis has gained significant traction in analyzing public opinion and social media data, particularly for understanding societal events, movements, and protests. The Bangladesh Student Movement 2024 serves as an impactful case study for sentiment analysis. Social media platforms, particularly Facebook and X (formerly known as "Twitter") became the primary channels for public expression, offering rich textual data for sentiment analysis. By analyzing Bangladeshi social media data, we assessed how sentiments evolved across different phases of the movement, such as its initiation, peak activities, and eventual outcomes.

Sentiment analysis has been widely applied to political discourse and public opinion mining on social media platforms. In the context of India's farmers' protest, around 20,000 tweets were analyzed using Bag of Words (BoW), TF-IDF, and traditional classifiers including Naive Bayes, SVM, and Random Forest, where Random Forest achieved the highest accuracy of 96.6% [1]. In another study on the 2019 Indian General Elections using 3,896 tweets, LSTM (with TF-IDF trigram) achieved the best accuracy of 82.78%, while Random Forest (with TF-IDF unigram) provided competitive performance with faster training time [2].

Deep learning approaches, especially transformer-based models, have demonstrated superior performance. A BERT model fine-tuned on 140 datasets related to the Black Lives Matter (BLM) movement achieved an AUC of 0.97 (train) and 0.94 (test) [3]. Another Facebook-based BLM study using 7,137 comments applied sentiment tools like Liu Hu (−1.41 avg.), VADER (−0.099), and Ekman's model (40.17% happiness) to assess emotional responses [4].

Research on the 2020 US Presidential Election used Naive Bayes on 18 million tweets, achieving 94.58% accuracy and 94.81% F1-score [5]. In Nigeria's 2023 election, LSTM, peephole LSTM, and TSRLSTM models were evaluated on election-related tweets, with TSRLSTM showing superior sentiment classification [6].

Other works include sentiment analysis on the Boycott Chinese Products and Bollywood Nepotism movements [7], and a political news sentiment project where a Hungarian sentiment dictionary was tested against SVM and Logistic Regression—BERT again outperformed all traditional methods [8].

Multilingual sentiment analysis has also gained attention. A Bangla GRU-based model predicted social movements using Twitter data, enhanced via hyperparameter optimization [9]. A study on the Syrian refugee crisis analyzed 2.38 million tweets in Turkish and English, highlighting cross-cultural sentiment shifts [10]. Spanish [11], German [12], and Hindi [13] sentiment studies further explored linguistic nuance using models like CRFs, RNNs, and Naïve Bayes.

Topic modeling and misinformation detection have also been explored. In a COVID-19 study using 10,254 headlines, LDA outperformed NMF and LSA with a coherence score of 0.66 [14]. Similarly, SentiDiff introduced a diffusion-based sentiment propagation method, outperforming traditional SA models by up to 8.38% [15].

In domain-specific applications, sentiment analysis has been applied to online shopping in Bangladesh using SVM (88.81% accuracy) [16], and to product review classification using BERT-large, BoW, and D-RNNs [17]. For Turkish financial sentiment, SVM and MLP reached accuracies of 89% and 88%, respectively [18].

Overall, these studies show that while classical models like Random Forest and SVM remain strong baselines, transformer-based models like BERT and hybrid deep learning models (e.g., LSTM, GRU) offer greater contextual understanding and accuracy in political and social sentiment classification tasks.

II. Methodology

This study follows a structured pipeline which is shown as a diagram in figure 2 to prepare social media data of Bangladesh Quota Movement 2024 for sentiment classification and topic modeling.

A. Data Collection

The raw data was collected manually from public Facebook posts and comments and tweets related to the 2024 Bangladesh Student Movement. To capture the sentiment dynamics and topic shifts across time, data was collected from three distinct phase.

1) Before the Quota Reform Movement (June 1 – June 30, 2024): Comments during this period reflect early dissatisfaction and job-market concerns, focusing on unfair recruitment practices and the demand for merit-based systems.

2) During the Quota Reform Protests (July 1 – July 10, 2024): This period covers the peak of the student-led movement. Thousands of students participated in protests demanding the cancellation of the 30% quota system in government jobs. Facebook became a critical platform for live updates, awareness, and mobilization.

3) After the Movement Became an Anti-Government Uprising (July 11 – July 20, 2024): Following violent police crackdowns, widespread arrests, and alleged manipulation of mainstream media, public sentiment shifted sharply. The focus of discourse moved from quota reform to systemic corruption, human rights violations, and calls for the resignation of the ruling party and Prime Minister Sheikh Hasina. This phase saw hashtags like `#ResignHasina`, `#DownWithDictatorship`, and `#SaveDemocracy` go viral.

B. Language Normalization

The dataset included texts in English, Bengali, and Romanized Bengali. All non-English texts were translated into English to ensure consistency. Translations were primarily done using automated tools (e.g., Google Translate) and manually verified by native speakers to preserve sentiment and context.

C. Data Annotation

Each text entry was manually labeled into one of three sentiment classes:

- **-1** – Negative
- **0** – Neutral
- **1** – Positive

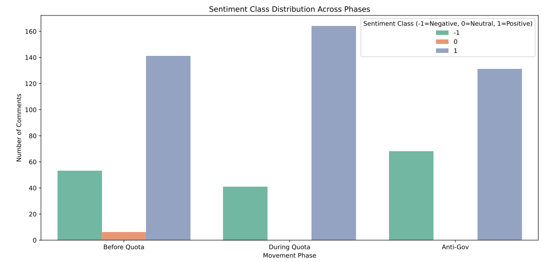

Fig. 1. Overview of the dataset divided into three distinct files, each corresponding to a specific time span of the movement.

Manual annotation was performed by trained annotators with contextual understanding of the socio-political situation. Conflicting or ambiguous entries were resolved through group consensus. The cleaned and labeled data was then organized into three folders based on their corresponding phase of the movement: `Before_quota.xlsx`, `During_Quota_movement.xlsx`, and `Anti_Govt.xlsx`. Each file includes key columns that structure the dataset for analysis:

- **Text** – The English-translated social media content
- **User** – The anonymized identifier of the user
- **Platform** – The platform (e.g., Facebook or Twitter) from which the data was collected
- **Date** – The original timestamp of the post or comment
- **Class** – The manually assigned sentiment label

This structured format allowed for efficient loading, filtering, and sentiment-based analysis across all phases of the movement.

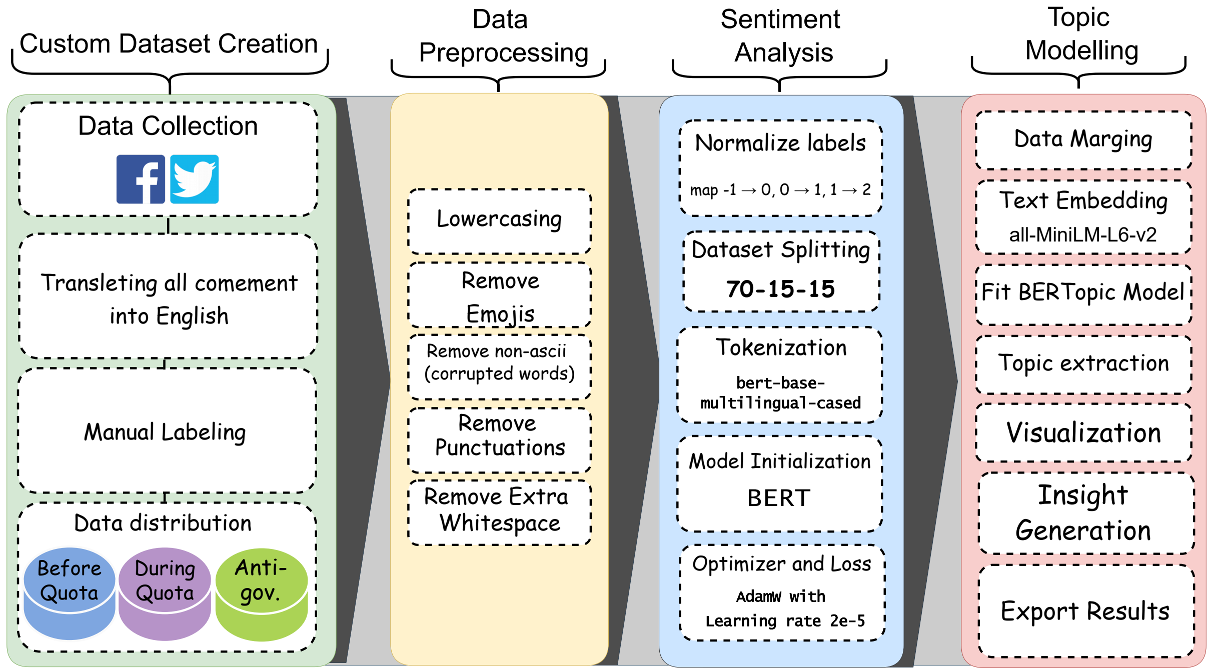

Fig. 2. Proposed methodology pipeline illustrating the complete workflow, including raw data collection, manual labeling, preprocessing, sentiment classification using BERT, and thematic analysis through BERTopic-based topic modeling.

D. Text Preprocessing

Prior to model training and analysis, several preprocessing steps were applied to standardize and clean the dataset. First, all text was converted to lowercase to ensure uniformity and minimize duplication due to case differences. Emojis were removed using the `emoji` library to eliminate non-verbal expressions that do not contribute to textual sentiment analysis. Additionally, non-ASCII characters were stripped from the text to maintain encoding compatibility and avoid tokenization errors. All punctuation marks were removed using regular expressions to focus the analysis on core lexical content. Finally, extraneous whitespace, including tabs and multiple spaces, was normalized to a single space to improve text consistency. These preprocessing steps helped reduce noise and prepared the text data for efficient natural language processing.

E. Sentiment Analysis

To investigate the emotional tone and public opinion across different phases of the movement, sentiment analysis was conducted using a fine-tuned BERT-based architecture. The final dataset consisted of text comments manually labeled into three sentiment classes: negative (-1), neutral (0), and positive (1). These labels were converted to numerical categories (0, 1, 2) for compatibility with classification algorithms.

The preprocessed text data was tokenized using the `BertTokenizer` from the HuggingFace `transformers` library. A `BertForSequenceClassification` model based on the `bert-base-multilingual-cased` checkpoint was employed to support multilingual content. The dataset was divided into training (70%), validation (15%), and test sets (15%). A custom PyTorch `Dataset` class was implemented to handle batching and tokenization. Training was conducted using the AdamW optimizer with a learning rate of $2e$-5 and early stopping based on validation loss. Evaluation metrics included Accuracy [19], Precision [20], Recall [20], F1-Score [20], Mean Absolute Error (MAE) [21], Matthews Correlation Coefficient (MCC) [22], Cohen's Kappa [23], and Confusion Matrix [20] analysis.

Multiple training curves and diagnostic plots were generated to validate performance, including loss and accuracy trends across epochs and ROC curves for each sentiment class.

F. Topic Modeling

In parallel with sentiment analysis, topic modeling was performed to uncover the major themes and discourse topics evolving over the course of the movement. The BERTopic algorithm was selected due to its ability to combine transformer-based embeddings with clustering for interpretable topic discovery.

First, the cleaned textual content was encoded using the `all-MiniLM-L6-v2` SentenceTransformer model to generate dense sentence embeddings. BERTopic was then applied with UMAP for dimensionality reduction and HDBSCAN for clustering. The algorithm was configured to return probability distributions over topics, allowing nuanced analysis.

The model generated coherent topics with top representative keywords and documents. Visualizations included a topic bar chart (top 10 topics), intertopic distance map, term rank relevance plot, and topic evolution over time based on post dates. Word clouds were also generated to offer intuitive overviews of prominent keywords across topics. The topic frequency table summarized each topic with its top words and frequency count.

In summary, sentiment analysis quantified the polarity of user opinions, while topic modeling identified the key subjects being discussed in each phase of the movement. These combined approaches enabled a holistic understanding of public sentiment and thematic trends throughout the social unrest.

III. Results and Discussion

A. Sentiment Classification Performance

To evaluate the performance of our BERT-based sentiment classifier, we report the key evaluation metrics on the held-out test dataset.

Metric	**Score**
Accuracy	80.22%
Precision (Macro-Averaged)	51.01%
Recall (Macro-Averaged)	47.47%
F1-Score (Macro-Averaged)	48.56%
Matthews Correlation Coefficient (MCC)	0.4655
Cohen's Kappa Score	0.5420

TABLE I. Performance metrics for the sentiment classification model

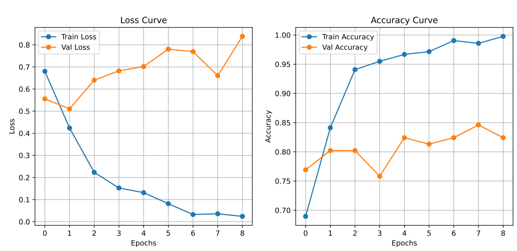

Fig. 3. Training and Validation Accuracy vs Epochs

B. Confusion Matrix Analysis

A normalized confusion matrix was plotted to better understand classification accuracy per class. The model demonstrated strong class-wise performance in capturing the positive sentiments.

C. ROC Curve

To further validate class separability, we plotted the multi-class ROC curve using a one-vs-rest approach. Among all the sentiment classes, class 2 achieved high area under the curve (AUC) values which indicates strong predictive confidence.

These results collectively affirm the robustness of the BERT-based sentiment classification model in capturing nuanced emotional tones embedded in social media discourse surrounding the movement.

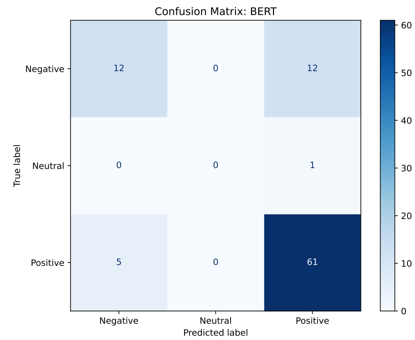

Fig. 4. Confusion Matrix of Sentiment Classification

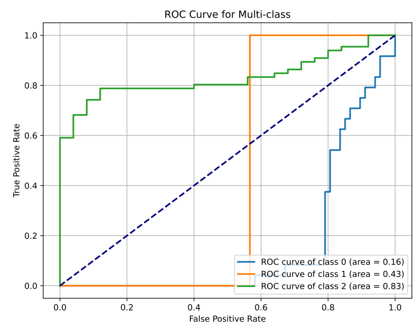

Fig. 5. ROC Curves for Multi-class Sentiment Prediction

D. Topic Modeling Results

To explore the thematic structure of public discourse during the movement, we employed BERTopic for unsupervised topic modeling across all three phases. To visualize topic distribution, we generated a combined word cloud illustrating the most dominant keywords across topics.

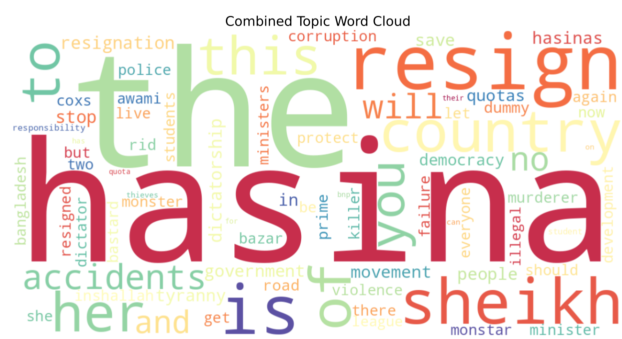

Fig. 6. Combined word cloud generated from all discovered topics, illustrating the most frequently occurring and thematically significant terms discussed throughout the different phases of the movement.

Table II presents sample topics with their top-ranked keywords. Furthermore, a topic similarity matrix was computed to understand semantic overlaps, highlighting closely related or evolving themes over time.

TABLE II. Topic Modeling Results: Topics, Top Words, and Counts

Topic	Details
0	**Top Words:** quotas, to, the, can, on **Count:** 165
1	**Top Words:** bangladesh, the, awami, of, in **Count:** 78
2	**Top Words:** movement, the, inshallah, will, students **Count:** 58
3	**Top Words:** hasina, her, and, monster, is **Count:** 40
4	**Top Words:** government, the, corruption, development, is **Count:** 35
5	**Top Words:** resign, now, you, is, resigned **Count:** 32
6	**Top Words:** country, dictatorship, save, tyranny, democracy **Count:** 30
7	**Top Words:** sheikh, hasina, resignation, hasinas, resign **Count:** 16
8	**Top Words:** accidents, stop, people, road, but **Count:** 12
9	**Top Words:** coxs, bazar, you, murderer, protect **Count:** 11

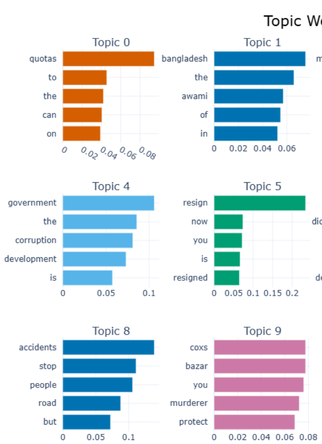

Fig. 7. Bar chart of topic word scores showing the most representative keywords for the top discovered topics. The scores reflect the importance and relevance of each word within its respective topic cluster.

The topic similarity matrix (visualized in Figure 8) reveals clusters of related topics, indicating how certain themes, such as reform and resistance, were semantically aligned throughout the phases. These results support the observation that public discourse evolved from issue-specific concerns (e.g., job reform) to broader political resistance.

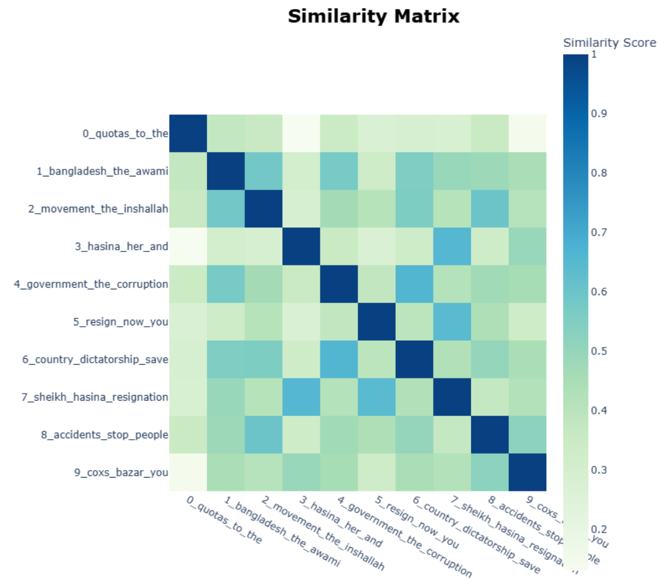

Fig. 8. Topic similarity matrix generated by BERTopic, illustrating the semantic relationships and distances between the discovered topics. Darker regions indicate stronger similarity, revealing thematic overlap across discourse clusters.

IV. Discussion

The sentiment analysis results demonstrate that the BERT-based classifier was highly effective in identifying sentiment polarity within the social media posts associated with the Bangladesh Quota Reform Movement. Through manual annotation and preprocessing, sentiment analysis captured the evolving tone of public discourse, starting with hopeful reform-focused language, moving into frustration during the protests, and culminating in sharp political criticism and disillusionment. This pattern aligns closely with the real-world timeline of the movement's escalation from a student-led demand for reform into a nationwide anti-government expression.

The topic modeling analysis complemented these findings by uncovering ten key discourse themes that surfaced throughout the timeline. Initially, discussions focused on quota fairness, student protests, and meritocracy. As events progressed—particularly in response to reported police violence, mass arrests, and state-controlled media—public conversation shifted toward issues like government corruption, dictatorship, and explicit calls for resignation. These themes were not only semantically distinct but also reflected increasing public polarization and urgency. The term distributions and cluster similarities revealed how closely interlinked the major concerns were: calls for justice, freedom, and democratic restoration were not isolated but part of an interconnected discourse. The progression and clustering of topics suggest a transformation in public sentiment—transitioning from issuebased protest to broader civic unrest and political resistance.

Overall, the combined sentiment and topic modeling pipeline provided a comprehensive understanding of how public discourse evolved during this politically significant event. The model's ability to uncover both the emotional tone and thematic structure of social media narratives offers valuable insights for social scientists, policymakers, and researchers studying digital activism, political communication, and public opinion dynamics.

V. Conclusion and Future Work

In this study, we presented a comprehensive sentiment and topic analysis of the Bangladesh Quota Reform Movement using a custom-curated dataset segmented into three distinct phases: before the movement, during the protests, and after its transformation into an anti-government uprising. Leveraging transformer-based models such as BERT for sentiment classification and BERTopic for topic modeling, we successfully captured both the emotional polarity and thematic shifts present in public discourse across social media platforms. The results clearly demonstrated the transition in public sentiment—from initial reform-focused engagement to widespread political dissatisfaction and calls for governmental change. Our analysis revealed how political movements evolve in real-time within digital spaces, highlighting the importance of context-aware NLP systems in socio-political research. Moving forward, we aim to enhance the dataset by incorporating more diverse and multilingual sources, enabling broader applicability across cultural and linguistic boundaries. We also plan to apply advanced data augmentation techniques to balance class distribution and improve model robustness. Additionally, our dataset—`ShadheenBangla`—has the potential to serve as a benchmark for future studies in political sentiment detection, protest prediction, and misinformation tracking. We encourage researchers to explore this dataset further for a wide range of NLP and computational social science applications.

Ultimately, this work lays the foundation for scalable, automated frameworks capable of analyzing political movements through the lens of public sentiment and thematic trends, contributing meaningfully to both data science and democratic discourse.

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