

Bengali Newspaper Genre Classification

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I. Introduction:

In this project, I focus on the challenging task of **news text classification in Bengali**, addressing the distinct linguistic and cultural variations that exist across different regions. Bengali, with its rich diversity of dialects and idiomatic expressions, presents a unique challenge in accurately classifying news texts. This complexity becomes even more evident when dealing with various domains such as entertainment, sports, and national news for each characterised by its own stylistic and contextual nuances.

My motivation for this project is multifaceted. Firstly, I aim to address the significant gap in **text classification technologies for Bengali**, a language spoken by millions yet underrepresented in digital text analysis. The potential applications of this work are wide-ranging, from helping media organisations organise their content more effectively to enabling linguistic studies on regional trends and cultural narratives.

For this purpose, I have employed a combination of **XGBoost**, **Support Vector Machine (SVM)**, and **Naive Bayes** models. This approach allows me to leverage the strengths of both modern and traditional NLP methods to achieve more comprehensive and accurate classification results.

II. Dataset Description:

Dataset Description

Source: <https://www.kaggle.com/datasets/disibig/bengali-news-dataset>

Reference: Bengali News Dataset. (2019, December 25). Kaggle. <https://www.kaggle.com/datasets/disibig/bengali-news-dataset>

Description:

The dataset consists of 11,324 text samples, and the objective is to apply machine learning and deep learning models for genre classification.

The genres to be predicted are: sports, state, Kolkata, entertainment, international, and national.

Dataset Overview:

Number of Samples: 11,324

Features: Textual data from Bengali news articles

Target Classes (Genres): sports, state, kolkata, entertainment, international, national

Data Characteristics: The dataset contains categorical text samples.

Class Distribution:

The dataset exhibits noticeable class imbalance, with the "Kolkata" class being significantly overrepresented (4,625 samples) and the "travel" class having only one instance. Addressing this imbalance is essential for ensuring model robustness and generalisation.

Dataset Overview:

Number of Samples: 11,324

Features: Textual data from news articles

Target Classes (Genres):

- 'sports'
- 'state'
- 'Kolkata'
- 'entertainment'
- 'international'
- 'National'

Data Characteristics:

The dataset contains categorical text samples.

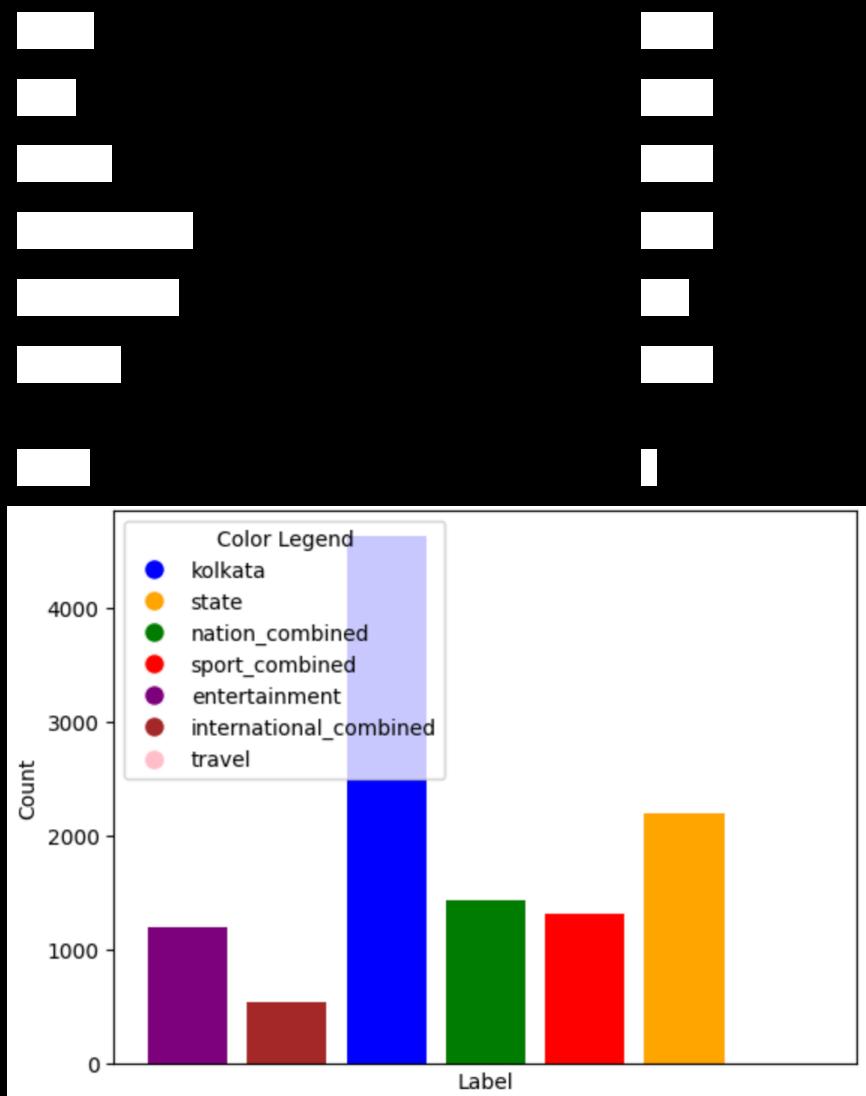
The number of samples in each class:

The dataset exhibits class imbalance, with varying sample sizes across different genres. Notably, the "Kolkata" class is significantly overrepresented, comprising 4,625 samples, while the "travel" class has a notably lower representation with only 1 sample.

Addressing the imbalanced nature of the dataset, particularly for the "Kolkata" and "travel" classes, may be essential for ensuring model robustness and generalization across all genres.

Label Name

Number of samples



III. Data Preprocessing:

Data Preprocessing

Null Value Handling:

Initial inspection revealed no null values in either the “Articles” or “Labels” columns. Nonetheless, I removed any potential null instances to maintain data integrity.

Label Consistency Resolution:

I identified redundant or inconsistent labels such as *world* and *international*, *sport* and *sports*, and *national* and *nation*. To ensure consistency and uniformity, I standardised these into singular representations:

- Merged *world* and *international* → **world**
- Unified *sport* and *sports* → **sport**
- Combined *national* and *nation* → **national**

Test Data Incorporation:

I appended the test data to the refined training dataset to create a more comprehensive corpus, ensuring consistent label structures across all data.

Outcome for Further Analysis:

The consolidated dataset was then prepared for subsequent stages such as **feature engineering**, **model training**, and **evaluation**, ensuring harmonised labels for accurate classification.

Data Splitting

I employed a **70–30 split**, allocating 70% of the dataset for training and 30% for testing.

This ensures a balance between model learning capacity and evaluation reliability.

To maintain reproducibility, I set `random_state=42`, allowing consistent results across multiple runs.

IV. Model Training and Testing:

To achieve robust news text classification in Bengali, we undertook a systematic approach to model training, employing three distinct classifiers: Support Vector Machines (SVM), Naive Bayes, and the eXtreme Gradient Boosting (XGBoost) algorithm. The reason behind this is to harness the unique strengths of each classifier to enhance the overall performance in handling the linguistic differences and cultural variations prevalent in Bengali text related to news.

Support Vector Machines (SVM):

SVM is a powerful and versatile supervised machine learning algorithm that has proven effective in various text classification tasks. In our project, SVM is employed to discern patterns and boundaries within the feature space of Bengali news texts. By mapping the input data into a higher-dimensional space, SVM strives to find an optimal hyperplane that maximally separates different classes, making it well-suited for complex and non-linear classification problems. Through careful parameter tuning and kernel selection, we aimed to optimise the SVM model for the nuances present in diverse news domains. Now, applying this algorithm to the dataset, we can see that the accuracy of this model is 0.8039735099337748. This is acceptable for the requirements of this project.

Naive Bayes:

Naive Bayes classifiers are renowned for their simplicity and efficiency in text classification tasks. Leveraging probabilistic principles, Naive Bayes models assume independence between features, making them particularly effective in handling high-dimensional data such as word occurrences in text. In the context of Bengali news text classification, Naive Bayes allows us to capture the likelihood of certain linguistic patterns or vocabulary usage associated with different news categories. This simplicity is advantageous, especially in scenarios where computational resources may be a constraint. Using this approach on the dataset, we can now observe that the model's accuracy is 0.44388849177984274. This is not suitable given the project's objectives.

eXtreme Gradient Boosting (XGBoost):

XGBoost is a state-of-the-art ensemble learning algorithm that has demonstrated exceptional performance in various machine learning competitions. By constructing an ensemble of weak learners (typically decision trees) in a boosting framework, XGBoost iteratively refines its predictions, focusing on instances where previous models have underperformed. For our Bengali news text classification, XGBoost provides the flexibility to capture intricate dependencies and interactions within the linguistic features, enhancing the model's ability to generalise across diverse news domains. When we apply this approach to the dataset, we can observe that the model's accuracy is 0.7713024282560706. Which is appropriate for the project's requirements.

V. Model Selection/Comparison Analysis:

SVM Classifier:

- Accuracy:80.4%

- Insights: The Support Vector Machine (SVM) model outperforms Naive Bayes with significantly higher accuracy. It showcases reasonably good precision and recall scores for certain categories like "Kolkata," "state," and "sports," indicating better classification capabilities

in these classes. However, some categories such as "international" and "nation" exhibit low precision and recall, suggesting difficulties in accurately predicting sentiments for these categories.

	Precision	Recall	F1-Score	Support
entertainment	0.81	0.83	0.82	249
international	0.56	0.35	0.43	91
kolkata	0.85	0.92	0.88	956
nation	0	0	0	2
national	0.7	0.69	0.69	273
sports	0.9	0.81	0.85	243
state	0.75	0.72	0.74	445
Accuracy	0.8		0.8	2265
Macro Avg	0.51	0.48	0.49	2265
Weighted Avg	0.8	0.8	0.8	2265

Naive Bayes:

Accuracy:44.4%

- Insights: The Naive Bayes model demonstrates a relatively low accuracy in sentiment classification across various categories. It particularly struggles with precision, recall, and F1-scores in multiple categories, showcasing limitations in accurately identifying and classifying sentiments, especially for minority classes. The confusion matrix highlights challenges in effectively predicting diverse sentiment categories, with notable misclassifications in several classes.

Class	Precision	Recall	F1-Score	Support
entertainment	0.96	0.15	0.27	286
international	0.5	0.01	0.01	374
kolkata	0.98	0.18	0.31	331
national	0.42	1	0.59	1128
sports	0.7	0.01	0.02	553
state	0	0	0	124
Accuracy	0		0.44	2798
Macro Avg	0.51	0.19	0.17	2798
Weighted Avg	0.59	0.44	0.31	2798

XGBoost Classifier:

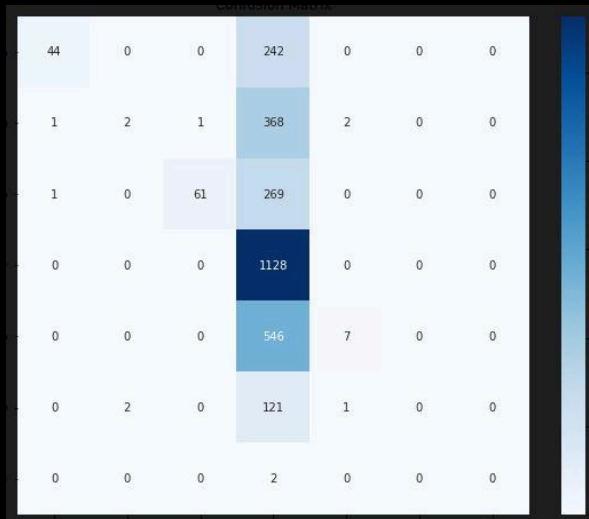
- Accuracy: 77.1%

- Insights: The XGBoost model demonstrates performance between Naive Bayes and SVM. While its accuracy is closer to SVM, it shows varying precision and recall scores across different categories. Similarly to SVM, it exhibits challenges in predicting sentiments accurately for categories like "international," "nation," and "world," as indicated by low precision and recall scores.

Class	Precision	Recall	F1-Score	Support
entertainment	0.8	0.8	0.8	249
international	0.55	0.19	0.28	91
kolkata	0.78	0.94	0.85	956
national	0.71	0.55	0.62	273
sports	0.85	0.7	0.77	243
state	0.74	0.7	0.72	445
accuracy			0.77	2265
macro avg	0.49	0.43	0.45	2265
weighted avg	0.76	0.77	0.76	2265

Comparative Insights:

- The SVM model showcases the highest overall accuracy among the three models, followed by XGBoost and then Naive Bayes.
- SVM and XGBoost exhibit similar challenges in predicting sentiments for certain categories, especially "international" and "nation," where both models display lower precision and recall scores.
- Naive Bayes struggles the most in accurately classifying sentiments across all categories, especially for minority classes, indicating limitations in its predictive capabilities for sentiment analysis tasks.



Confusion Matrix of SVM Classifier



Confusion Matrix of Naive Bayes

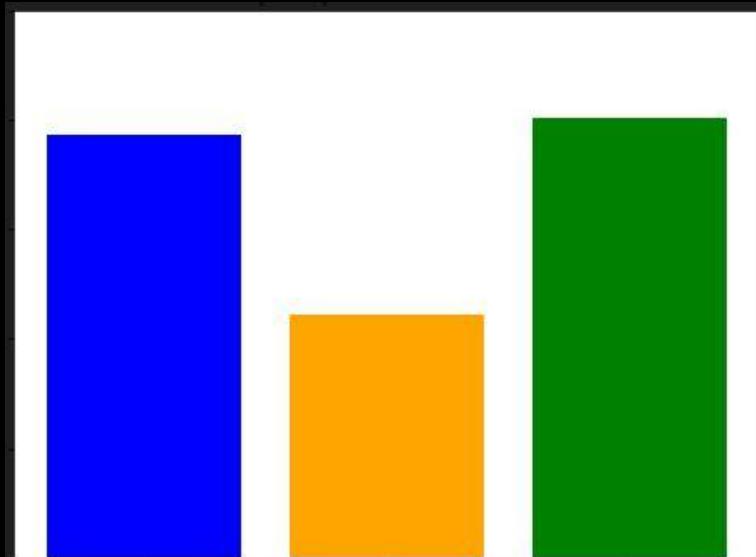
Model Recommendation:

- Considering Performance: The SVM model demonstrates the highest overall accuracy and relatively balanced precision and recall scores across multiple categories, making it a strong candidate for sentiment analysis in this context.
- Room for Improvement: Further investigation into misclassification patterns, additional feature engineering, or hyperparameter tuning might enhance the models' performance, especially for categories with lower precision and recall scores.

CONFUSION MATRIX									
	positive	neutral	negative	dislike	like	neutral	dislike	like	positive
positive	198	1	28	0	8	0	6	8	0
neutral	15	17	18	0	25	0	2	14	0
negative	5	0	898	0	10	0	4	39	0
dislike	0	0	2	0	0	0	0	0	0
like	7	10	59	0	151	0	8	38	0
neutral	0	0	0	0	0	0	4	0	0
dislike	18	0	33	0	9	0	171	12	0
like	6	3	107	0	10	0	7	312	0
positive	0	0	2	0	0	0	0	0	0

Confusion Matrix of XGB_Classifier

In summary, based on the provided results, the SVM classifier emerges as the most favourable model for sentiment analysis due to its higher accuracy and relatively balanced predictive performance across various sentiment categories.



Accuracy Comparison

VI. Conclusion:

In conclusion, our endeavour in Bengali news text classification unveiled valuable insights into model performances for sentiment analysis. We navigated the complexities of Bengali linguistics and cultural nuances by employing SVM, Naive Bayes, and XGBoost classifiers. While Naive Bayes showcased simplicity, it struggled with overall accuracy and minority class predictions. In contrast, SVM displayed superior accuracy with balanced precision and recall, making it an optimal choice. XGBoost showed promise but encountered challenges akin to SVM. Our findings affirm SVM as the frontrunner due to its superior accuracy and consistent performance across diverse categories. Further refinement through feature engineering or hyperparameter tuning

could fortify model robustness. This study not only contributes to Bengali NLP but also underscores the significance of tailored approaches for accurate sentiment analysis in diverse linguistic landscapes.