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Emotion Classification in Bangla Text Data Using Gaussian Naive Bayes Classifier: A Computational Linguistic Study

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ABSTRACT

Emotion analysis from Bengali text data is challenging due to the intricate structure of the language itself and lack of resource availability tailored to Sentiment Classification. In this paper, the authors have used machine learning algorithms, particularly Gaussian Naive Bayes and Support Vector Machine, for the classification of six emotions in Bengali text. The data is comprehensively pre-processed through segmentation, emoticon handling, removal of stop words, and stemming. It uses feature selection techniques like unigram, bi-gram, and term frequency-inverse document frequency to improve classification accuracy. The main aim of the paper is to present an in-depth analysis of emotion detection in Bengali text, which would be very helpful to scholars working on Natural Language Processing (NLP) problems in non-English languages. This research, hence, fills up the gap in emotion analysis research for Bengali text, which has comparatively remained underexplored compared to other languages. The methodology involves dataset preparation, extensive preprocessing, feature extraction with selection, and classification. After rigorous experimentation, the accuracy attained with the GNB classifier is 93.83%, proving the effectiveness of the proposed model in capturing subtle emotional nuances in Bengali text.

1. INTRODUCTION

1.1 Objective

The analysis of emotions is an important part of natural language processing. Emotion categorization is the process of studying a speaker's expression to find out whether he or she is approaching a certain issue with a positive or negative attitude. The most important goals for Emotion Analysis from Bangla Text Data Processing are highlighted in this section. The following are some of the goals:

- Bangla is a language having an exceedingly adaptable sentence structure. Assume that the English language follows the following structure: Subject (s) + Verb (v) + Object (Obj). (For instance, I am rice.) Any structure ordering is incorrect in English, yet any structure ordering is correct in Bangla. (Example: আমি ভাত খাই, ভাত আমি খাই, খাই আমি ভাত) and has the same meaning.
- Two variants of the Bangla language exist. One is tasteful or virginal, and the other is colloquial.
- Vowels, Consonants, and Symbolic Sign Vowels: The Bangla language has vowels, constants, and symbolic sign vowels.
- Compound Letter or Diphthong (যুক্তবর্ণ) Identification: It is a special property of the Bengali language, but it gives another challenge for modelling the Bangla language [1].
- Symbolic Sign: The letters that are vowels become a symbolic KAR such as আকার, ইকার, ঈকার, উকার, ঊকার, একার, ওকার, ঐকার, ঔকার, ঋকার [2]. Bengali script is left-to-right. Word boundaries are denoted by spaces. Uncased letters are arranged according to the location and style of articulation. Characters in writing

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combine to make a single starting point as shown for the word MAAMAA (uncle) as follows: For instance: ম (Letter- M) + (Vowel- AA) + ম (Letter- M) + (Vowel- AA) = মামা.

- Other Indications: হসন্ত, ব-ফলা, ম-ফলা, র-ফলা, য-ফলা, রেফ; for instance: প্রকাশ (Disclose), ব্যস্ত (Busy), চর্চা (Practice). Sometimes it's challenging to find the word in this.
- There is still no standard keyboard for typing Bangla [3]. Aside from these issues, there are others, such as a large vocabulary and the same word having several meanings depending on where it appears in a sentence.

1.2 Aim

This experiment mainly aims to develop and convert a data corpus into a suitable model for embedding documentation representing a statistical vector and to evaluate the performance and accuracy of classifiers using various master learning approaches in the field of Bengali sentiment analysis. This can be summarized as our research objective:

- Maintain a corpus of Bengali standards of emotional classification.
- Categorizing materials based on specific human emotions.
- Create an embedding document model that shows numerical vectors, so that algorithms for machine learning can work with them.
- Comparison of deep learning performance and classical machine learning methodologies for Bengali emotional analysis.

1.3 Historical Background

As far as the authors are aware, no work has been done using valency analysis to detect sentiment or my opinions from the Bangla text. The writers of [3] found and parsed verbs in the Bangla language using valency-based verbs. Nonetheless, this page is a list of various efforts on sentiment recognition from Bangla texts. This post, on the other hand, discusses some recent work on sentiment analysis in Bangla texts [4]. Suggested an automated sentiment detection technique for Bangla text based on a machine learning algorithm. They also invent some major barriers to Bangla language processing [5]. Proposed a theme-based or event-based emotion tracking system using SENTIWordNET [6] and WORDNET Affect [7] for annotated news and blog corporations in Bangla [8]. Acknowledges the emotion of English by pre-processing to collect comments on specific topics from blogger members [9]. Detect the Bangladeshi opinion using a support vector machine based on the news corpus. In [10], a half-supervised method for categorizing emotions is suggested using a mix of active learning, and group training to detect ambiguous and unambiguous assessments. It combines user feedback into the sorting process, which helps to determine which dimension the Emotion Detection dataset should cluster [11]. A revision of a Valen-based document for the English language is presented in this document. Valence was used for sentiment detection, and this has been introduced in Bangla for emotion detection.

1.4 Motivation

The analysis is a more important aspect of NLP of emotions from Bangla text data. Emotion rank often refers to examining a speaker's expression to ascertain whether they have a favourable attitude about a particular topic. Since e-commerce is expanding so quickly, everyone can be significantly impacted by emotion analysis in real life. Online product reviews have emerged as a crucial source of information for consumers making purchasing decisions for prototypes. How to automatically categorize and extract the emotion from reviews that are too numerous for customers to read hourly has become a significant research issue. In this proposal, an emotion analyser that can identify Bangla emotions or opinions is presented.

- The release of a carefully annotated corpus of Bangla emotions that considers the variety of expressions of fine and coarse-grained emotions found in social media handbooks.
- For using traditional machine-learning techniques, which are typically effective in categorizing the six emotion kinds.
- To determine which machine-learning model performs best in identifying emotion brackets by comparing its courtly performance with alpha.
- Pre-processing the data in a way so that it's readily usable by experimenters.
- Employment of deep continual models on a Bangla and Romanized Bangla handbook corpus.
- Pre-train dataset of one ticket for another (vice versa) to prove its use.

After watching these, deciding to do probing on this subject. It can help us a lot and it is an important area to do probing.

1.5 Problem Statement

The matter statement is not usually as clear in a document of this type. It is frequently divided into several distinct topics, and a thorough analysis of sentiment depends on a host of factors, such as (but not limited to):

- These texts occasionally include a variety of emotions related to two or more situations.
- These kinds of texts can occasionally include both kinds of feelings. that is, both positive and negative. Finding the most successful one in this situation could be a big problem.
- In certain situations, the issues are frequently transformed into multi-subjective sentiment analysis.
- Within the case of huge web-based companies researching many thousands or maybe many opinions on different products, and easily checking out pre-defined “good” or “bad” words within the comments is not enough. With the increase of machine learning, especially, deep neural networks, and sentiment analysis, the matter of understanding the emotional tone of a text has been solved with very high accuracy. This article, by points out the simplest thanks to solving this problem today with word representations,

deep learning and GPUs, and entertainment industry cases, where sentiment analysis is often applied.

1.6 Scope

With the help of science, communication between people has become as simple as a cup of tea [12]. Through social media, people may directly access their opinions, memories, thoughts, facts, and emotions with others in their own culture and traditions. Cybercrime and cyber-bullying are on the upswing because of the increased usage of social networking sites, and most of the victims are women. As a result, the predictive method has a lot of potential for detecting text. Text analysis is a difficult undertaking in the Bangla language. Computational techniques connected to machine learning have put a lot of attention into this field in recent years. Emotion analysis is also frequently utilized in psychological studies. It's used to figure out what a country's happy planet index is. Being also helps folks to be happier and live healthier lifestyles. It is also used to locate emotional marketing. Moreover, we can know which kind of people purchase, which type of product. Linguistic emotion analysis is difficult for people and machines alike. It also necessitates superior natural learning mechanisms for the development of emotional models.

2. RELATED WORK

Emotion analysis has become an interesting topic among researchers in the age of social media and micro-blogging sites [13]. EA appears to be practiced in a variety of linguistic domains, including English, French, Chinese, Arabic, and others. Due to some technical and empirical constraints, however, the extent of its progress in Bengali Language is insignificant. There hasn't been much research done in the field of "Emotion Analysis from Bangla Text Data. “The majority of the paper has concentrated on Sentiment analysis, which has three types of sentiment: "Positive," "Negative," and "Neutral. “However, for emotional analysis, there are supposed to be six types of emotions such as “Happy, Sad, Disgust, Fear, Surprise, Angry.” The summary and comparison of related work is also in the table 6.

Mahmudun et al. (2016) proposed a sentiment detection strategy mainly based on machine learning techniques in classification with tf-idf for edifying terms and achieved an accuracy of 83% [14]. Modernism and ideogram n-grams with Naive Bayes was suggested by the author of [15] for sentiment polarity in Bangla tweets utilizing SentiWordNet features and achieved an accuracy of 48.5% with Multinomial NB on a dataset containing 1000 training samples and 500 test samples. A study on emotion tagging was carried out by the author of [16], where Bengali blog material was manually annotated and achieved an accuracy of 58.7% with CRF and 70.4% with SVM. In [17], researchers presented a blog-based emotion analysis system for Bengali, analyzing more than 1100 texts using morphological analyzers and reporting a precision score of 0.59, reminder score of 0.64, with an F2-1 score of 0.62. Tripto and Ali (2018), have proposed a multi-label emotion detection approach on comments from YouTube videos in Bengali, English, Roman English, and obtained the Sentiment label accuracies as 65.97 percent and 54.24 percent for the 3-class and 5-class labels with 59.23 percent precision [18]. A recent study compared five conventional machine learning-based methods for fine-grained Bangla emotion classification. In the previous work, the non-linear SVM with the RBF kernel was observed to obtain an accuracy of 52.98% with an F1 score of 0.33 while investigating feature selection and preprocessing strategies [19].

Comparatively speaking, sentimental analysis has garnered more research than emotion analysis. Turkish academics Tocoglu, Okan, and Alpkocak investigated how well deep neural networks performed when analysing emotion from tweets in Turkish [20]. LSTM, ANN, convolutional neural networks (CNN), and RNN were the three main deep learning architectures on which they concentrated. They aggregate the Turkish Twitter feed. They automatically labelled each tweet for six different emotional expressions using a lexicon-based technique. CNN received the greatest accuracy score of 0.74 as a result.

The authors of [21] presented a method they called "Context-Based Emotion Detection", which used an estimating net, ESiN, to classify words into three classes: emotional keywords, modifier words, and metaphor words. In the results, they achieved accuracy over 80% for the Neutral class and 70% for the Emotional class. Their tools included a lexicon with 65,620 words and a POS tagger to tag the text. The authors Omor et al. presented the deep learning architecture for emotion detection – EmoDet – that also outperformed all other solutions: an RNN using LSTM cells to 82.20% accuracy and LSTM combined with textual and emoticon statistics to 89% accuracy [22]. Preprocessing included text normalization, stemming, and punctuation handling, with the tuning of parameters through GridSearchCV. The results for machine learning models also turned out to be very accurate – Linear SVC showed an accuracy of 80.93%, and Logistic Regression – 77.96%.

3. METHODOLOGY

After looking through numerous corpus datasets, eventually located the needed dataset, "Emotional Analysis from Bangla Text Data." With a collection of comments and emotion labels (such as happy, sad, angry, disgusted, surprised, and fear) for each of those comments, the primary objective of this thesis was to classify the comments using the emotion label using Naive Bayes classifier. To improve classification performance, various methods for feature selection were examined. Because they may affect the result of this supervised approach, each of these strategies was essential. Consequently, an overview of architecture methods has been provided in this section.

The system is divided into two phases: one is training, and another is testing. Before feeding the training set to the classifier, it goes through many pre-processing phases and then several feature selection approaches. After that, the practice data runs through the parallel process, predicting possible sensation labels for each instrument. The system's efficiency is then evaluated by comparing the predefined emotion labels to the predicted ones. Fig 1 and 2 shows the architecture’s visual representation of training and testing phase.

The suggested approach consists of four stages that go in order:

- Prepare the dataset
- Perform pre-processing
- Choose a feature
- Classify.

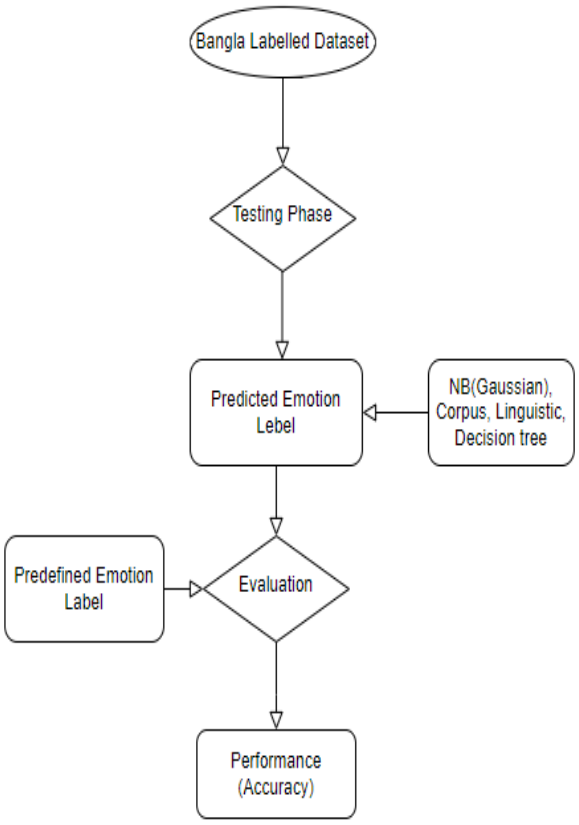

Fig. 1. Architecture of testing phase

3.1 Dataset Preparation

The data set hooked in this study includes a massive amount of member feedback collated through various FB(Facebook) groups as well as some public posts from well-known bloggers. The feedback was gathered based on a variety of socio-political topics. The authors annotated the dataset based on the existence of terms and phrases pertaining to emotional content, as well as the overall emotion expressed in the comments only looked at 7924 comments from six different emotion classes: joyful, sad, disgust, fear, surprise, and anger. The above dataset was split into two parts, shown in table 1 with 7924 comments used as training and 3412 comments used as testing.

3.2 Pre-processing

Stop words, punctuations, numbers, and symbols were among the worthless and duplicate data in the dataset's comments. Thus, it has been processed to make the next stages easier. The data and cleaned in the following manner.

- *Text Sectionalisation*:

First, all extraneous hyphens, commas, dots, and other symbols were eliminated. Numbers and punctuation were also eliminated from the text. After that, each sentence was tokenized into a single word. Tokenizing the words in phrases was accomplished here using the standard Python split function.

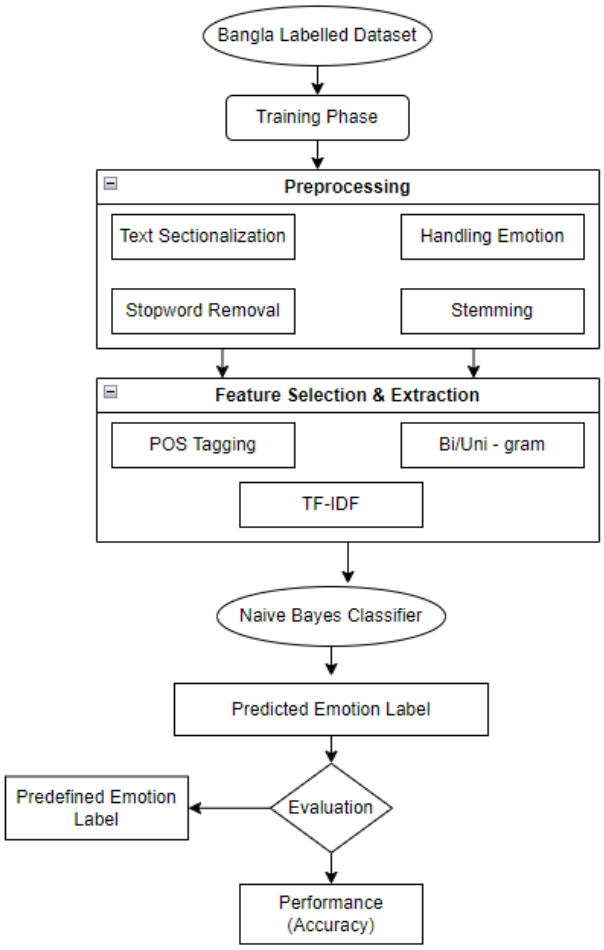

Fig. 2. Architecture of training phase

Table 1. Distribution of Class in the dataset.

Label	*Train Dataset*	*Test Dataset*
Happy	2316	1069
Surprise	721	364
Fear	468	237
Angry	1830	698
Disgust	905	346
Sad	1682	698
Total	7924	3412

- *Handling Emotion:*

Because the text data was considered, all of the emoticons in the comments were removed. A sequence of punctuation was constructed to exclude.

- *Remove halt terms:*

The halt terms were removed from each set of data. Because stop words such as (এবং, অথবা, অথচ, হয়, অতএব, হতে, থেকে, চেয়ে) are the most repeated terms. Stop words were filtered and eliminated.

- *The process:*

A term can take on several different meanings. To make the data easier to process, here stem each token into its core word. Bangla contains many inflected words, making it challenging to understand. Here, prepared prefix lists, suffixes, nouns, verbs, and articles such as (আমরা, আমি, আমাদের, আমার). The stems were removed from the left or right.

3.3 Feature Selection & Extraction

One of the most crucial steps in the analysis of emotion detection from text data, feature selection and extraction must be finished because it will impact the outcome. For this reason, selecting an excellent feature is essential for earning better results. So, selecting features is an important step for this kind of research. Taking counsel from prior used feature selection, here used various aspects to evaluate this processed data after the pre-processing phase was completed and used a combination of strategies to achieve the best possible result. Also used those datasets to create our expanded Emotional dictionary, which employed a good result.

- *Sentence Split:*

To break down a large string or sentence into a smaller string or sentence and decode encrypted string or text sentence split is used. In Python, the split () function is used which returns a list of separated words from a whole sentence. Moreover, in the sentence split, if anyone gives a sentence, then it will give output in different words present in it. Mainly words are separated by space. Like an example, ঢাকা নয় যশোরে প্রথম হয়েছিল মঙ্গল শোভাযাত্রা. It will be printed such as:

ঢাকা
নয়
যশোরে
প্রথম
হয়েছিল
মঙ্গল
শোভাযাত্রা

- *Unigram and Bi gram:*

A review's unigrams and bigrams are utilized to assign a score to it and hence classify it as positive or negative emotions. In this case, performance for unigram and bigram is observed to determine the optimal model for precisely identifying emotion from Bangla text. Uni-gram can be defined to indicate a one-word sequence where Bi-gram consists of a two-word sequence of a word. To obtain the whole scenario, however, a combination of the n-grams features and additional features is also required. In the work, a bi-gram yields a comparatively better result than a unigram. The previous tag is used by the Bigram Tagger subclass as part of its context. The context of the Tri-gram Tagger subclass includes the previous two tags. For, the additional examination, used bi-grams, to experiment with features from the used dataset that indicate sad emotion:

Table 2. Unigram and bi-gram

Sample Text	মঙ্গল শোভা যাত্রা অইসলামিক কাজ
Unigram Feature	'মঙ্গল', 'শোভা, 'যাত্রা', 'অ', 'ইসলামিক', 'কাজ'
Bi-gram Feature	'মঙ্গল শোভা, 'যাত্রাঅ', 'ইসলামিককাজ'

- *TF-IDF:*

TF-IDF is a method that delegates reflection of the word in a corpus (Collection of the document) document of a numerical weightage of words. TF is the short form of Term Frequency, and IDF is the short form of Inverse Document Frequency. This formula is used for information recovery and text mining. To use this method, there are formulas such as,

$$\mathrm{TF}\ (\mathrm{w}) = \frac{(\text{Number of times word w arrives in the letter})}{(\text{Total number of words in the letter})} \quad (1)$$

$$\mathrm{IDF}\ (\mathrm{w}) = \frac{\log(\mathrm{e})\ (\text{Total numbers of letters})}{\text{number of letters with word w}} \quad (2)$$

$$\mathrm{TF} - \mathrm{IDF}\ (\mathrm{w}) = \mathrm{TF}\ (\mathrm{w}) * \mathrm{IDF}\ (\mathrm{w}) \quad (3)$$

3.4 Classification

By using Gaussian Naive Bayes to construct the desired accuracy once the feature selection and extraction step has been finished. For conditional probability datasets, the Naive Bayes method assists in acquiring the desired accuracy. The probability for each data is also counted in this categorization. The Gaussian Naive Bayes can provide accurate results for analysing emotion for textual datasets.For the implementation, here utilized basic Python language. It examines every sentence from the collected datasets and counts the probability of every single word using Gaussian Naive Bayes. The following is the primary equation for the Naive Bayes algorithm, which is used to determine probability or percentage of chance:

$$P\left(\frac{A}{B}\right) = \frac{P\left(\frac{B}{A}\right).P(A)}{P(B)} \quad (4)$$

In this, the posterior probability is P (A|B), the prior probability is P(A), the likelihood is P(B|A), and the probability of evidence is P(B).

A supported vector machine (SVM), which utilizes classification methods for two group problems classification, may also be an MCL algorithm that might be utilized for each grouping problem. Emotion recognition from Bangla text data is a new and challenging subject in the artificial intelligence field. In this paper, SVM is used to recognize emotion from Bangla text data. The performance of SVM on emotion recognition from Bangla text data was good and it was compared with GNB.

4. REVIEW BASED ON RESULT

After applying Gaussian naïve Bayes in both train and test datasets. By using reliability, recall, and F1-score for each emotion class, such as average accuracy, to measure the efficacy of our proposed method. If this paper considers every emotion in the list, then the prediction for each emotion will show its accuracy to find out how this emotion can be predicted according to a sentence. For the train paper got the best model Gaussian naive bayes. After checking the accuracy, it was

93.83%. Here observe that the models predict the happy class with a good rate, but this model fared badly for the Fear class. This is because the training dataset was not balanced well, with the fear class having the fewest training samples. This, however, essentially replicates a real-world situation, making the approach more generalizable**.**

Table 3. Detailed evaluation using the best model

Emotions	*Accuracy*
Happy	0.291
Sad	0.212
Angry	0.231
Surprise	0.091
Disgust	0.114
Fear	0.059

If the sentence split is considered, then for every word of the sentence there will be accuracy for each sentence.

Table 4. Sentence split and accuracy

দেশকি	*মধ্যম*	*আয়ের*	*দেশে*	*রুপান্তর*	*হচ্ছে*
0.003	0.006	0.003	0.38	0.0025	0.301

If a random sentence is chosen, then how can it be defined that it is included in which category it is calculated by using countprobabiltyNB**.**

$$\text{Accuracy} = \frac{\text{correct\_prediction}}{\text{total sentences}} * 100 \quad (5)$$

Here, the sad bar is the biggest among all the 6 categories of emotions. Here being able to get a 99.8 percent overall accuracy rating. Being also used an SVM to classify the results for this same combination. In comparison to GNB, SVM's total score was not high enough.

Table 5. Classifiers

Classifiers	*Accuracy*
GNB	0.9383
SVM	0.716

In addition, comparing our best model to some of the previous works stated in the literature review section. In aspect of below table, a comparison with comparable works is shown. of approaches and outcomes. It was discovered when analysing that the dataset size, and classifier utilized for the classification ambition have a significant impact on the outcome work.

5. DISCUSSIONS

In this context, an emotion classification model over Bangla text data is developed and evaluated in the present study. This work thereby aimed at filling up a certain lacuna that exists in the current research on emotion analysis with respect to Bangla, which has very different kinds of challenges, both in structure and resource constraints, than other languages currently and specifically tailored for sentiment classification.

Table 6. Comparison with relevant state of artwork

Author	*Paper*	*Algorithm/ Approach*	*Result (Accuracy/F1-Score)*
K. M. Azharul Hasan, 2014 [4]	Sentiment Detection from Bangla Text using Contextual Valency Analysis.	• SentiWordNet • Valency analysıs	Positive(90%) Negative(80%) Neutral(60%)
M. Rahman, 2019 [19]	Comparison of Classical Machine Learning Approaches on Bangla Textual Emotion Analysis	• POS Tagging • SVM/KNN • Classifier • Unigram • tf-idf	47.6% (F1)
Nafs Irteza Tripto, 2018[18]	Detecting Multilabel Sentiment and Emotionns from Bangla YouTube Comments.	• LSTM method • CNN method • SVM • NB • Tf-Idf	65.97%
Eftekhar Hossain, 2007 [25]	Sentiment Polanity Detection on Bengali Book Review using Multinomial Naive Bayes	• Logistic Regression • Multinomial NB • SVC • SGD classifier	(MNB) 87%
Mahammad Mahmudur Nabi, 2016 [14]	Detecting Sentiment from Bangla Text using Machine Leaming Technique and Feature Analysıs.	• Bag of words • Tf-idf • POS Tagging	83%
M. A.M.Shaikh, 2007 [23]	Assessing Sentiment of Text by Semantic Dependency and Contextual Valence Analysis.	• WordNet-Affect • Contextual valance to triplet.	83.59%
Mansur Alp tocoglu, 2019 [20]	Emotion Analysis from Turkish Tweets Using Deep Neural Network.	• Lexicon-based approach • ANN • CNN • LSTM	(CNN) 74%
Sara Azmin, 2019 [24]	Emotion detection from Bangla Text Corpus using Naive Bayes Classifier.	• NB	78.60%
Our Model	Emotion Classification in Bangla Text Data Using Gaussian Naive Bayes Classifier: A Computational Linguistic Study	• GNB	93.83%

This work is significant to the environment in the context it caters to because it works toward making emotion classification possible in Bangla, a language spoken by millions but inadequately represented in NLP research. The complicacy of the structure of the Bangla language with its adaptable sentence formation and symbolic characters makes it

demanding to have a customized approach to sentiment analysis. This study, therefore, is very relevant to come up with specific models that can capture emotions most accurately in any piece of text written in Bangla.

As regards specification comparisons, this work used GNB and SVM classifiers to compare which of these two models is better at classifying emotions from Bangla texts. The choice of these classifiers was informed by both their prior success at working with text data and by their ability to model conditional probabilities on the one hand, and the ability to create decision boundaries on the other. The methodological rigors for the study included thorough data preprocessing, feature selection through unigrams, bigrams, and TF-IDF; rigorous model training and testing are planned. Great care was taken in developing the dataset logic, which comprised wide-ranging feedback obtained from Facebook groups and public posts by bloggers, annotated with six distinct emotions: happy, sad, angry, surprise, disgust, and fear. This dataset was further divided into training and testing sets to ensure the model evaluation is robust. Preprocessing steps involved dropping stop words, punctuation, numbers, and emoticons, besides stemming, to standardize data for improving model performance.

Comparative analysis of the results presented that GNB did better as compared to the SVM classifier with an accuracy of 93.83%. This high accuracy thus proves the effectiveness of the GNB model in capturing the emotional context of Bangla text. In contrast, an accuracy of 71.6% was achieved by the SVM classifier, proving that while it was effective, it wasn't quite as robust as GNB for this task. The detailed evaluation metrics showed that the GNB classifier performed very well on the 'happy' class but poorly on the 'fear' class, likely since this emotion has a large class imbalance in the training data. These results have profound practical implications. Applications in real life can use the high accuracy of the GNB model in several ways, such as in social media monitoring, where knowing the user's emotions helps in sentiment analysis and trend prediction. Further, in customer feedback systems, it can be used for the automatic classification and enshrining of responses to user sentiments with the view of improving customer service and satisfaction. Moreover, it can develop Bangla automated response systems that will make contextually appropriate responses based on detected emotion and provide better user experience.

This paper is, therefore, a valid contribution toward the development of Bangla NLP through the effectiveness of the GNB classifier in emotion classification. It thus prepares a platform on which issues of language-specific approaches, rigorous preprocessing methods, and informative feature selection would stand highly required for such robust models of emotion classification. One could go for hybrid models in the future that combine classical machine learning with deep learning to come up with better classification accuracy and resolve the pitfalls in this study.

6. CONCLUSION

The original aim of the study was to propose a solid model of emotion classification in Bangla text data. The machine learning technique would answer the inherent challenges present while working with this highly flexed language with a constrained set of resources for sentiment classification. This research works toward classifying six different emotions: happy, sad, angry, surprise, disgust, and fear by making use of GNB and SVM classifiers. Furthermore, this was supposed to be accompanied by constructing a complete dataset, extended preprocessing, and the use of advanced feature selection methods so that the research provided high classification accuracy. According to the aims that were set, in the research, there were much better results. This is the fact that the GNB classifier showed remarkable accuracy of 93.83%, the best one, outperforming the SVM one that was measured to 71.6%. The high accuracy rate therefore indicates that the GNB model could capture most of the emotional subtleties in the Bangla text, hence contributing profoundly to the domain of natural language processing with non-English languages. It is due to the methodological rigor of this study in developing a diverse dataset and using strict preprocessing and feature selection techniques that the obtained results are possible.

However, this journey from the first goals to the last results was not all rosy. One of the biggest gaps noticed was the class imbalance in the training data for certain emotions, the class 'fear' having poor performance of the model for that class. Nonetheless, the study established with some success the strengths of the GNB classifier concerning Bangla text data handling, even in complex conditions. The preprocessing steps include stop-word removal, emoticon handling, and stemming, which allow the cleansing of the dataset and hence improve the quality of the dataset. The gap between initial goal and the outcome achieved shows the complexity of emotion classification in Bangla text. This gap was bridged through careful dataset preparation, innovative ways of conducting feature selection, and indeed through applying strong machine learning algorithms. The high rate of accuracy by the GNB model, particularly in predicting the class "happy", indicates the effectiveness of the approach taken. The 'fear' class, however, was observing challenges, which showed some directions for the development task that might be investigated for future improvement in, say, creating a dataset that is more balanced and some advanced techniques for handling the data imbalance.

This work is a remarkable improvement over the automatic classification of emotions related to Bangla text, which is a very complex and less explored area. In particular, the development and evaluation of the GNB classifier were large steps forward in this direction. This research does not simply fill an important gap in the literature but also lays the platform for further research into classical machine learning and deep learning techniques, thereby increasing the classification accuracies. The means to cope with the other complicated linguistic issues in Bangla and high accuracy have turned this work into a massive contribution to natural language processing in practical applications.

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