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Bangla hate speech detection by embedding and hybrid machine learning algorithms

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Abstract

The worrisome increase in hate speech in Bangladesh, driven by the rapidly expanding social media user base, has adversely affected cybersecurity and online safety. Most hate speech detection technologies overlook less commonly spoken languages, such as Bangla, in favour of more widely used ones. This project aims to address the gap by identifying hate speech in Bangla through the utilisation of sophisticated word embedding techniques (Word2Vec, GloVe, and FastText) and machine learning algorithms (Multinomial Naive Bayes, Random Forest, K-Nearest Neighbours, and Extreme Gradient Boosting). We used a dataset of 30,000 annotated messages, encompassing both positive and hate speech, to train and test the models. FastText combined with hybrid RF and SVM yielded the highest performance among the models, with an accuracy of 96.03%. The system's generalisability and usefulness were evident when it identified hate speech not included in the training data. Enhancing the identification of harmful content in Bangla is essential for the burgeoning digital ecosystem in Bangladesh, hence contributing to cybersecurity. This endeavour establishes a foundation for future study by efficiently employing advanced word embedding and machine learning techniques to identify hate speech in Bangla. It could significantly influence the advancement of more secure digital environments and the overall condition of internet security.

Keywords: Glove; Fasttext; Word2Vec; Hybrid; Hate speech; Normal speech; Word embedding; Cybersecurity; Tokenization; Stop word; NLP.

1. Introduction

In today's hyper-connected environment, social media and digital platforms are integral to daily life, facilitating communication, content distribution, and global interaction. The rapid digital transition has exacerbated the spread of harmful material, particularly hate speech, threatening online safety and inclusivity. This issue is especially pertinent in regions like Bangladesh, where internet usage is increasing. Bangladesh presently has over 125 million internet users, with a growing number participating on platforms such as Facebook, Twitter, and YouTube. Despite the rise in digital involvement, the identification of hate speech in Bangla is markedly less developed than in English, leading to a substantial shortfall in content moderation efforts [1]. The increase in online hate speech presents considerable difficulties. It affects individual users, resulting in psychological distress, and may also lead to real-world violence by inciting bias and harassment. Furthermore, hate speech can intensify wider socioeconomic issues, eroding community cohesion and disrupting public order. This is particularly alarming in countries like Bangladesh, where social media is a crucial platform for political and social dialogue. In addition to challenges in content screening, hate speech is regarded as a cybersecurity concern. Digital platforms function as global public spaces, and protecting their users has become a

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critical issue for both platform owners and regulators. Hate speech can lead to cyberbullying, online harassment, and perhaps coordinated cyber-attacks. Moreover, unfettered hate speech can provoke more severe threats, such as disinformation operations or extremist mobilisation, thereby exposing broader cybersecurity vulnerabilities. The primary hate speech detection technologies mostly focus on commonly spoken languages, mainly English. This leads to languages like Bangla, spoken by over 230 million people globally, receiving insufficient assistance from technologies designed to detect and mitigate harmful internet content [2]. Many global platforms have implemented hate speech detection algorithms; however, these systems often lack the linguistic expertise required to control Bangla content effectively. Modern society employs the internet to connect individuals from various cultures and languages. Nonetheless, hate speech has become a significant concern in this expansive digital landscape. Hate speech in regional languages, especially Bangla, which boasts a substantial speaker population, necessitates detection and intervention. Prominent social media platforms enable networking, information transmission, and the articulation of ideas. By January 2022, social media users will attain 3.6 billion, indicating a 49% increase [3]. The data is up to date as of October 2023. Prominent websites encompass Facebook, Instagram, Twitter, and YouTube. Regrettably, hate speech and hatred taint it. The prevalence of abusive language in user-generated online content has been extensively examined in recent years. What is "hate speech"? A universal definition of hate speech does not exist. Any communication aimed at an individual due to their race, skin colour, ethnicity, religion, gender, or sexual orientation, intended to intimidate or provoke violence, qualifies as hate speech. In 2022, Bangla ranked as the tenth most spoken native language, with 265 million speakers. They constitute 3.05 per cent of the global population. [4]. From January 2022 to 2023, 47.61 million Bangladeshis utilised the Internet due to its extensive availability. As more individuals accessed the internet, they felt liberated to articulate their thoughts in forums and social media platforms. This research investigates the identification of hate speech in Bangla, focussing on precision and the selection of algorithms. It arises from a profound comprehension of the necessity for a secure and inviting online environment for Bangla speakers and others. This project is based on a meticulously curated assemblage of 30,000 text samples, encompassing both positive and hate speech. The significance of data collecting, sometimes undervalued, is essential for the efficacy of content moderation systems. The project's methodology depends on the dataset's diversity to capture the complexities and subtleties of human communication in the Bangla language. The second essential phase, data preprocessing, encompasses classification, cleaning, lowercase conversion, and tokenisation. These ostensibly mundane tasks initiate the project's pursuit of precision and algorithm enhancement. Data is categorised as either positive or hate speech. This categorisation, however straightforward, is crucial in supervised machine learning, where algorithms utilise labelled data to forecast unseen data. Data cleansing diminishes noise and enhances data quality, safeguarding the model. Lowercasing standardises the text and mitigates case discrepancies, while tokenisation disaggregates it into words and subwords. This phase connects language by deconstructing the content into manageable segments that are understandable to machine learning algorithms. Word embeddings are essential for expressing linguistic complexity. GloVe, Word2Vec, and FastText constitute our methodologies for word embedding. These tools assist the project in comprehending the intricacies of word relationships in Bangla and the profundity and nuance of human communication. The project's success depends on selecting the optimal method. The RF and SVM Hybrid, Random Forest, XGBoost, and Multinomial Naive Bayes are evaluated for this purpose. XGBoost, a gradient-boosting technique, is the victor in text categorisation. It attains optimal accuracy when integrated with meticulously chosen FastText embeddings, exemplifying the project's commitment to precision and efficiency. Accuracy is not merely a statistic; it assesses the project's ability to distinguish hate speech from legitimate content, which is essential for online safety. Nevertheless, the project's significance transcends precision. A distinctive feature of the model is its ability to detect hate speech without explicit training. The project's adaption demonstrates its resilience and relevance in an era of evolving internet abuse and emerging hate speech. This study project surpasses exceptional accuracy. It advocates for safer and more inclusive internet environments for Bangla speakers and improvements in automated content oversight. In a multilingual digital context, the insights from this study transcend a single language. They illustrate the potential of machine learning, natural language processing, and linguistic comprehension to foster respect, inclusivity, and security in digital environments, enhancing online communities globally.

In this paper, we will discuss the following: Section II provides a summary of pertinent literature. Section III goes over the Methodology in detail. Section IV presents the experiment's results, and Section V evaluates our model. Additionally, Section VI discusses the Conclusion and Upcoming Projects.

2. Literature review

Natural Language Processing and machine learning are frequently employed to address voice processing challenges. It is essential to encourage individuals to adopt healthier lifestyles. Despite our issue and methodology differences, some scholars have already employed analogous methodologies. These are the studies that were analysed:

Das el. at. [5] A popular NLP method called encoder-decoder-based machine learning was recommended to categorise Bengali Facebook comments. They trained and tested their model using seven categories of 7,425 Bengali hate speech comments. The attention-based decoder outperformed the other two encoder-decoder algorithms with 77% accuracy.

Mumu et al. [6] presented a hybrid model that combines a Convolutional Neural Network (CNN) with a Long Short-Term Memory (LSTM) architecture. The databases have been configured to accommodate cases of both depression and non-depression. The optimal performance in the Bengali Facebook status dataset was achieved by employing a hybrid neural network incorporating word embedding techniques. A Support Vector Machine (SVM) model, in conjunction with a count vectoriser, was utilised to make predictions on a limited dataset of Bengali Facebook updates. The methodology presented in this research study provides advantages and facilitates the implementation of a deep learning framework.

In their study, Hossain, Junaid, et al. [7] employ machine learning techniques to categorise films. This study employed diverse training models to generate a dataset derived from the spoken content of YouTube videos. Deep learning and machine learning methods were used in their research. The deep learning model, which consists of gated recurrent units (GRU) and logistic regression, demonstrated superior performance on the given dataset.

In their publication, Khan et al. [8] present a comprehensive analysis of an automated text mining system designed to ascertain the sentiment of a given portion as perceived by the reader. The present performance encompasses a range of emotions, including sadness, anger, shock, and apprehension. The topics of abuse and religion are also addressed. The dataset was trained using machine learning techniques. Out of the five approaches employed, the Support Vector Machine (SVM) approach demonstrated a height accuracy of 62%.

Debele el. At [9] uses deep learning to merge audio and textual data, making it effective against hate speech in Amharic social media. They compiled 1,459 videos from the video-sharing website. Our research uses Google's Speech-to-Text API to transcribe recorded audio into text. MFCC and word2vec were used to decipher the sounds. This research included four distinct deep-learning strategies. Amharic hate speech can be identified with 88.15 per cent accuracy by the multi-modal model using BILSTM, which beats the other trial.

Rahman et al. [10] extracted joyful, furious, and enthusiastic moods from a Bengali text by combining a unique Word to Index model with Word2vector, Skip-Gram, and Continuous Bag of Words (CBOW). Using a skip-gram model, the authors classified these feelings with a 75% accuracy rate. They also employed CNN and LSTM models on their dataset.

Seshadri el. at. [11] categorised tweets as good, harmful, or neutral. As contestants, SAIL 2015 task organisers gave Twitter Tamil, Hindi, and Bengali data. The proposed system attained state accuracy of 88%, 72.01%, and 65.16% for Tamil, Hindi, and Bengali languages, respectively, for SAIL 2015 information

Al-Amin, Islam el. at.[12] used word2vec to classify Bangla sentences' optimism and negativity. Researchers determined word sentiments by computing polarity scores. The author used 90% of the data as a training sample due to poor accuracy, but this paper used 80% for the word2vec model and got good accuracy.

2.1. Comparison with other work

Table 1 illustrates the comparison of our work with others. The examination of this table indicates that the existing literature has limited algorithms and exhibits low accuracy. No innovative techniques are employed. Our research employs numerous advanced methodologies, all demonstrating exceptional accuracy [13]. Before this, highly advanced methods were not utilised. Our research is, thus, innovative and remarkable.

Table 1 Comparison Table with other work

Other work		**Our work**
Author Name	Algorithm & Accuracy	Algorithm & Accuracy
Das el. At.	CNN &77%	Fasttext, Glove, Word2Vec XGB, Multi SVM and RF& 96.03%
Khan el. At.	SVM, & 62%	
Debele el. At.	BILSTM 88.81%	
Al-Amin el. At.	Word2Vec & 90%	

3. Material and methods

Figure 1 illustrates the methodological framework for this study. In this project, I implemented six phases to attain the intended goal. Initially, I gathered data and implemented a significant component of this project: data preprocessing. Subsequently, I implemented classification data and subsequently employed tokenisation technology. Upon completing all four elements, I implemented the Glove, Word2Vec, and Fasttext embedding methods alongside the hybrid algorithms RF and SVM, RF, XGB, and multinomial ML. The concluding phase is the execution:

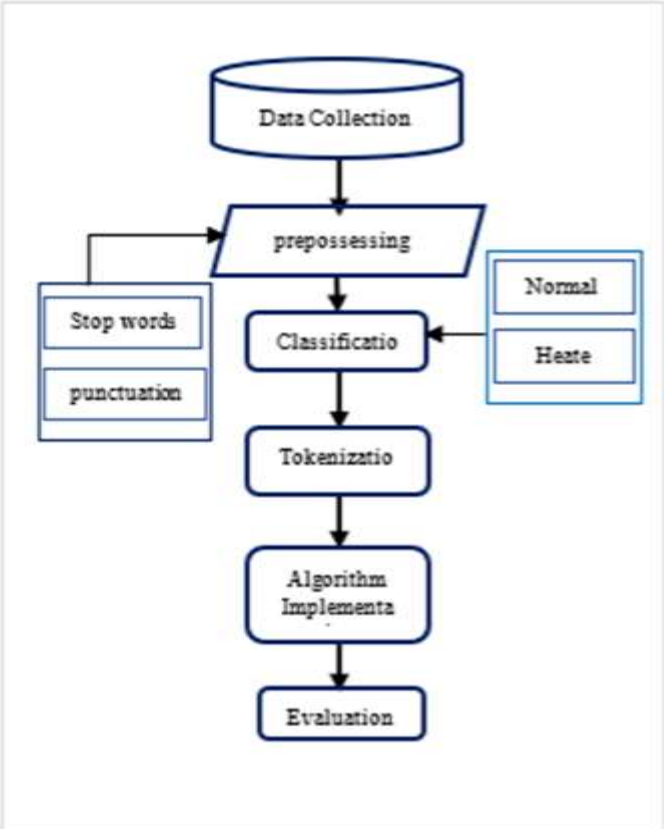

Figure 1 Methodology Diagram.

3.1. Data collection

The initial phase of this investigation involved compiling a substantial Bangla dataset comprising both affirmative and negative instances of hate speech. This dataset relies on the identification of hate speech and ensures the utilisation of a varied array of expressions and linguistic patterns. I have gathered thirty thousand examples of both hate speech and fair speech from various social media platforms and employed them in this essay.

3.2. Dataset pre-processing and representation

The data preparation is a crucial phase in this undertaking. Data classification involves dividing the dataset into two categories: one comprising average content and the other consisting of hate speech. The integrity of a dataset can be ensured by a procedure termed "data cleaning," which involves eliminating superfluous or erroneous information. To ensure uniformity, we have converted all text to lowercase. Tokenisation divides text into smaller parts, tokens, which can be handled individually.

Table 2 presents the sample from our utilised dataset. The dataset had two classes, positive and negative, designated as 0 and 1, respectively. Our dataset consists of textual data, necessitating the conversion of our class into a numerical value for machine comprehension [14].

Table 2 Sample Data representation and labeling

Raw Data	Type	Label
I never thought the ending would be like this, it's really amazing.	Normal	1
The wives of good boys are so ultra-modern, they ruin the lives of good boys.	Hate	0

3.2.1. Tokenization & Stop word removing

Tokenisation necessitates the dissection of the review text into its constituent phrases. Tokenisation enhances model performance in identifying text patterns by treating each word as an autonomous unit [15]. Stop words are commonly used yet extraneous terms that may diminish the effectiveness of a statement. They were excluded as they are not relevant to the identification of emotions [16]. We diminish dimensionality and assist the model in recognising essential phrases associated with customer sentiment by removing stop words from the dataset. Instruments such as NLTK, spaCy, or Scikit-learn facilitate the elimination of stop words from datasets.

Table 3 The tokenisation table for our dataset**.**

Raw Data	Type	Tokenization Data
The wives of good boys are so ultra-modern, they ruin the lives of good boys.	Hate	‘'The', 'wives', 'of', 'good', 'boys', 'are', 'so', 'ultra-modern,', 'they', 'ruin', 'the', 'lives', 'of', 'good', 'boys
I never thought the ending would be like this, it's really amazing.	Normal	‘'I', 'never', 'thought', 'the', 'ending', 'would', 'be', 'like', 'this,', "it's", 'really', 'amazing.'
What better thing can a rude, stupid person give than this?	Hate	‘'What', 'better', 'thing', 'can', 'a', 'rude,', 'stupid', 'person', 'give', 'than', 'this?'

3.3. Data Classification

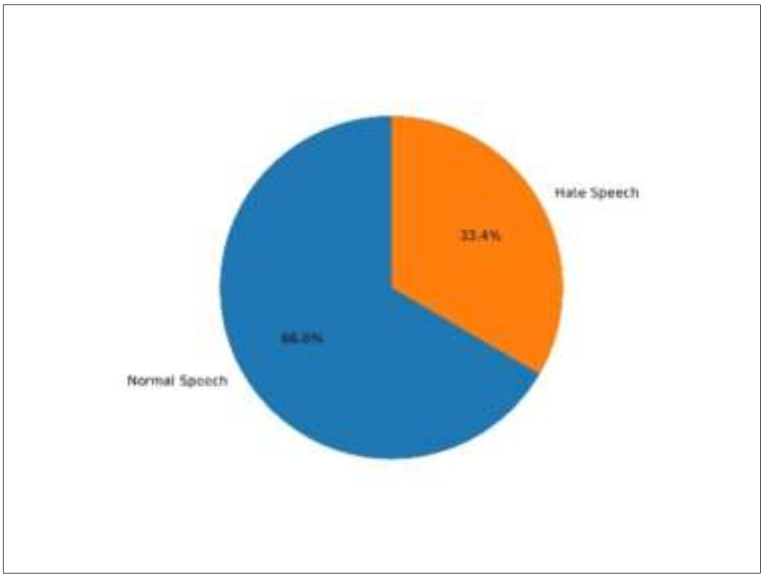

Figure 2 Methodology Diagram

Figure 2, a pie chart, illustrates the distribution of the e-commerce clothes review dataset categorised by positive and negative ratings. The data indicate that positive reviews surpass negative ones. The balanced distribution shows that training and assessing sentiment analysis machine learning models necessitates a balanced dataset [17]. Algorithms can more effectively identify positive or negative sentiment patterns, minimising bias towards either category when the sample is uniformly distributed. Attaining significant classification effectiveness and ensuring precise forecasts in real-world scenarios necessitate this balance. In social platforms, comprehending hate, normal speech, and client feedback is essential for enhancing products and services. For our investigation, we meticulously examined over thirty thousand records. This extensive dataset exhibited a consequent imbalance. Accurate data is essential for any significant research. This underscores the importance of transitioning to a balanced dataset. The dataset has been augmented to attain a more equitable outcome. Figure 2 illustrates the completed balanced dataset. The research indicates that 66.6% of the communication comprises normal speech, whereas 33.4% is hate speech.

3.4. Model selection and algorithms

This study evaluated multiple machine learning techniques to determine Bangla's most effective model for detecting hate speech. The models investigated included an XGB Classifier, Random Forest, Multinomial Naive Bayes, and a Hybrid of Random Forest and Support Vector Machine. XGB and Random Forest have shown proficiency in managing high-dimensional text input, achieving an accuracy range of 90% to 95% and demonstrating robust performance. Nonetheless, in the realm of hate speech recognition in Bangla, the Random Forest-SVM Hybrid model emerged as the unequivocal victor. Above all other models, it attained a remarkable accuracy of 96.85% with a 30% test split [18]. Compared to the different models, Multinomial Naive Bayes exhibited subpar performance, proving effective for fundamental text categorisation.

3.5. Evaluation

The results showed that ensemble models, and the Random Forest-SVM Hybrid in particular, are better able to understand the nuances of the Bangla language, which in turn allows for more accurate hate speech detection. The study did point out some problems, particularly with removing false negatives, so there has to be further tweaking to detect less overt forms of hate speech.

4. Results and discussion

We employed three embedding methods, Word2Vec, GloVe, and FastText, to train and test our data [19]. In this instance, we utilised entirely distinct data for testing, which was not derived from the training set. We employed four distinct algorithms across the three methodologies. The prevalent machine learning methods include XGB Classifier, Random Forest, Multinomial Naive Bayes, and the Random Forest and Support Vector Machine blend. Additionally, we have utilised 30 to 70% of the test data to validate our employed methods. Our test data exhibited strong performance across all areas, with optimal results within the 30% to 40% range. Our algorithms achieved optimal results at 30%.

The accuracy of the glove method is illustrated in Table 4. The implemented algorithm demonstrates a satisfactory value at 30% of the test outcome. In this approach, XGB and RM exhibit nearly identical values; however, the superior choice is the RF classifier, which achieved 94.03% accuracy. The Glove approach demonstrates the lowest value among the three applied methods.

Table 4 Glove Method

Test data use rate	Algorithm			
	XGB Classifier	**Random Forest**	**Multinomial NB**	**RF and SVM Hybrid**
30%	91.48%	94.03%	85.96%	85.63%
40%	93.20%	93.24%	86.02%	85.61%
50%	92.05%	91.18%	85.19%	85.72%
60%	90.40%	89.49%	86.16%	85.82%
70%	88.81%	87.89%	86.03%	85.35%

Table 5 presents the accuracy results of the Word2Vec methodology. All implemented algorithms achieved outstanding results. The XGB classifier attained the highest performance among the four algorithms, reaching 90.33% with 30% of the test results. Alternative algorithms perform effectively using this strategy. Word2Vec offers no more excellent value than the GloVe approach, although it does not yield optimal results.

Table 5 Word2Vec Method

Test data use rate	Algorithm			
	XGB Classifier	Random Forest	Multinomial NB	RF and SVM Hybrid
30%	90.33%	89.77%	80.12%	89.09%
40%	89.12%	88.60%	80.17%	88.95%
50%	88.30%	87.55%	80.01%	88.92%
60%	86.99%	86.09%	79.82%	88.97%
70%	85.60%	84.54%	79.69%	88.59%

The "Fast Text Report" table juxtaposes four machine learning algorithms: XGB Classifier, Random Forest, Multinomial Naive Bayes (NB), and a hybrid Random Forest-Support Vector Machine model. The algorithms are assessed based on their accuracy (%) at test data utilisation rates of 30%, 40%, 50%, 60%, and 70%. The XGB Classifier exhibits strong performance, achieving 95.87% accuracy with a 30% test data split and 91.87% accuracy with a 70% data split. XGB demonstrates robustness and consistency across data partitions. The Random Forest approach has commendable performance, achieving a maximum accuracy of 95.21% with 30% test data and maintaining 90.60% accuracy with 70% test data, so illustrating its reliability over varying data volumes. Nonetheless, Multinomial Naive Bayes (NB), a widely utilised method, exhibits suboptimal performance in this instance. This model achieved its highest performance of 86.16% with a 60% test data split, followed by 85.96% at 30% and 86.03% at 70%, indicating potential unsuitability for this task. The hybrid model of Random Forest and SVM outperforms other techniques, particularly at a 30% test data split, achieving the highest accuracy of 96.85%. The hybrid model attains 92.58% accuracy at a 70% test rate with elevated test data rates.

The table indicates that the Random Forest and SVM Hybrid model surpasses the XGB Classifier and Random Forest algorithms, attaining elevated accuracy throughout varying test data consumption rates. Although frequently employed in several applications, Multinomial Naive Bayes is the least effective for this case.

Table 5 Fasttext Method

Test data use rate	Algorithm			
	XGB Classifier	Random Forest	Multinomial NB	RF and SVM Hybrid
30%	95.87%	95.21%	85.96%	96.85%
40%	95.39%	93.98%	86.02%	94.81%
50%	84.17%	93.16%	85.19%	93.54%
60%	89.09%	92.29%	86.16%	93.53%
70%	91.87%	90.60%	86.03%	92.58%

4.1. Analysis

The Random Forest and SVM Hybrid model is the most effective of the models in the table. Its 96.85% test data rate was the highest. Despite using a larger fraction of test data, the hybrid model effectively detects hate speech in Bangla [20]. However, Multinomial Naive Bayes performs worse in every test split than the others. These findings suggest that the alternative models outperform Naive Bayes in this context. When comparing the three models, the Random Forest-SVM Hybrid model achieves better results in identifying hate speech in Bangla than XGB or Random Forest alone. As a result, we can see how merging algorithms can boost prediction strength and general accuracy.

5. Evaluation

Figure 3 shows the confusion matrix of this project. Accuracy is the proportion of correctly classified instances over the total instances:

Accuracy = (TP + TN) / (TP + TN + FP + FN)
= (81 + 96) / (81 + 96 + 0 + 16)
= 177 / 193 ≈ 0.917

So, the accuracy is approximately 91.7%. Error Rate is the percentage of instances misclassified: Error Rate = 1 - Accuracy = 0.917 = 0.083 or 8.3% Positive class recall (Sensitivity or True Positive Rate) is the percentage of positive examples accurately identified as positive: Recall = TP/(TP + FN) = 81/16 = 0.835 (83.5%). Negative class recall (Sensitivity or True Negative Rate) is the percentage of actual negative cases accurately predicted as negative: TN / (TN + FP) = 96 / (96 + 0) =1 or 100%. The confusion matrix delineates four primary outcomes: true negatives, false positives, false negatives, and true positives, offering a thorough assessment of the model's performance metrics [21]. The model achieved 98 true negatives—accurately classified instances of normal speech—and recorded 0 false positives—instances of normal communication erroneously tagged as hate speech. It is essential to acknowledge that the model failed to identify 16 instances of hate speech (false negatives) in practical applications, as indicated in the matrix. This underscores a minor challenge in the comprehensive collection of hate speech. The model accurately identified eighty-one instances of hate speech.

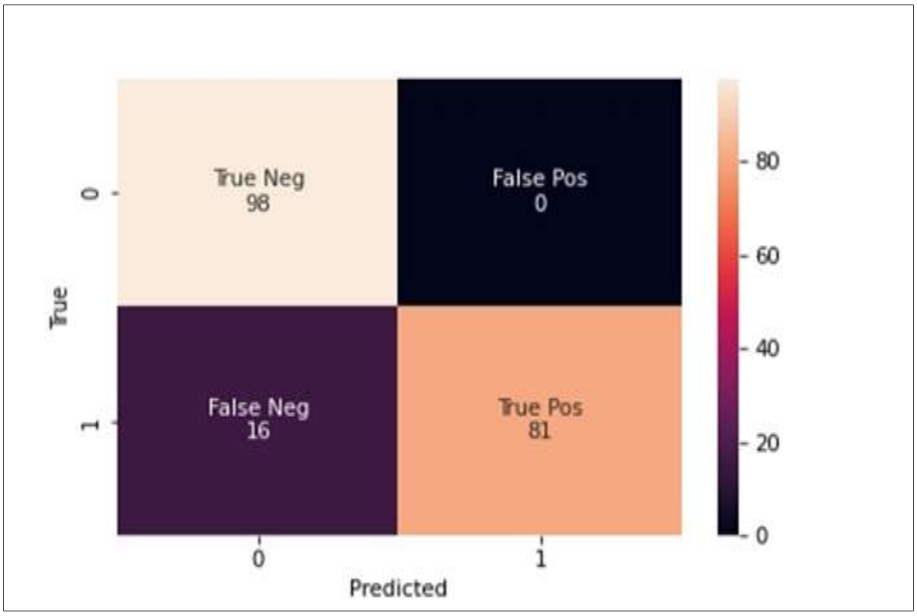

Figure 3 Confusion Matrix.

Figure 4 depicts a bar chart that compares the actual and expected instances of hate speech with standard conversation. The blue bars represent the observed values, whilst the orange bars indicate the values predicted by the model. The actual incidences of hate speech exceed the model's predictions, indicating that the algorithm may underestimate its prevalence [22]. The anticipated values for regular speech closely align with the actual instances, indicating a higher accuracy in detecting normal speech than hate speech. The algorithm performs adequately with standard speech but encounters difficulties in detecting hate speech, as illustrated by this bar chart that visualises the error distribution between the two categories.

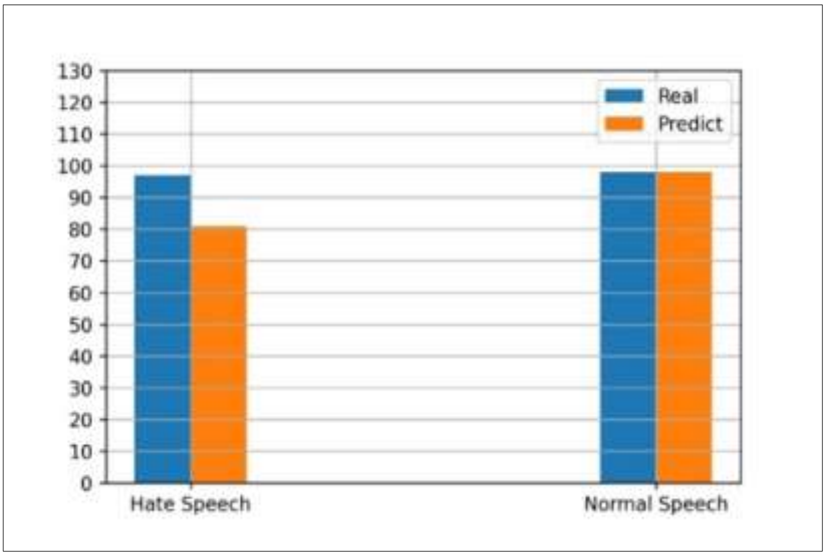

Figure 4 Evaluation Graph

5.1. Decision

Combined, these graphs provide a fascinating picture of the model's performance. The confusion matrix gives more nuanced insights into the model's capacity to distinguish between the two types of speech, while the bar chart shows better accuracy in regular speech identification [23]. In terms of identifying hate speech, both images highlight areas that might be improved, particularly in relation to reducing the number of false negatives.

6. Conclusion

This project, which addresses Bangla hate speech, has succeeded in its goal of clarity and efficiency. Our formal and data-driven conclusion aims for maximum accuracy and the best algorithm. The initiative recognised data's relevance early on. The careful selection of a broad dataset of positive and hate speech formed the foundation of our methodological rigour. In this dataset, we strive to capture the subtleties of human communication in the Bangla language. Data preparation methodically mapped our route to success. Though simple, classification, data cleansing, lowercase conversion, and tokenisation built our analytical depth. Data classification was crucial to supervised machine learning, dividing it into categories. Glove, Word2Vec, and FastText were essential to our search for maximum accuracy. These methods helped our project understand word relationships and reveal Bangla's expressive depth. The project uses Word2Vec, Glove, and Fasttext. Here, FastText performed best at 96.85%. Predict Multinomial, Random forest, RF and SVM Hybrid, and XGB with fasttext. RF and SVM Hybrid were the most accurate. When combined with carefully selected FastText embeddings, RF and SVM Hybrid, a text categorisation expert, won. Besides statistics, this shows our model's capacity to discriminate hate speech from valid information. Furthermore, our project's greatest triumph is its versatility. In an ever-changing digital environment with hate speech, our model's exceptional ability to recognise untrained abuse highlights its practical and real-world application. In conclusion, this study project displays our technical expertise and calls for action. We emphasise Bangla speakers' need for a safe and inclusive online environment while contributing to automatic content control. Our search for the best algorithm and accuracy shows our dedication to keeping the digital world safe and worldwide. We conclude with formal and data-driven conclusions that mark a fresh beginning in the fight for digital respect, diversity, and security. In the future we will develop a web and mobile application for easy to use this application.

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