Unveiling The Multifaceted Dynamics of Banglish Online Communication: A Comparative Analysis of Sentiment, Toxicity, Hate and Threats

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **"Unveiling the Multifaceted Dynamics of Banglish Online Communication: A Comparative Analysis of Sentiment, Toxicity, Hate, and Threats"**, submitted by Tarequl Islam Tareq, ID No: 201-15-3583 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *24th January,2024*.

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of Fahad Faisal, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Banglish, a Bengali-English language, is gaining popularity online. However, navigating its complexities presents challenges for Natural Language Processing (NLP) methods due to its linguistic fusion and lack of resources. This research explores the multifaceted analysis of Banglish text, including tasks like toxicity detection, identity hate prediction, threat assessment, and insult recognition. Using a dataset of 15,370 Banglish comments from social media platforms, the study investigates the effectiveness of four machine learning models: Support Vector Classifiers (SVCs), Random Forests Classifiers (RFCs), Long Short-Term Memory (LSTM) networks, and Bi-Directional LSTMs. Support Vector Machines (SVM) outperform other models in sentiment analysis, identifying Banglish text sentiment with 87% accuracy. This allows businesses and social media platforms to customize information and services based on this performance. With an 85% accuracy rate, SVCs are also excellent at anticipating potential toxicity. SVC also predicts insult and hate-speech with 75% and 77% accuracy for promoting safer online conversation. They also lead the industry with a 73% accuracy rate in identifying potential threat from Banglish text, ensuring a safer online environment. The study explores the effectiveness of Support Vector Machines (SVM) in Banglish text classification, highlighting their potential in handling intricate aspects. However, further research is needed on transfer learning strategies, domain-specific word embeddings, and ethical issues in code-mixed language processing. The research also addresses practical issues like danger assessment.

Keywords— Banglish text classification, Code-mixed language processing, Advanced NLP Technique, Support Vector Classifiers, AUC Score, Accuracy Comparison.

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CHAPTER 1

Introduction

1.1 Introduction

In the digital sphere, Banglish—a code-mixed language that combines Bengali and English—is becoming more and more popular. This study investigates text classification in Banglish, a novel field that presents opportunities and difficulties for researchers studying natural language processing and has the potential to promote inclusivity, safer online environments, and better user experiences [15,16]. Banglish, a widely used language on social media, presents unique challenges for Natural Language Processing (NLP) methods due to its natural blend of Bengali and English, requiring models that can recognize minute details and contextual cues, different dialects and colloquialisms, and the scarcity of NLP resources like big datasets and trained language models.[17]. The research aims to combat online harms by identifying hate speech, insults, and threats in Banglish comments, safeguarding vulnerable users, and making online environments safer. Sentiment analysis helps companies understand customer opinions and customize offerings, while correct handling of code-mixed languages promotes inclusion and allows diverse communities to fully engage in the digital sphere[15].This research advances natural language processing (NLP) by exploring advanced methods and modifications for code-mixed languages, thereby paving new research and improvement avenues[16].This research aims to expand Banglish text classification by incorporating tasks like threat assessment, insult recognition, toxicity detection, and identity hatred prediction. It uses a specific Banglish dataset and investigates feature engineering methods to manage complexity and address data scarcity. The study provides insights into experimental design, outcomes, constraints, and future paths, potentially improving user experiences, promoting diversity, creating safer online spaces, and advancing Natural Language Processing (NLP) by efficiently processing languages with mixed codes. The study aims to understand Banglish sentiment, a crucial aspect of marketing and service customization for Bangla-speaking communities. It uses deep learning algorithms to extract sentiment and context, including hate speech identification, threat assessment, and insult detection. The strategy prioritizes ethical factors like data gathering, bias-aware model building, and safe storage procedures. The classifier will provide the clean feed in Banglish communication. The objective is to improve online experiences for Bangla-speaking users by enabling safer spaces and promoting inclusion and diversity.

1.2 Motivation

Banglish, a fusion of Bangla and English, is a prominent part of the multilingual online community. Its speakers use social media and forums to express themselves, but it also exposes issues like hate speech, cyberbullying, and online toxicity, emphasizing the importance of text classification. Negativity in Banglish online spaces is common, with hate speech, insults, and discriminatory language targeting specific groups due to race, religion, or other identities. Efficient classification methods can flag hazardous content, allowing platforms to take appropriate action and create a safer online environment. Accurate detection of insults and threats in Banglish comments can protect vulnerable users and encourage responsible online conduct. Traditional text classification algorithms often overlook the complexities of code-mixed languages like Banglish, limiting their access to language technology. By developing effective Banglish text classification models, inclusivity and equitable online opportunities can be achieved. Analyzing emotions and opinions in Banglish can advance cultural understanding and empower Banglish speakers to use online platforms effectively. Banglish, a combination of English and Bangla, presents challenges for Natural Language Processing (NLP) systems. Research in Banglish text categorization can advance NLP, develop transfer learning approaches for other languages, and address online hazards. This research aims to strengthen Banglish-speaking groups and expand NLP frontiers.

1.3 Rationale of the Study

Understanding Banglish online discourse presents challenges due to its growing internet language and code-mixed character. Machine learning can help alleviate these issues by examining Banglish comments on multiple sites, examining sentiment, toxicity, identity hate, insults, and threats. Machine learning algorithms can improve online environments by identifying offensive language and promoting productive communication. They can moderate comments containing cyberbullying or harassment, fostering a more polite community. Platforms can create customized algorithms to promote positive content and reduce exposure to negativity. A dataset of 15,370 Banglish comments provides a useful starting point for investigating machine learning in this understudied field. The study will explore methods to reduce sparse data effects and explore potential directions for further investigation. Overall, this project aims to enhance Banglish internet discourse knowledge and utilize machine learning for societal benefit, fostering safer, inclusive, and engaging online communities for the Banglish-speaking community.

1.4 Research Question

Q1. How can certain language subtleties seen in Banglish comments be recognized and included to an all-encompassing toxicity detection framework?

Q2. To what extent can current natural language processing (NLP) algorithms be used to analyze massive datasets of Banglish comments for specific purposes like sentiment analysis and toxin detection?

Q3. What effects do linguistic and cultural differences have on machine learning models' accuracy and dependability when it comes to identifying toxicity, sentiment, and other elements of Banglish comments?

Q4. How may examining Banglish comments for toxicity, hate speech, and other problematic language affect society and policy, and how might these findings help guide community moderation tactics and online safety programs?

1.5 Expected Output

- ➢ The research aims to create and improve algorithmic models for Bengali social media text analysis, aiming to create advanced natural language processing (NLP) algorithms that can accurately detect linguistic markers and depression patterns.
- ➢ The study aims to identify linguistic markers and expressions in Bengali social media content associated with offensive words, aiming to create a comprehensive list of linguistic features indicating potential mental health issues.

- The study suggests an ethical framework that helps practitioners and academics ensure professional standards and safeguard privacy when evaluating private interactions on Bengali social media platforms.
- The study aims to confirm machine learning models' accuracy in identifying objectionable words in Bengali social media data, evaluating their sensitivity, specificity, and accuracy.
- The study aims to improve diagnostic resources for practitioners in Bengali’s communication by incorporating linguistic and cultural factors.
- The study's findings will provide a foundation for future research on the intersection of linguistic diversity and social media, potentially guiding researchers across different languages and cultural contexts.

1.6 Project Management and Finance

This thesis requires strict project management, which includes data collection, the preprocessing phase model construction, and result interpretations. Databases, figuring out infrastructure, and software instruments will be protected to ensure the study's smooth progression.

1.7 Report Layout

This research paper comprises five chapters: Introduction, Literature Review, Proposed methodology, Results and Discussion, Conclusion, and Future work. It covers the objectives, motivation, expected outcome, project management, finance, report layout, related works, comparative analysis, problem scope, challenges, research subject, instrumentation, data collection procedure, statistical analysis, proposed methodology, implementation requirements, results and discussion, impact on society, environment, ethical aspects, and sustainability plan. The paper concludes with a summary, conclusions, and implications for further study.

CHAPTER 2
Background

2.1 Preliminaries/Terminologies

It is high time to acquire a strong understanding of our main concept, words, procedures that are relevant to understand the dynamic activities through Banglish Online Communication. By introducing the Banglish language we establish the context. Who are unfamiliar with this we provide a prominent and clear theoretical concept with a framework for understanding the impact of our research.

2.1.1 Banglish Language

Banglish is an emerging language variety in Bangladesh where the word is blending with Bengali script with English word and grammar. It's informality, a hybrid nature which dominates online and creates unique challenges for analysis.

2.1.2 Natural Language Processing (NLP)

The gap between human languages and computers helps to combine with the NLP bridge. Analyze text data, extracting meaning and insights for our proposed work. For online Banglish language it's crucial for better understanding.

2.1.3 Machine Learning

Machine learning is a subfield of artificial intelligence that focuses on the development of algorithms and models that learn data without explicit programming. Developed an algorithm to analyze Banglish text and perform tasks for evaluation.

2.1.4 Sentiment Analysis

Sentiment analysis involves automatically identifying the emotional tone or opinion expressed in text. We utilize this technique to understand the overall sentiment of Banglish online discussions and gauge the emotional landscape of these interactions.

2.1.5 Toxicity Detection

Toxicity detection focuses on identifying harmful or offensive language in text. This includes hate speech, insults, and threats. By detecting these elements, we can assess the levels of toxicity prevalent in Banglish online spaces.

2.1.6 Hate Speech

Hate speech is language targeting individuals or groups based on protected characteristics (e.g., race, religion, gender) with the intent to incite violence or discrimination. Recognizing and analyzing hate speech in Banglish online discourse is crucial for promoting a safer online environment.

2.1.7 Insult Analysis

An insult is a statement intended to offend or humiliate someone. Distinguishing insults from playful banter or sarcasm in Banglish text can be challenging due to its informal nature. We aim to understand the prevalence and dynamics of insults in online interactions.

2.1.8 Threat Detection

A threat expresses an intention to harm someone, ranging from physical violence to online harassment. Accurately identifying threats in Banglish online platforms is vital for ensuring user safety and security.

2.1.9 Algorithm Models

In our research, we employ various Algorithm, such as Support Vector Machines and Naive Bayes classifiers. These models, trained on Banglish-specific data, are tailored to perform the analysis tasks we require, like sentiment classification or toxicity detection.

2.1.10 Model Evaluation

Model evaluation assesses the performance of predictive models using various metrics. Common evaluation metrics include accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves. These metrics provide insights into the effectiveness of a model's predictions.

2.2 Related Works

Bogoradnikova et al. [1] discussed a methodology for identifying emotions and sentiments in user-generated notes. They employed foreign word embedding due to their limited proficiency in Russian. An evaluation is conducted to assess the efficacy of a support vector machine and a deep neural network in the domains of mood analysis and poison identification. The algorithms were trained on an English dataset using antagonistic domain adaptation and a bilingual language model. M. S. Jahan et al. [2] thoroughly examine the progress made in natural language processing and deep learning technologies during the last ten years. Adhering to the PRISMA criterion for systematic reviews, this study explores important terminology, processing pipelines, and fundamental methodologies used in the area, with a specific emphasis on deep learning architectures. The study provides a thorough examination of current surveys, pulling from reliable sources like the ACM Digital Library and Google Scholar. It also critically evaluates the limits of these surveys. F. Poletto el al. [3] conducts a comprehensive examination of community-contributed materials, including development methods, issue focus, language coverage, and other relevant characteristics. The results of this investigation highlight a varied and growing environment within the community. The evaluation uncovers many concerns and pinpoints specific areas that may be enhanced, highlighting the necessity of focusing on improving the overall quality and coherence of the existing resources. J. Risch et al. [4] suggests improving training data by incorporating transfer learning techniques. The study explores the practical implementations of this strategy, namely in areas such as semi-automated comment moderation and troll identification. The study seeks to demonstrate the efficacy and applicability of transfer learning in real-life situations. Furthermore, the article finishes by delineating upcoming obstacles and tackling existing constraints, deriving insights from recent scholarly papers. Zaheri et al [5] reveals that LSTM, with a 20% higher true positive rate than Naïve Bayes, could revolutionize comment classification. Researchers used Amazon Web Service (AWS) to optimize their work process, achieving the best results of over 70%. This demonstrates how intelligent data science can contribute to a more virtuous virtual society. S. Carta et al. [6] presents a new method for doing a multi-class multi-label categorization of talks. The focus is on classifying them into six types of toxicity. The methodology is grounded in supervised learning, and empirical evidence showcases its superiority compared to the current cutting-edge techniques that depend on the conventional bag-of-words model. The main novelty comes in utilizing distinct sets of word embeddings, demonstrating the efficiency of this approach in obtaining improved classification performance. The results indicate that the suggested supervised method provides improvements compared to existing techniques, especially those using the traditional bag-of-words model. A. Gaydhani et al. [7] work utilizes Twitter datasets for experiments, employing n-grams as characteristics. The work entails feeding the term frequency-inverse document frequency (TFIDF) values of these n-grams into several machine learning models. The evaluation on test data demonstrates an impressive accuracy percentage of 95.6%. M. F. Mridha et al [8] developed and tested the L-Boost algorithm, a modified AdaBoost using a pre-trained BERT word embedding vector model, achieving 95.11% accuracy on three datasets. V. Rupapara et al [9] present a regression vector voting classifier (RVVC) to identify objectionable remarks on social media. The method, which combines logistic regression and support vector classifier, was tested on both imbalanced and balanced datasets. The RVVC performed best with the TF-IDF feature, achieving an accuracy of 0.97. M. A. Saif et al [10] utilized neural network models, Conv, LSTM, and Conv + LSTM, along with logistic regression, to identify objectionable material. Conv + LSTM achieved the highest accuracy, with results of 0.9820 and 0.9645, respectively. Malmasi et al [11] develop a supervised classification algorithm, using character n-grams, word n-grams, and word skip-grams, accurately identified hate speech on social media with 78% accuracy across three classifications. Numerous studies have yielded a range of methods and strategies in the subject of sentiment analysis. Using a new word-to-index model with Word2vector, Skip-Gram, and Continuous Bag of Words (CBOW), the authors [12] achieved 75% accuracy using Skip-Gram. An N-gram language model based on contextual similarity is proposed in the study [13] to identify the stems or root forms of Bangla words. The authors used a 6-gram model to identify stems with an accuracy of 40.18%.The authors [14] provided a Bengali version of the WordNet Affect lists generation procedure, which is currently available in English. As a result, for the six emotion classes, the Kappa Coefficient (k) demonstrates a moderate agreement, ranging from 0.44 to 0.56.

2.3 Comparative Analysis and Summary

A few research has explored machine learning for task detection using various algorithms, neural networks, Naive Bayes, BERT variations, Bi-LSTM, CNN, Fast-Text, CDAE, ensemble techniques, and SVM. The table compares the descriptions, techniques, and findings of these publication, revealing the efficacy of various algorithms for detection tasks and revealing strengths and drawbacks for future research and implementation.

Table: 2.1: Overview of Associated research work

Index No.	Name of the Author	Type of work	Used Algorithm(s)	Best Accuracy
1	Bogoradnikova et al. (1)	Identifying emotions and sentiments	SVM, DNN, Transfer Learning	N/A
2	M. S. Jahan et al. (2)	sentiment analysis	Review paper	N/A
3	F. Poletto el al. (3)	Comprehensive examination of community-contributed	Review paper	N/A
4	J. Risch et al. (4)	comment moderation and troll identification	Transfer Learning	N/A
5	Zaheri et al. (5)	LSTM for comment classification	LSTM	Over 70%
6	S. Carta et al. (6)	Multi-class multi-label classification of talks	supervised learning	Not specified
7	Nayan et al. (7)	Toxicity Detection from social media comment	CNN, SVM, RF, LSTM	95.30%
8	M.F. Mridha et al. (8)	Offensive text detection from Bengali post	LSTM	95.11%
9	V. Rupapara et al.(9)	hate speech detection	RVVC	0.97
10	M. A. Saif et al. (10)	Neural networks for hate speech detection	Conv + LSTM	0.9820
11	Nauros et al. (11)	Hate speech detection from Bangla language	SVM+ char n grams	89.1%
12	Rahman et al. (12)	Word-to-index model for sentiment analysis	Word2Vec, Skip-Gram	75% (Skip-Gram)
13	Urmi et al. (13)	N-gram language model for Bangla stem identification	6-gram model	40.18% (stem identification)
14	Das & Bandyopadhyay et al (14)	Bengali WordNet Affect lists generation	Bengali WordNet Affect lists	Kappa Coefficient (k) 0.44-0.56

This comparison table helps in understanding the effectiveness of machine learning in task detection.

2.4 Scope of the Problem

The goal is to automate content moderation and analysis in Banglish comments by detecting sentiment, toxicity, identity hate, insults, and threats. The goal is to create precise models for sentiment analysis, threat assessment, toxicity assessment, identity hatred assessment, and insult prediction. The model's interpretability will provide insight into decision-making procedures. The aim is to reduce internet harm, encourage research in social media analysis and Banglish language processing, and provide guidance on content moderation tactics for Bangla-speaking communities.

2.5 Challenges

2.5.1 Data Quality and Missing Values

The model's effectiveness may be affected by a small dataset of 15370 comments, code-mixing in Bengali due to its combination of Bengali and English, and class imbalance in sentiment/toxicity categories. The accuracy and consistency of manual labeling are crucial for reliable model training.

2.5.2 Feature Engineering and Selection

The study focuses on identifying informative features like word/character n-grams, sentiment lexicons, and syntactic patterns for prediction jobs, addressing code-mixing efficiently, and creating engineering features that highlight relevant topics like sentiment and toxicity.

2.5.3 Model Generalization and Interpretability

The text outlines the process of identifying relevant traits for prediction tasks, managing code-mixing, and engineering features, as well as developing techniques for processing and expressing linguistic features in code-mixed languages, and emphasizing toxicity and emotion.

2.5.4 Hyper parameter Tuning and Regularization

The model's performance can be enhanced by optimizing hyperparameters for optimal accuracy and generalization, and avoiding overfitting through strategies like dropout.

2.5.5 Model Evaluation and Clinical Applicability

The evaluation involves assessing performance using metrics like precision, recall, F1-score, and AUC-ROC, and evaluating the model's practical impact in actual content analysis and moderating situations.

2.5.6 Ethical Considerations and Privacy

AI's responsibility lies in ensuring impartiality and fairness in models, preserving user privacy during data collection and analysis, and promoting accountability and openness in model creation and application.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

The research aims to use machine learning to analyze Banglish comments on social media platforms for offensive comment prediction, focusing on developing culturally sensitive dark side detection models while ensuring ethical considerations, privacy protection, and responsible data use. Detection and prediction purposes, machine learning, and deep learning are mostly used. This study uses a literature review to develop a methodology for detecting offensive words in Bengali social media content. It uses linguistic analysis, cultural sensitivity analysis, and Natural Language Processing (NLP) and Machine learning (ML) to identify linguistic markers. The methodology ensures ethical considerations, privacy, and reliability, and uses statistical analyses to interpret findings. It is continuously improved and refined to stay relevant. Python was used as a data mining tool, Google Collaboratory was used as a collaborative tool, and Microsoft Excel was used as the dataset, stored in a csv file.

3.2 Data Collection Procedure/Dataset Utilized

Bengali social media dataset: 15,370 texts labeled for sentiment, toxicity, hate speech, insult, and threat. Web scraped, manually annotated for positive/negative, high/low levels. Each label binary (0/1).

Table 3.1: Attributes

Attribute Name	**Comment_ text**	**Rating/ Sentiment**	**Insult**	**Threat**	**Toxic**	**Hate speech**
Data Type	String	Int	Int	Int	Int	Int
Level	N/A	Negative=0/ Positive=1	Low=0/ High=1	Low=0/ High=1	Low=0/ High=1	Low=0/ High=1

3.3 Statistical Analysis

The EDA (exploratory data analysis) is the first stage of data analysis, where we analyze and visualize the dataset's properties. It identifies hidden patterns, outliers, and correlations using various methods. EDA provides valuable insights into the data structure and alternative research paths, influencing subsequent studies and directing research paths.

3.3.1 Histogram Visualization

Exploratory data analysis (EDA) was utilized to create colorful histograms, which were used to visually represent the numerical characteristics of the dataset, considering all relevant factors.

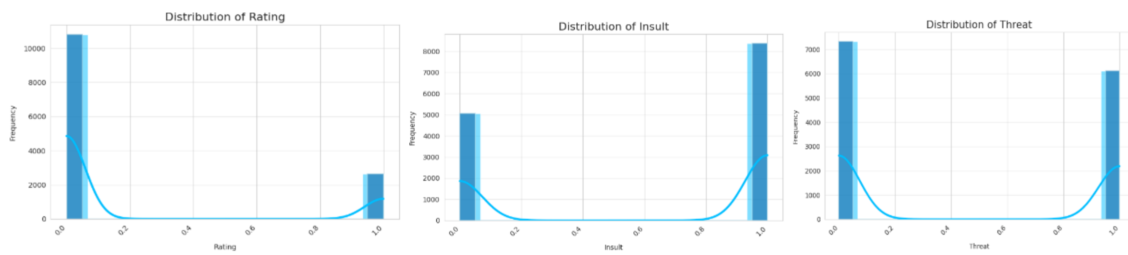

Fig.3.1: Rating/sentiment, Insult, Threat level Histogram

The distribution of rating, Insult, Threat within the study comment is shown by the histogram of rating. Here rating ranges are 0 and 1. The x-axis indicates the level and y-axis indicate the frequency of rating/sentiment, Insult, Threat with positive and negative.

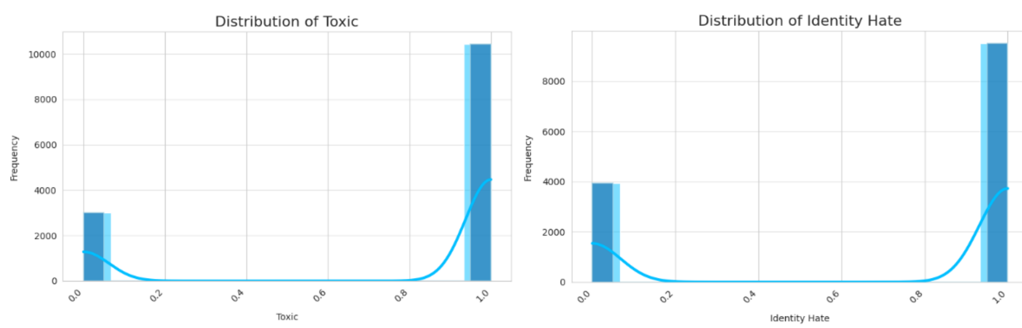

Fig.3.2: Toxic, Identity Hate level Histogram

The distribution of Toxic, Identity Hate within the study comment is shown by the histogram of rating. Here rating ranges are 0 and 1. The x-axis indicates the level and y-axis indicate the frequency of Toxic, Identity Hate with positive and negative. The visualization further depicts the value distribution and quantity of each targeted class,

3.3.2 Comment Data Visualization

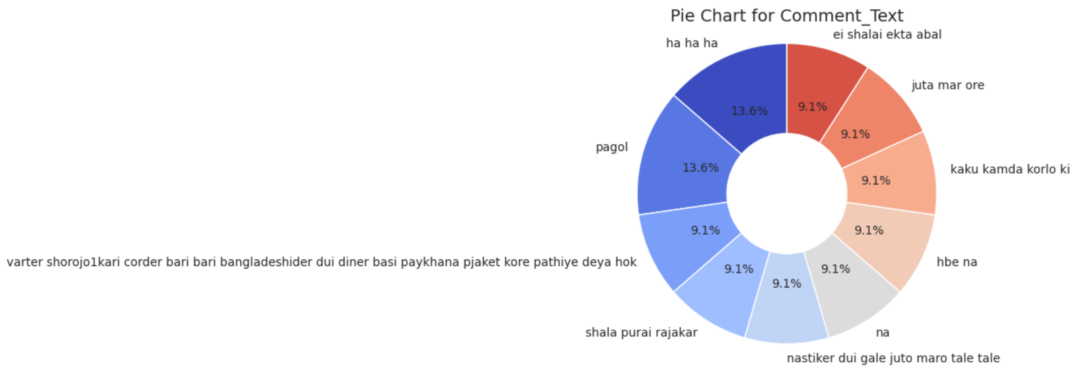

Fig.3.3: Banglish Comment pie chart

The distribution of this pie chart shows the important sentence in my dataset. The image displays a pie chart with segments labeled in Bengali, indicating a distribution of categories or frequencies for 'Comment_Text'. Each segment represents a different proportion of the data, with various comments or phrases.

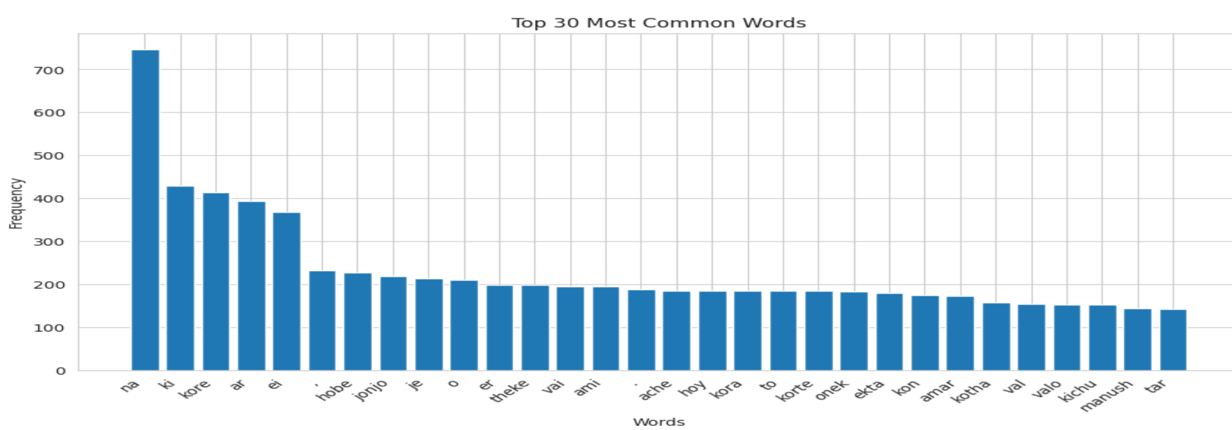

Fig.3.4: Top-30 comment Histogram

The distribution of Top-30 comment Histogram within the study comment is shown. The x-axis indicates the Top-30 comment word and the y-axis indicates the frequency of word number. The image is a horizontal bar chart titled "Top 30 Most Common Words". It shows the frequency of words on the y-axis and the corresponding words on the x-axis. The bars decrease in length from left to right, indicating that the most common word appears over 700 times, while the 30th most common word appears just over 100 times. The words are not clearly readable, but the chart effectively conveys the distribution of word frequencies.

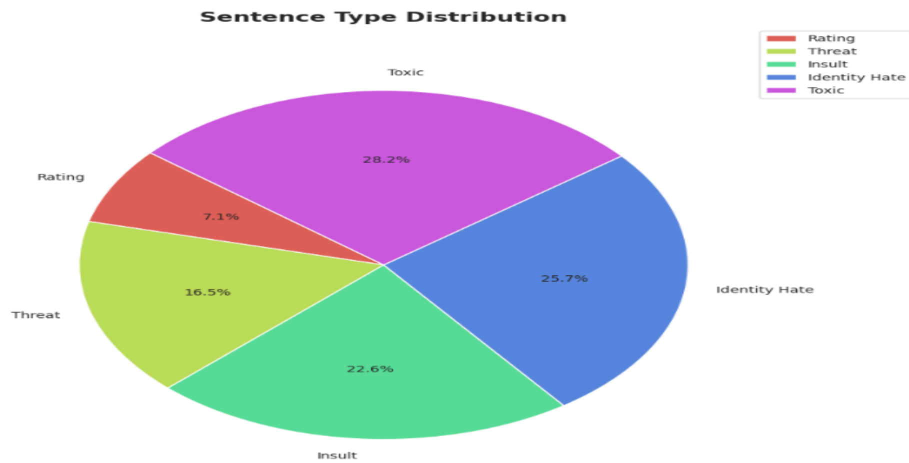

Fig.3.5: Class distribution in pie chart

The image is a pie chart titled "Sentence Type Distribution" with five categories, each represented by a different colour and a corresponding percentage of the whole: Toxic: 28.2%, Identity Hate: 25.7%, Insult: 22.6%, Threat: 16.5%, Rating: 7.1%. The chart is used to visualize the proportion of each sentence type within a dataset or a collection of texts. The largest segment is Toxic, followed closely by Identity Hate and Insult, with Threat and Rating being the smaller portions.

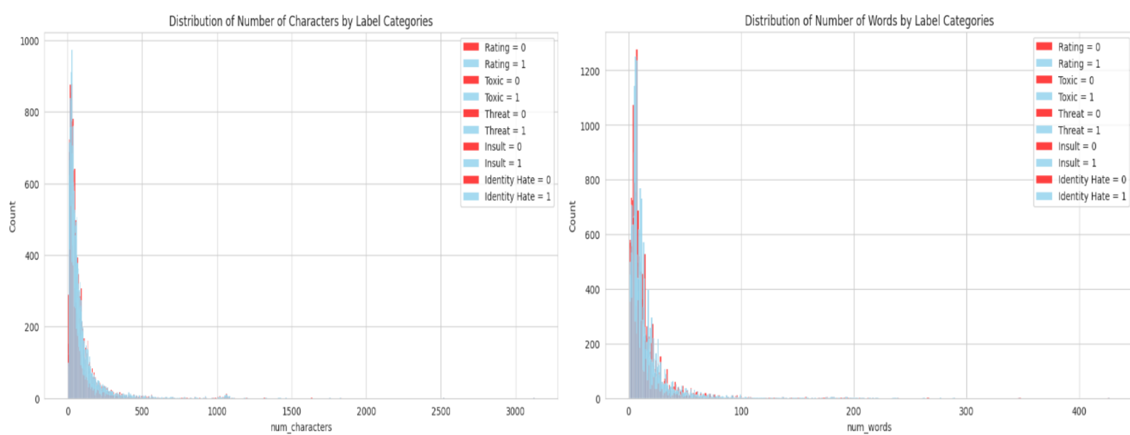

Fig.3.6: Distribution of Number of Words and Character by Level

The Distribution of Number of Character and word by Level Histogram within the study comment is shown. The x-axis indicates the attributes with level color and the y-axis indicates the frequency of number of characters and words.

3.3.3 Violin Plot Visualization

Violin plots were used in our exploratory data analysis (EDA) to display the distribution of attributes. These plots combine boxplots and kernel density estimation, providing a comprehensive view of the distribution of these attributes for each level category.

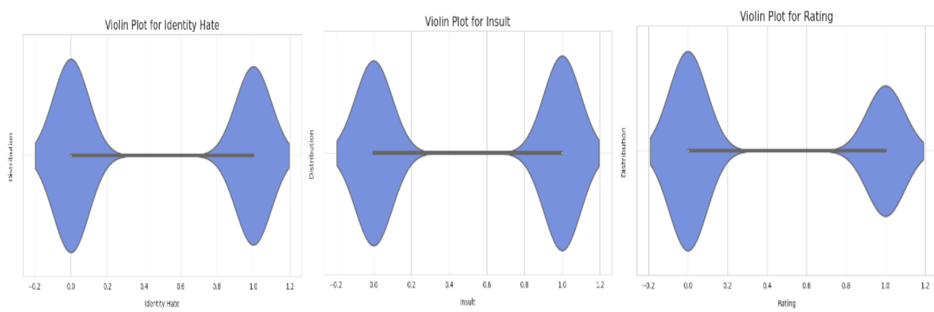

Fig.3.7: Violin plot of Identity hate (hate speech), Insult, Rating/Sentiment vs. Distribution

The violin plot shows that individuals with high-risk levels have a greater range of low-risk levels, suggesting higher distribution levels, as demonstrated by the violin plot.

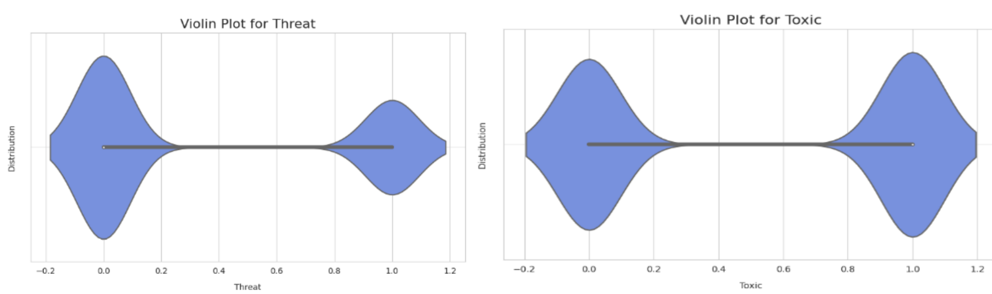

Fig.3.8: Violin plot of Threat, Toxic vs. Distribution

The violin plot shows that individuals with high-risk levels have a greater range of low-risk levels, suggesting that Threat, Toxic is linked to higher distribution levels, as demonstrated by the violin plot.

3.3.4 Word Cloud Visualization

Word cloud visualization is a visual representation of the frequency and importance of words in a text, with each word's size and boldness indicating its frequency and potential impact. The larger and bolder the word, the more significant it is.

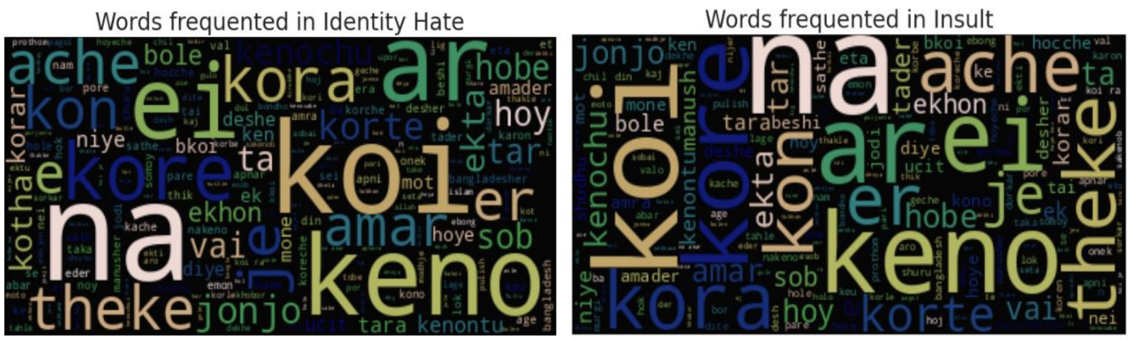

Fig.3.9: Word frequented in Identity hate and Insult

In this word cloud visualization, the frequented words are visualized. Which words in Identity hate and Insult are visualized here. Size is related to frequency. Size bigger to lower totally depends on that word frequently. The image is a word cloud, a visual representation of word frequency within a given text, titled "Words Frequented in Identity hate and Insult." The most prominent words, likely the most frequent, are "na", “Koi” and "keno," displayed in larger fonts at the center. Surrounding them are various other words in different sizes and orientations, indicating lesser frequencies.

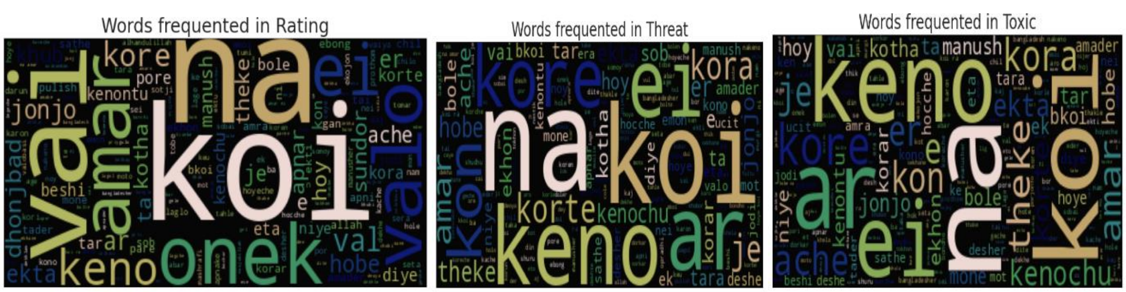

Fig.3.10: Word frequented in Rating(sentiment), Threat and Toxic

In this word cloud visualization, the frequented words are visualized. Which words in Rating(sentiment), Threat and Toxic are visualized here. Size is related to frequency. Size bigger to lower totally depends on that word frequently. The image is a word cloud, a visual representation of word frequency within a given text, titled "Words Frequented in Rating (sentiment), Threat and Toxic." The most prominent words, likely the most frequent, are "na", “Koi” and "kore," displayed in larger fonts at the center. Surrounding them are various other words in different sizes and orientations, indicating lesser frequencies.

3.3.5 Correlation of each Features

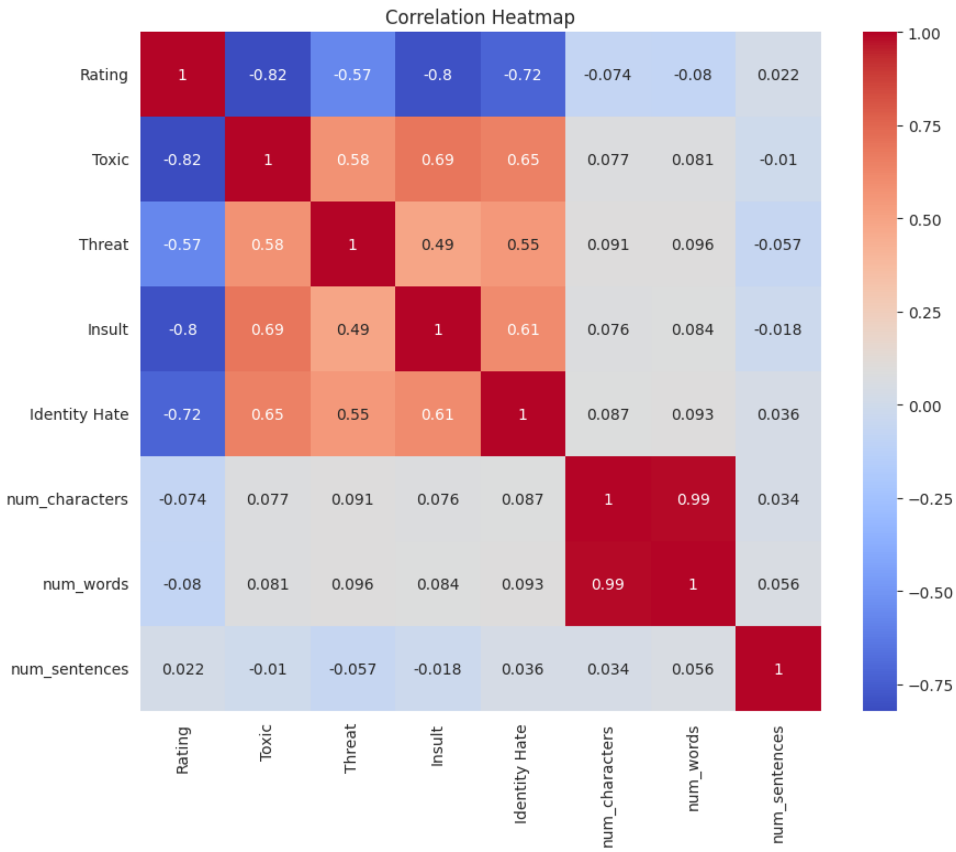

Fig 3.11: Correlation Heat map Analysis.

A correlation heat map is a visual representation of a dataset's correlation matrix, which displays the correlation coefficient between each pair of variables. The correlation coefficient, ranging from -1 to 1, indicates the strength of the linear link between two variables. The heat map's diagonal cells are all white, and it can be used to identify patterns in the data, such as highly correlated pairings of data suggesting a relationship between variables. It can also help identify clusters of variables with strong correlations.

3.3.6 Pair plot Visualization

Pair Plots are a visual tool used to analyze data connections between numerical variables. They consist of a scatter plot matrix with each plot representing the correlation between two variables. The diagonal plots are kernel density estimates (KDEs), which provide more information than histograms for continuous variables.

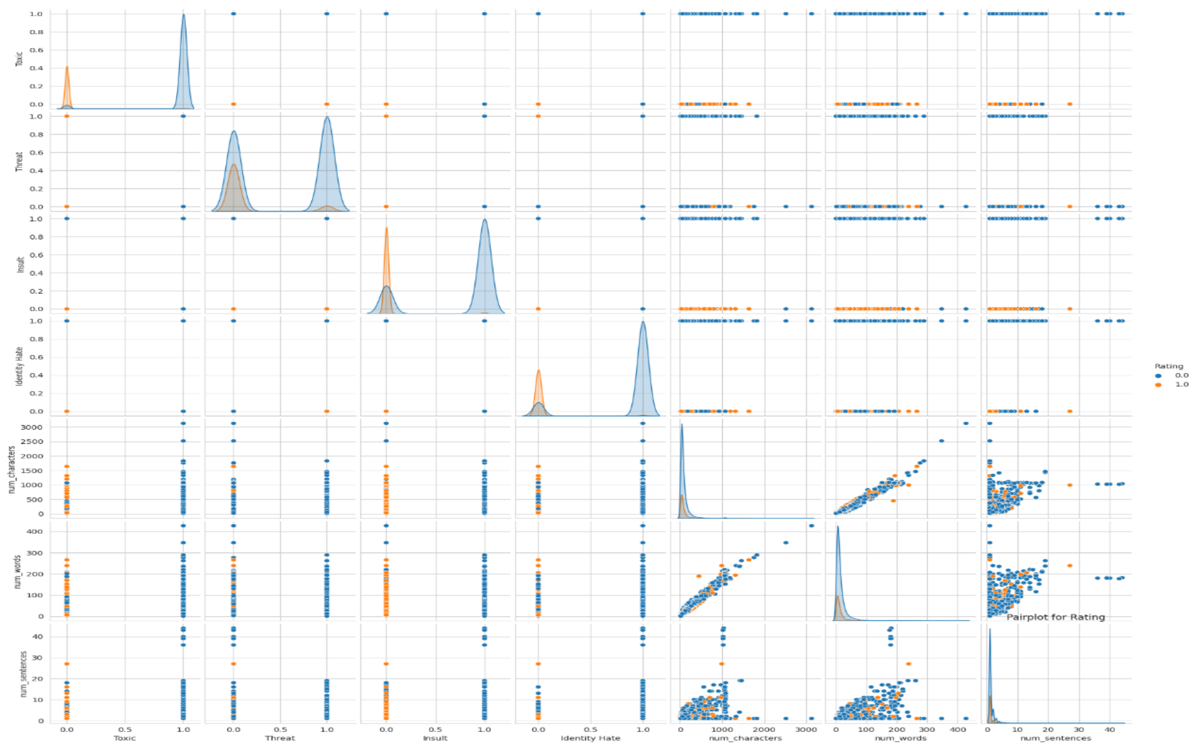

Fig 3.12: Pair plot Visualization

The 'hue' parameter sets the 'Level (low and High)' parameter to color data points based on their level, allowing for the observation of changes in relationships between numerical variables at different levels. Pair plots are particularly useful for spotting trends, correlations, and anomalies in data

3.4 Proposed Methodology/Applied Mechanism

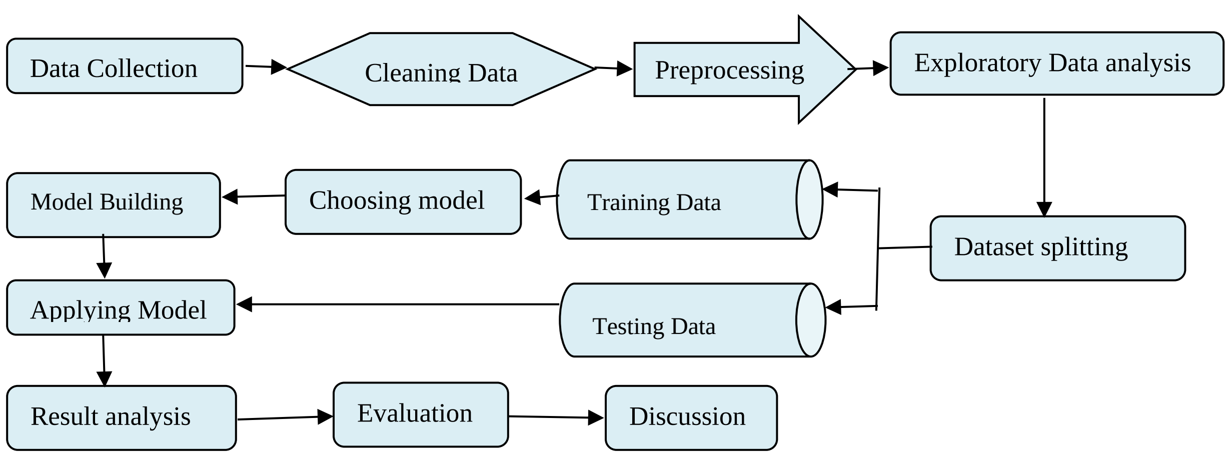

Fig.3.13: Proposed Methodology

To build a system needs to assemble a framework and fig 3.13 shows the diagram of the methodology of a system.

3.4.1 Data Preprocessing

Data preprocessing is required to gain an efficient dataset. At first, I remove null value then remove the duplicate value which are available min my dataset. Then I preprocess my Text data by removing stop ward. And also tokenized by me for visualization.

3.4.2 Model Description

Machine learning techniques are utilized to estimate unwanted words in Banglish Text, including forecasts, data analysis, and four types of algorithms. These models were chosen based on their suitability for the study's objectives and their ability to manage the dataset's specifics.

- **Long Short-Term Memory (LSTM): Long** Short-Term Memory (LSTM) addresses the vanishing gradient problem, making it suitable for speech recognition and natural language processing due to its self-regulating gates.
- **Bidirectional Long Short-Term Memory (Bi-LSTM):** Bidirectional Long Short-Term Memory (Bi-LSTM) is a bidirectional LSTM architecture that improves sequential data modeling for applications such as natural language processing by taking into account past and future contexts.
- **Support Vector Machine (SVM):** SVM, a powerful machine learning method, excels in Bengali social media for regression and classification, reducing misclassification errors, optimizing class margins, and detecting culturally sensitive depression.
- **Random Forest:** Random Forest is a versatile machine learning method that reduces overfitting and improves generalization by building multiple decision trees using bagging and random feature selection.

3.4.3 Model Configuration

Hyperparameter tuning maximizes predictive power and improves model performance and generalizability by optimizing model parameters through methods such as grid search or random search. In our applied algorithm we apply Hyperparameter tuning for maximize our accuracy to find out the unwanted word from Banglish text.

3.4.4 Model Training

Eighty percent of the dataset was employed in the model training process to produce highly predictive models. Enough observations were kept in this dataset, and the data was appropriately represented. SVM is one of the machine learning models that was trained to internalize patterns and features in the data. In order to guarantee the models' functionality and capacity to achieve study objectives, this laid the foundation for their evaluation and validation.

3.4.5Model Testing

2690 examples from the 20% of the sample were put aside for testing prediction algorithms. The confusion matrix, which offers a thorough analysis of categorization results and evaluates accuracy and potency, was used to gauge the models' generalization abilities.

Fig.3.14: Confusion Matrix Visualization

The image depicts a diagram with four interconnected cubes, each representing a different outcome of a binary classification: True Positive TP (red), False Negative FN (green), False Positive FP (purple), and True Negative TN (blue). This is a visual representation of a confusion matrix, a tool used in machine learning to measure the performance of an algorithm. Each cube's placement suggests the relationship between the outcomes, such as False Positives being opposite to True Negatives, illustrating the balance between error types in predictive modeling.

Table3.2: Measures of Accuracy

Metric	Description	Formula	Interpretation
Accuracy (A)	Overall accuracy of the prediction	A = (TP + TN) / (Total samples)	Greater values signify enhanced overall performance.
Precision (P)	percentage of correctly predicted favourable outcomes	P = TP / (TP + FP)	Reduced false positives are indicated by higher values.
Recall (R)	percentage of real positives that are appropriately identified	R = TP / (TP + FN)	Reduced false negatives are indicated by higher values.
F-Measure (F1)	harmonic mean of recall and precision, which balances both	F1 = 2 * (P * R) / (P + R)	Greater values signify an improved equilibrium between recall and precision.
ROC Curve	Illustrates, at different thresholds, the trade-off between true positive rate (TPR) and false positive rate (FPR).	Instead of a single number, a curve	Higher scores indicate greater overall performance, as measured by the area under the ROC curve (AUC).

3.5 Implementation Requirements

The research requires certain conditions for successful implementation to analyze data and evaluate advanced predictive models for offensive word analysis, including the following elements:

3.5.1 Computational Resources:

The availability of advanced computer power, including cloud computing services and high-performance clusters with sufficient RAM, storage, and processing capacity, is crucial for sophisticated predictive modeling.

3.5.2 Statistical Software:

The study recommends using statistical software programs Python libraries like scikit-learn for model implementation and data analysis in machine learning.

3.5.3 Data Preprocessing Tools:

Data preprocessing technologies, including transformation, cleaning, and normalization, are essential for ensuring data quality and preparing datasets for prediction models.

3.5.4 Predictive Modeling Libraries:

The integration of machine learning frameworks and libraries, such as scikit-learn, is crucial for sophisticated predictive model implementation.

3.5.5 Comparative Analysis Framework:

The framework aims to evaluate multiple prediction models using metrics like sensitivity, specificity, recall, precision, and receiver operating area.

3.5.6 Access Controls and Security Measures:

Implementing access controls and encryption or anonymization methods is crucial for safeguarding the confidentiality and integrity of sensitive data.

3.5.7 Ethical Review and Compliance:

The study is implementing ethical evaluation procedures, obtaining permission for changes, and conducting regular assessments to ensure compliance with ethical guidelines.

CHAPTER 4
Experimental Results And Discussion

4.1 Experimental Setup

This research employs a meticulous approach to dataset organization, model selection, and evaluation to assess the performance of machine learning models for Banglish comment classification. Approximately 15307 annotated comments were divided into training, validation, and testing sets, ensuring independence for model evaluation and providing a strong foundation for model development and assessment. The text underwent normalization, which involved removing punctuation, stop words, and non-alphanumeric characters. Machine learning models like SVC and RFC, Natural Processing Techniques (NLP) algorithm like LSTM, Bi-LSTM were used for classification, with hyperparameter tuning refined for better configurations and k-fold cross-validation enhancing training results reliability. The evaluation process incorporates a comparative analysis framework, assessing model performance using key metrics (accuracy, precision, recall, F1 score). The study uses iterative temporal analyses and user acceptance surveys to analyze Banglish text classification trends. Statistical tests are used to determine differences, and meticulous documentation ensures transparency. Results are compiled into a comprehensive report, providing insights into strengths and limitations.

4.2 Experimental Results & Analysis

We assessed 15307 data examples using a range of classifier and enhancing techniques.

4.2.1 Sentiment Analysis:

I. **Support Vector Machine (SVM) Classifier**

The confusion matrix displays the outcome of the perceptual model, which achieved 87% accuracy. The matrix demonstrates that the model successfully detected 2122 negative cases and 212 positive examples and that errors in classification are infrequent. The color intensity represents the frequency of predictions, with darker shades indicating higher numbers. The x-axis represents predicted labels, and the y-axis represents actual labels.

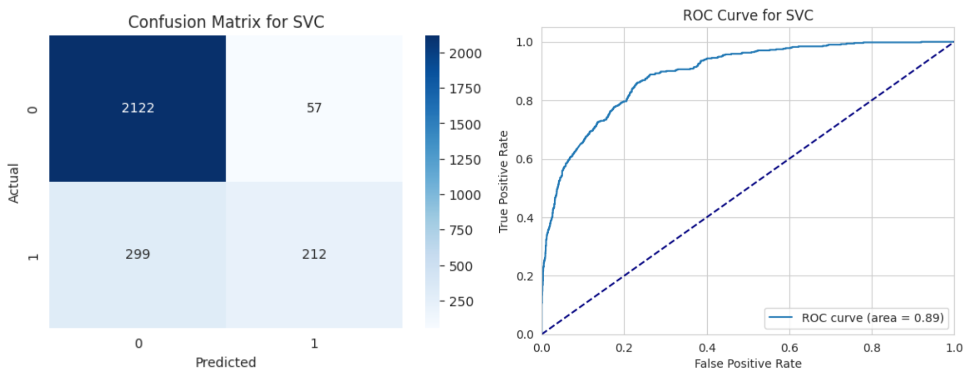

Fig 4.1: Confusion Matrix and ROC Curve of SVM Classifier.

With an AUC of 0.89 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

II. Random Forest Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 85% accuracy. The matrix demonstrates that the model successfully detected 244 negative cases and 2050 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

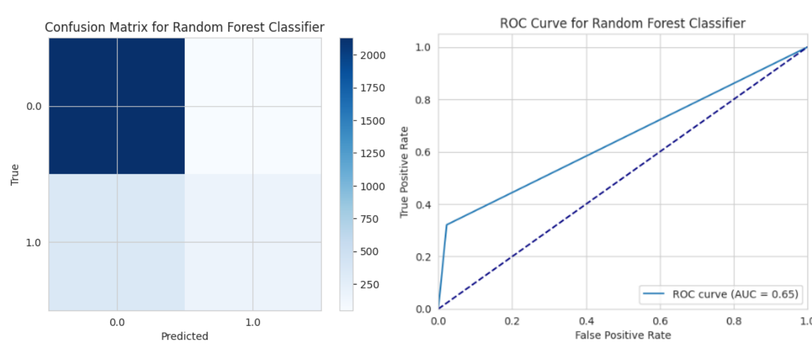

Fig 4.2: Confusion Matrix and ROC Curve of Random Forest Classifier

With an AUC of 0.65 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

III. Long Short-Term Memory (LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 85% accuracy. The matrix demonstrates that the model successfully detected 1990 negative cases and 288 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10.

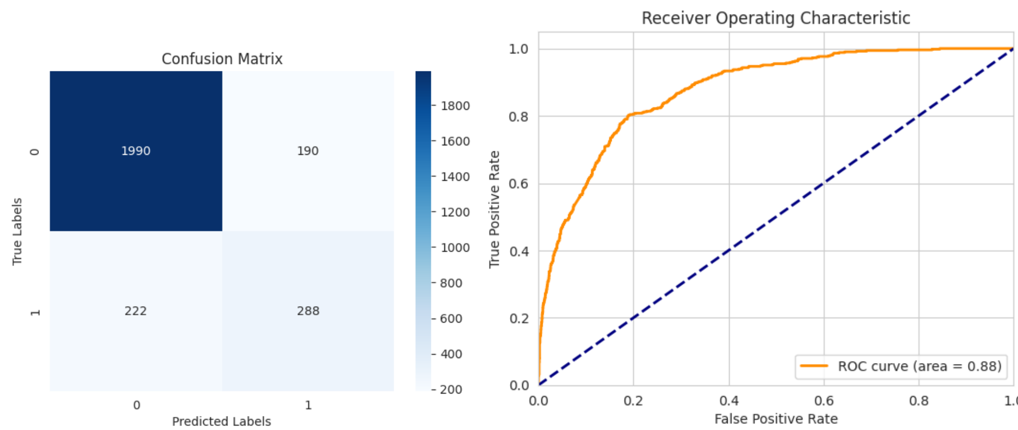

Fig 4.3: Confusion Matrix and ROC Curve of LSTM Classifier

With an AUC of 0.88 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

IV. Bidirectional Long Short-Term Memory (Bi-LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 84% accuracy. The matrix demonstrates that the model successfully detected 1956 negative cases and 305 indicating the number of positive instances correctly predicted. The color intensity represents the frequency of predictions, with darker shades indicating higher numbers. The x-axis represents predicted labels, and the y-axis represents actual labels. The matrix provides a visual and quantitative way to assess the performance of the classification model. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10.

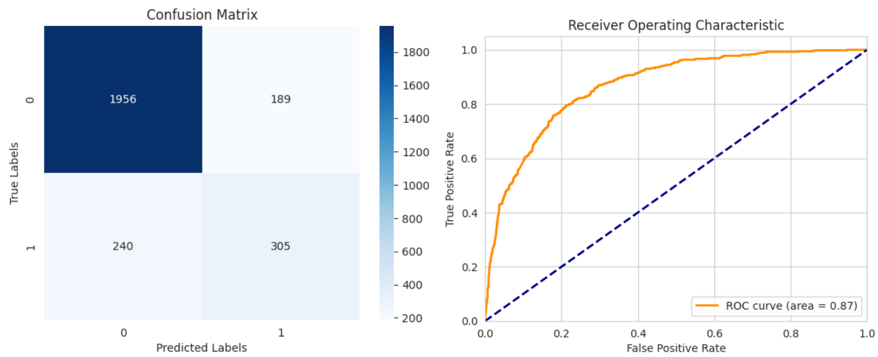

Fig 4.4: Confusion Matrix and ROC Curve of Bi-LSTM Classifier

With an AUC of 0.87 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

4.2.2 Toxicity Prediction:

I. Support Vector Machine (SVM) Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 85% accuracy. The matrix demonstrates that the model successfully detected 375 negative cases and 3035 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

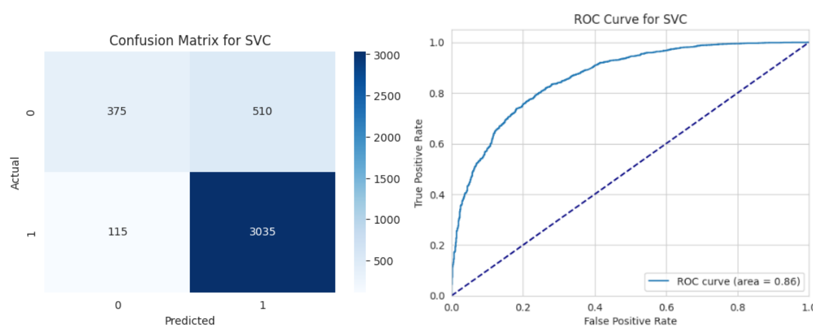

Fig 4.5: Confusion Matrix and ROC Curve of SVM Classifier.

With an AUC of 0.86 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

II. Random Forest Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 83% accuracy. The matrix demonstrates that the model successfully detected 385 negative cases and 1870 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

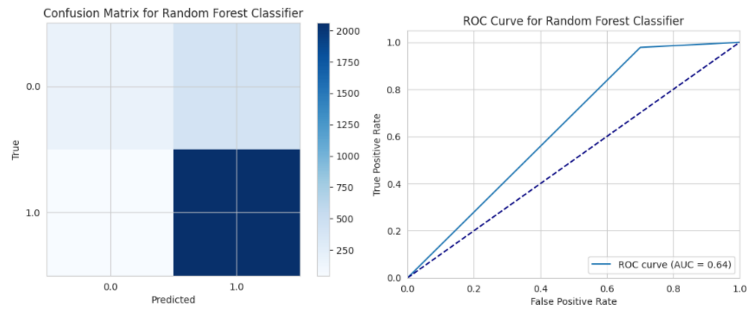

Fig 4.6: Confusion Matrix and ROC Curve of Random Forest Classifier

With an AUC of 0.64 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

III. Long Short-Term Memory (LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 82% accuracy. The matrix demonstrates that the model successfully detected 333 negative cases and 1880 positive successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10.

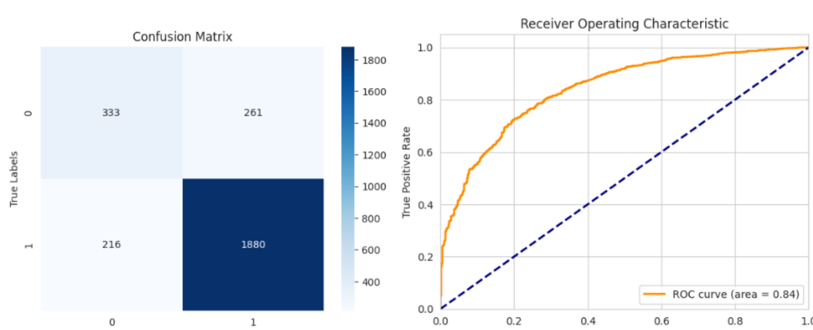

Fig 4.7: Confusion Matrix and ROC Curve of LSTM Classifier

With an AUC of 0.84 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

IV. Bidirectional Long Short-Term Memory (Bi-LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 81% accuracy. The matrix demonstrates that the model successfully detected 350 negative cases and 1829 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

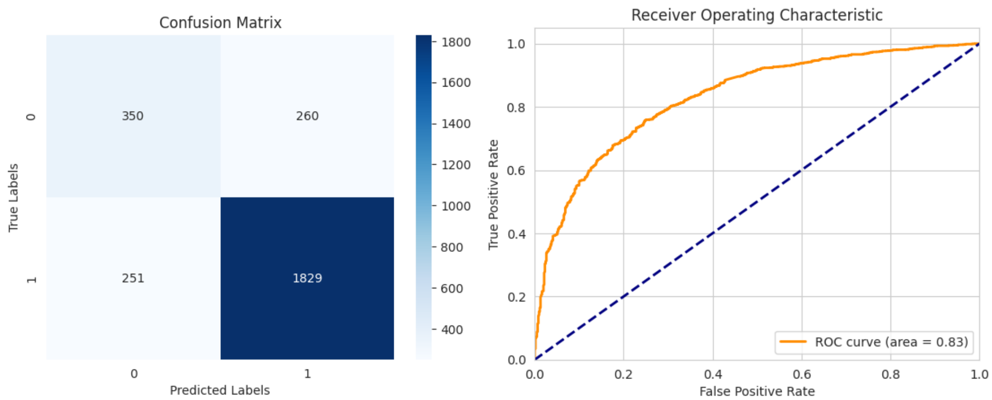

Fig 4.8: Confusion Matrix and ROC Curve of Bi-LSTM Classifier

With an AUC of 0.83 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones. We get this accuracy by using batch 12 and epoch 10.

4.2.3 Threat Prediction:

I. Support Vector Machine (SVM) Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 73% accuracy. The matrix demonstrates that the model successfully detected 1197 negative cases and 756 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

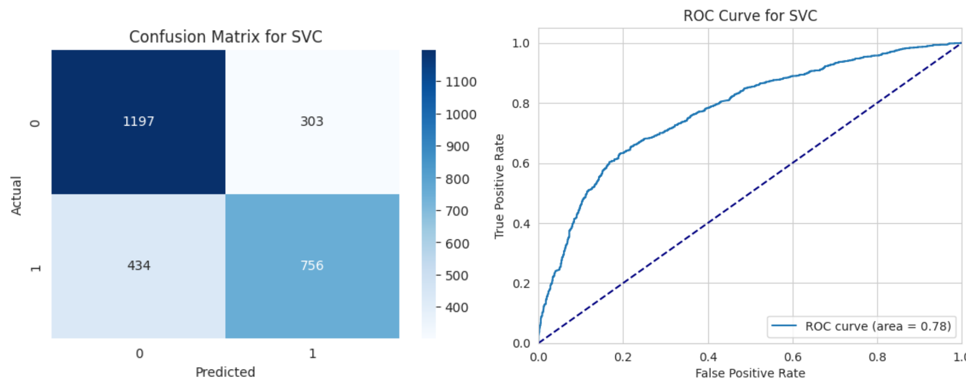

Fig 4.9: Confusion Matrix and ROC Curve of SVM Classifier.

With an AUC of 0.78 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

II. Random Forest Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 73% accuracy. The matrix demonstrates that the model successfully detected 1030 negative cases and 932 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

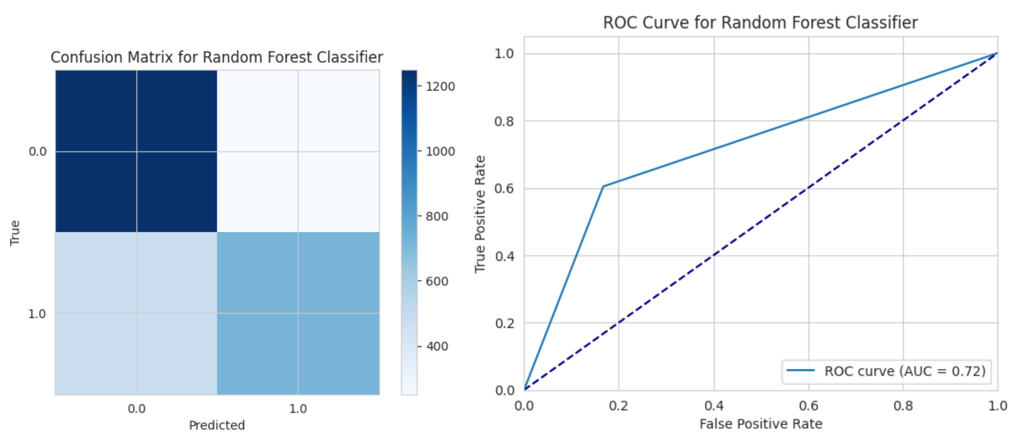

Fig 4.10: Confusion Matrix and ROC Curve of Random Forest Classifier

With an AUC of 0.72 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive amount of negative ones.

III. Long Short-Term Memory (LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 70% accuracy. The matrix demonstrates that the model successfully detected 1084 negative cases and 798 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

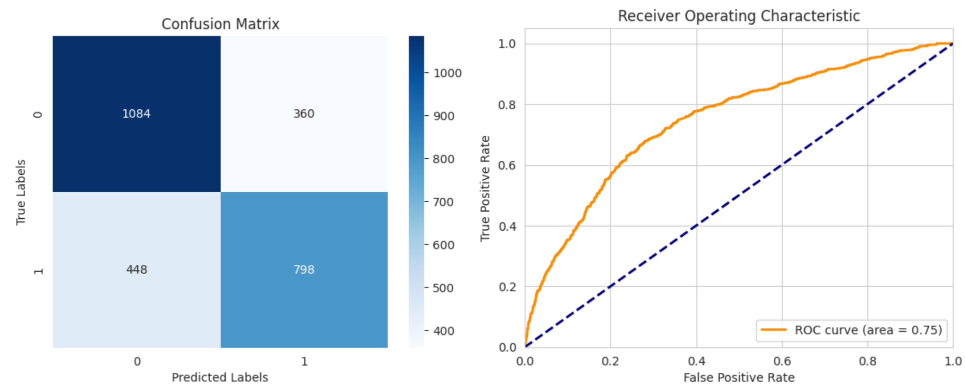

Fig 4.11: Confusion Matrix and ROC Curve of LSTM Classifier

With an AUC of 0.75 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones. We get this accuracy by using batch 12 and epoch 10.

IV. Bidirectional Long Short-Term Memory (Bi-LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 70% accuracy. The matrix demonstrates that the model successfully detected 1051 negative cases and 824 indicating the number of positive instances correctly predicted. The color intensity represents the frequency of predictions, with darker shades indicating higher numbers. The x-axis represents predicted labels, and the y-axis represents actual labels. The matrix provides a visual and quantitative way to assess the performance of the classification model. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10.

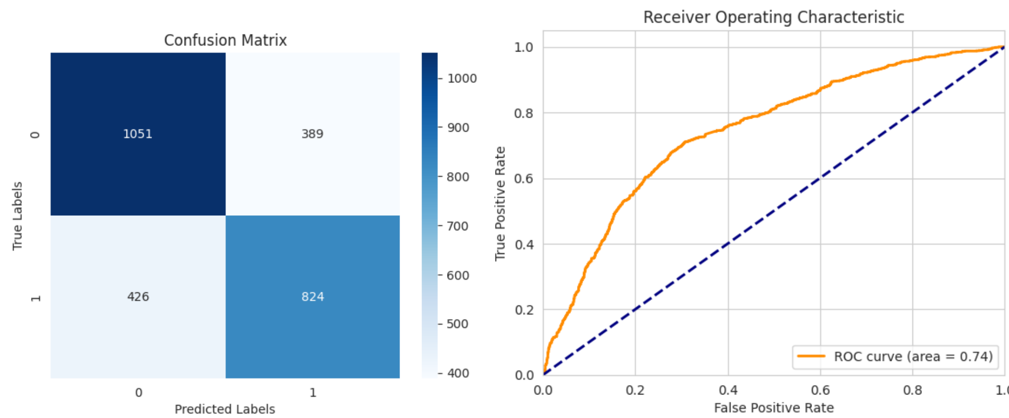

Fig 4.12: Confusion Matrix and ROC Curve of Bi-LSTM Classifier

With an AUC of 0.74 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

4.2.4 Insult Prediction:

I. Support Vector Machine (SVM) Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 75% accuracy. The matrix demonstrates that the model successfully detected 480 negative cases and 1528 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

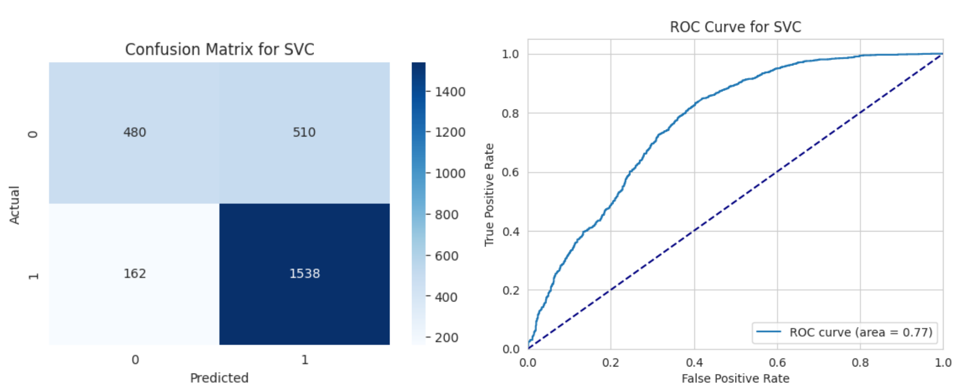

Fig 4.13: Confusion Matrix and ROC Curve of SVM Classifier.

With an AUC of 0.77 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

II. Random Forest Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 75% accuracy. The matrix demonstrates that the model successfully detected 445 negative cases and 1525 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent.

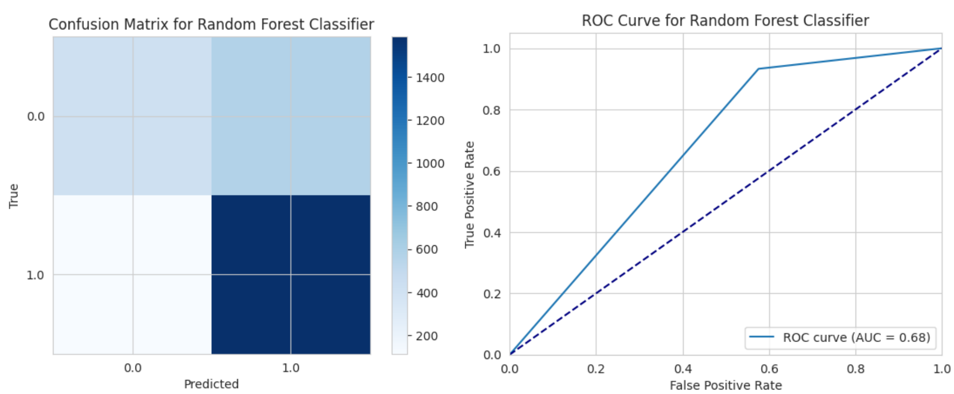

Fig 4.14: Confusion Matrix and ROC Curve of Random Forest Classifier

With an AUC of 0.68 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

III. Long Short-Term Memory (LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 70% accuracy. The matrix demonstrates that the model successfully detected 555 negative cases and 1338 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10. The matrix provides a visual and quantitative way to assess the performance of the classification model.

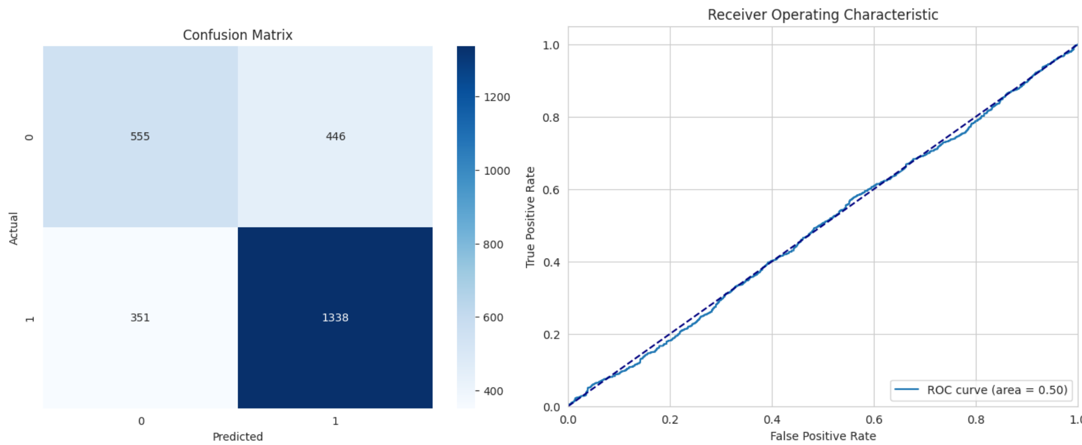

Fig 4.15: Confusion Matrix and ROC Curve of LSTM Classifier

With an AUC of 0.50 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

IV. Bidirectional Long Short-Term Memory (Bi-LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 69% accuracy. The matrix demonstrates that the model successfully detected 551 negative cases and 1304 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10.

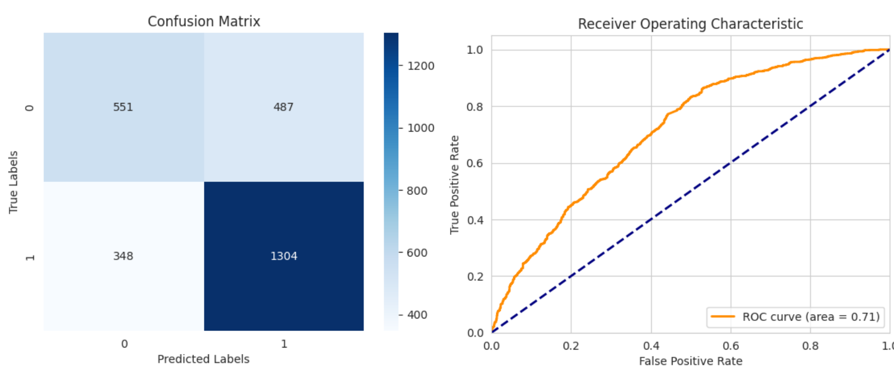

Fig 4.16: Confusion Matrix and ROC Curve of Bi-LSTM Classifier

With an AUC of 0.71 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive amount of negative ones.

4.2.5 Hate-Speech Prediction:

I. Support Vector Machine (SVM) Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 77% accuracy. The matrix demonstrates that the model successfully detected 296 negative cases and 1778 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. The matrix provides a visual and quantitative way to assess the performance of the classification model.

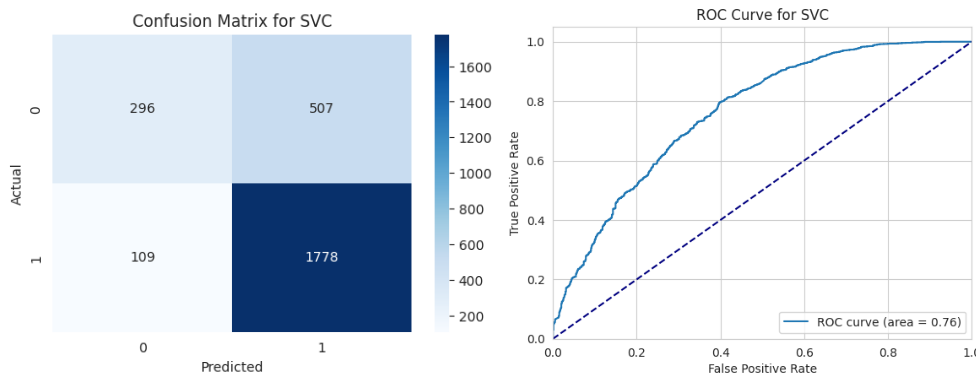

Fig 4.17: Confusion Matrix and ROC Curve of SVM Classifier.

With an AUC of 0.76 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

II. Random Forest Classifier

The confusion matrix displays the outcome of the perceptual model, which achieved 76% accuracy. The matrix demonstrates that the model successfully detected 250 negative cases and 1688 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. The matrix provides a visual and quantitative way to assess the performance of the classification model.

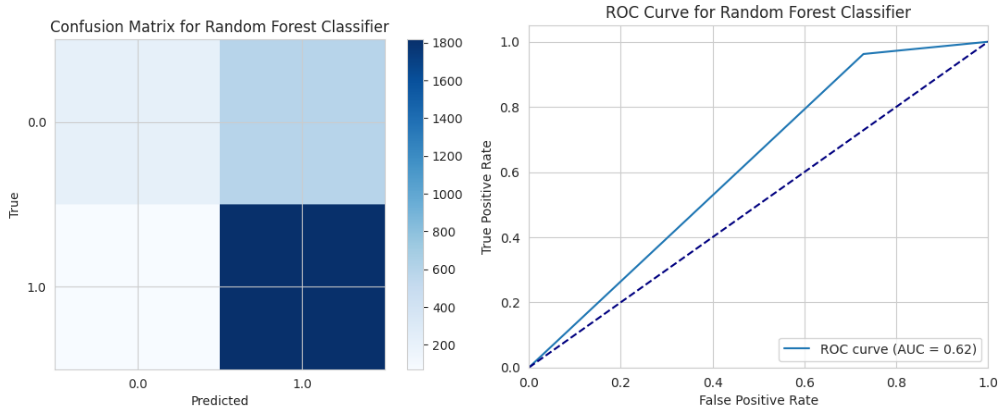

Fig 4.18: Confusion Matrix and ROC Curve of Random Forest Classifier

With an AUC of 0.62 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

III. Long Short-Term Memory (LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 75% accuracy. The matrix demonstrates that the model successfully detected 341 negative cases and 1686 positive examples. This demonstrates that the model is often successful in distinguishing between positive and negative cases, and that errors in classification are infrequent. We get this accuracy by using batch 12 and epoch 10.

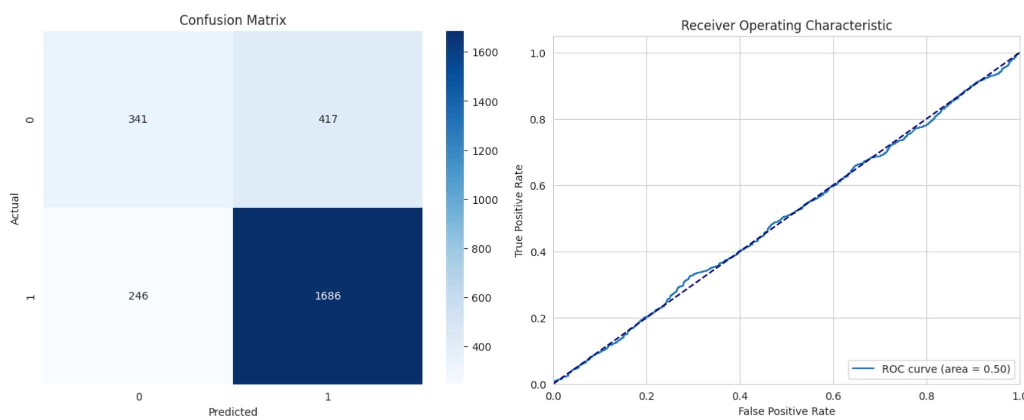

Fig 4.19: Confusion Matrix and ROC Curve of LSTM Classifier

With an AUC of 0.50 on the ROC curve, the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones.

IV. Bidirectional Long Short-Term Memory (Bi-LSTM)

The confusion matrix displays the outcome of the perceptual model, which achieved 73% accuracy. The matrix demonstrates that the model successfully detected 317 negative cases and 1660, indicating the number of positive instances correctly predicted. The color intensity represents the frequency of predictions, with darker shades indicating higher numbers. The x-axis represents predicted labels, and the y-axis represents actual labels. The matrix provides a visual and quantitative way to assess the performance of the classification model. We get this accuracy by using batch 12 and epoch 10.

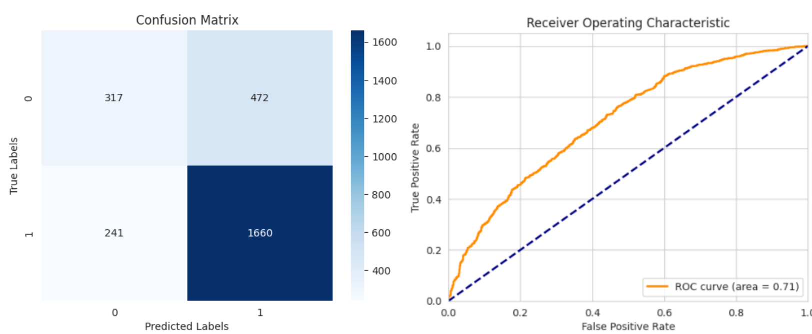

Fig 4.20: Confusion Matrix and ROC Curve of Bi-LSTM Classifier

With an AUC of 0.71 on the ROC curve, which suggests the classifier's performance is fair, as an AUC of 1 represents a perfect classifier, and an AUC of 0.5 represents a worthless classifier. the model is a reliable tool for classification tasks because it can distinguish between positive and negative samples well. The model can consistently identify positive situations despite misclassifying an excessive number of negative ones. The ROC curve is closer to the top-left corner than to the diagonal line, indicating that the classifier has a good measure of separability. The classifier is better than random guessing but is not perfect.

4.2.6 Classification and Accuracy Analysis

Table 4.1: Classification and Accuracy Table

Classification Name	Model	F1Score	Precision	Recall	AUC	Accuracy
Sentiment Analysis	**SVC**	**0.92**	**0.88**	**0.97**	**0.89**	**87%**
	RFC	0.68	0.84	0.85	0.65	85%
	LSTM	0.74	0.84	0.85	0.88	85%
	Bi-Lstm	0.74	0.84	0.84	0.87	84%
Toxicity Prediction	**SVC**	**0.55**	**0.77**	**0.42**	**0.86**	**85%**
	RFC	0.43	0.79	0.30	0.64	83%
	LSTM	0.58	0.61	0.56	0.84	82%
	Bi-Lstm	0.58	0.58	0.57	0.83	81%
Threat Prediction	**SVC**	**0.72**	**0.73**	**0.72**	**0.78**	**73%**
	RFC	**0.72**	**0.73**	**0.73**	**0.72**	**73%**
	LSTM	0.70	0.70	0.70	0.75	70%
	Bi-Lstm	0.69	0.70	0.69	0.74	70%
Insult Prediction	**SVC**	**0.59**	**0.75**	**0.48**	**0.77**	**75%**
	RFC	**0.69**	**0.75**	**0.42**	**0.68**	**75%**
	LSTM	0.68	0.70	0.55	0.50	70%
	Bi-Lstm	0.66	0.69	0.53	0.71	69%
Hate-Speech Prediction	**SVC**	**0.49**	**0.73**	**0.37**	**0.76**	**77%**
	RFC	0.40	0.75	0.27	0.62	76%
	LSTM	0.51	0.58	0.45	0.50	75%
	Bi-Lstm	0.47	0.57	0.40	0.71	73%

Table 4.1 presents that which algorithm provide the highest accuracy. When I used the SVC technique based on multiple factors to predict the condition text classification tasks, achieving high accuracy scores in the upper 87%. Sentiment analysis had the highest

accuracy (87%) through SVM, followed by threat prediction 73% where SVM and RFC both are in same state, insults 75% by RFC, and hate speech 77% through SVM. Predictions of toxicity had an 85% accuracy rate in SVM, indicating its potential for Banglish Text classification.

4.3 Discussion

From the Figure 4.21, Several machine learning algorithms were employed in the study to analyze sentiment, and the Support Vector Classifier (SVC) produced the most accurate findings, with 87% accuracy. With 85% accuracy, the Random Forest classifier ranked second and here uses hyper tuning, while LSTM had 85% accuracy. Bi-LSTM showed good predictive potential with an accuracy value of 84%. Where we add batch number 12 and epoch is 10 in both LSTM and Bi-LSTM and added 3 layers. The results improve our knowledge of how to classify Banglish texts for use in future research.

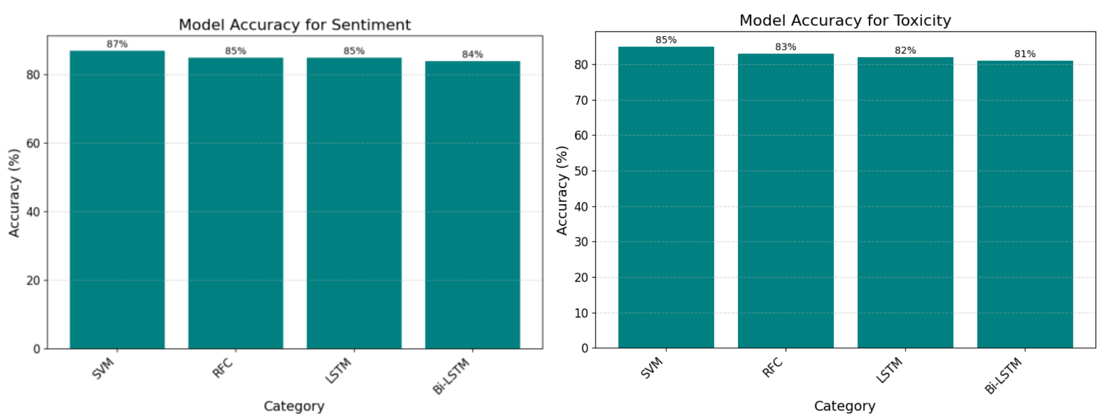

Fig 4.21: Comparison of Accuracy on Sentiment Analysis and Toxicity prediction.

From the Figure 4.21, Several machine learning algorithms were employed in the study to analyze Toxicity, and the Support Vector Classifier (SVC) produced the most accurate findings, with 85% accuracy. With 83% accuracy, the Random Forest classifier ranked second and here uses hyper tuning, while LSTM had 82% accuracy. Bi-LSTM showed good predictive potential with an accuracy value of 81%. Where we add batch number 12 and epoch is 10 in both LSTM and Bi-LSTM and added 3 layers. The results improve our knowledge of how to classify Banglish texts for use in future research.

From the Figure 4.22, Several machine learning algorithms were employed in the study to analyze Insult, and the Support Vector Classifier (SVC) and RFC produced the most accurate findings, with 73% accuracy. In RFC uses hyper tuning, while LSTM had 70% accuracy. Bi-LSTM showed good predictive potential with an accuracy value of 70%. Where we add batch number 12 and epoch is 10 in both LSTM and Bi-LSTM and added 3 layers. The results improve our knowledge of how to classify Banglish texts for use in future research.

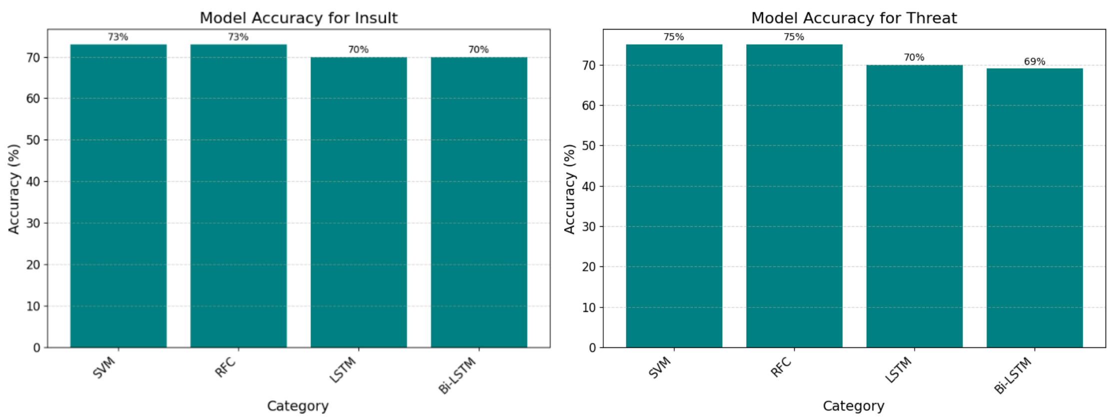

Fig 4.22: Comparison of Accuracy on Insult Prediction and Threat Prediction.

From the Figure 4.22, Several machine learning algorithms were employed in the study to analyze Threat, and the Support Vector Classifier (SVC) and RFC produced the most accurate findings, with 75% accuracy. In RFC uses hyper tuning, while LSTM had 70% accuracy. Bi-LSTM showed good predictive potential with an accuracy value of 69%. Where we add batch number 12 and epoch is 10 in both LSTM and Bi-LSTM and added 3 layers. The results improve our knowledge of how to classify Banglish texts for use in future research.

From the Figure 4.23, Several machine learning algorithms were employed in the study to analyze Hate-Speech, and the Support Vector Classifier (SVC) produced the most accurate findings, with 77% accuracy. With 76% accuracy, the Random Forest classifier ranked second and here uses hyper tuning, while LSTM had 75% accuracy. Bi-LSTM showed good predictive potential with an accuracy value of 73%. Where we add batch number 12 and epoch is 10 in both LSTM and Bi-LSTM and added 3 layers. The results improve our knowledge of how to classify Banglish texts for use in future research.

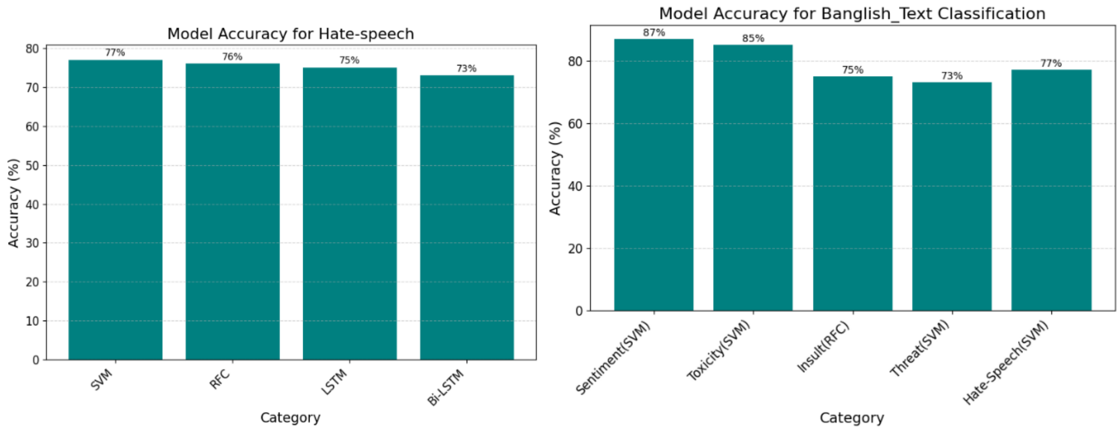

Fig 4.23: Comparison of Accuracy on Hate-Speech prediction analysis and model comparison.

From the Figure 4.23, chart titled "Model Accuracy for Banglish Text Classification." It shows the accuracy percentages of different models applied to text classification tasks in a language that appears to be a mix of Bengali and English, referred to as "Banglish." There are five categories, each with a corresponding bar to represent model accuracy:

Sentiment (SVM): 87%, Toxicity (SVM): 85%, Insult (RFC): 75%, Threat (SVM): 73%, Hate Speech (SVM): 77% The y-axis represents accuracy percentages, ranging from 0 to 80%, and each bar reaches the accuracy level achieved by the model in its respective category. The x-axis lists the categories of text classification. Support Vector Machine (SVM) models are used for sentiment, toxicity, threat, and hate speech detection, while a Random Forest Classifier (RFC) is used for insult detection. The chart indicates that the sentiment analysis model has the highest accuracy, while the threat detection model has the lowest.

CHAPTER 5

Impact On Society, Environment And Sustainability

5.1 Impact on Society

The impact of this study on society is multifaceted and far-reaching. By advancing the dark side of the Banglish language through predictive models, it contributes to positive and negative impact on society. By accurately predicting sentiment, toxicity and other harmful terms, can contribute to building more respectful and safe online communities. Cyberbullying, hate speech, online harassment are aiding this thesis work detection threat, insult and hateful comment. Improved better experience through Bangladeshi native language. May have a negative impact on this study. Privacy on data uses. The implementation of predictive models has the potential to streamline resource allocation within real time communities. The promise is this study to bring respectful well-being communication.

5.2 Impact on Environment

While the primary focus of the thesis on Banglish text classification lies in the environment of social impact, its potential implications deserve careful consideration. The integration of artificial intelligence (AI) may lead to minimizing negative consequences and promoting sustainability. The potential of this paper, decrease the reliance on paper-based processes and reducing streaming document analysis. This thesis can lead to more efficient human intervention for critical cases while saving time and resources. By detecting the dark side of the Banglish language can lead eco-friendly and efficient Banglish language processing tool. This thesis with potential social benefits are significant. By acknowledging positive aspects of AI solutions that minimize the environmental harm and ensure that this thesis not only benefits society but also contributes to a healthier planet for future generations.

5.3 Ethical Aspects

The era of Banglish text classification, while overflowing with potential for positive societal effect, isn't without its ethical contemplations. Exploring this complex landscape requires a nuanced approach that focuses on decency, straightforwardness, and responsibility. Machine learning models may perpetuate bias, perpetuating societal inequalities. Mitigating this risk requires data diversity, representativeness, and bias detection techniques. Privacy concerns arise from Banglish text data collection and analysis, necessitating robust anonymization, strict security protocols, and clear consent forms for informed decision-making. Engaging with the Banglish-speaking community is crucial for inclusivity and ethical outcomes in the development and deployment of Banglish text classification models. Ethical considerations are crucial for Banglish text classification researchers and developers to build responsible, inclusive language technologies, empowering Banglish speakers and promoting a just online landscape.

5.4 Sustainability Plan

This research's sustainability plan is a comprehensive roadmap for ethical, environmental, and societal responsibility, ensuring transparency and long-term impact on Banglish speakers, the digital ecosystem, and the planet. Our plan prioritizes diverse, representative Banglish datasets, ensuring ethical practices, informed consent, and privacy. Secure storage and responsible data sharing ensure integrity and accessibility for future researchers. Our model development and maintenance prioritize accuracy, efficiency, and sustainability. We collaborate with Banglish-speaking communities, prioritize energy-efficient computing, explore renewable energy options, and practice responsible waste management to minimize our carbon footprint. Ultimately the plan evolves with this research, focusing on inclusive, efficient, and ecologically sound technology for Banglish speakers. It serves as a blueprint for responsible technology development in a multilingual world.

CHAPTER 6

Summary, Conclusion, Recommendation And Implication For Future Research

6.1 Summary of the Study

This study is mainly focused on understanding of text classification tasks in the context of Banglish mixed language. Where sentiment analysis, toxicity prediction, identity hate prediction, insult prediction, and threat prediction are included. Manually annotated 15000+ Banglish comments record, which affordable and covered each task and to understand evolving trends, data was rigorously analyzed using temporal segmentation. The entire study process is based on ethical principles such as informed consent, privacy, and beneficence. Various machine learning classifiers were applied, hyper parameter tuning, and cross-validation, ensuring the reliability of predictive models also applied. The study's overarching goal is to contribute to sustainable and justify harmful activities, clean and social well-being communication.

6.2 Conclusions

Using a variety of machine learning models to examine a large dataset of Banglish comment we undertook a thorough investigation of multi activities of Banglish online communication. Our deep finding shows how machine learning (ML) and natural language processing (NLP) help to improve our thought and knowledge on dark side of Banglish communication assessment. Our investigation took five cases for sentiment analysis, for Hate speech prediction, for threat prediction, for toxicity prediction, for insult prediction Support Vector Classification (SVC) exhibiting the best accuracy rates and its provided 87% for Sentiment analysis. Other Toxicity 85%, Threat 73% and Hate-speech 77% are executed by SVC and In Insult only 73% are provided by RFC. With the help of python language and Anaconda tool (Jupiter Notebook IDE), this experiment was carried out.

6.3 Recommendation

Continuous effort with a large dataset or expanding data set of Banglish may be a diverse classification task. Future techniques for further exploration will be a suitable choice.

Machine learning models that effectively capture the hybrid and mixed languages could lead to significant improvement. Transfer learning techniques might enhance performance.

6.4 Implication for Further Study

Although this study has opened and offers new information on exploring multifaceted activities on Banglish language. Its limitations and potential research gap are important to recognize. Affordable mentioned models like Support Vector Classifier (SVC), Random Forest Classifier, LSTM, Bi-LSTM interpretability and model explain ability continue to be major obstacles. By addressing these issues, prediction models may be improved. Future research should focus on new models or deep learning techniques in the area of Banglish activities on social media. Multilingual approaches could provide valuable insights. There are exciting opportunities to improve better communication and crucial for both research and improve predictive models through the integration of continuous monitoring data with real-world scenarios applications.

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