BENGALI SLANG LANGUAGE DETECTION USING MACHINE LEARNING

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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 titled "**Bengali slang language detection using ML**", submitted by **Umme Arifa Rimi** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment 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 **15 July 2024.**

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I hereby declare that, this project has been done by us under the supervision of **Tania Khatun, Assistant Professor, Department of CSE** 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

The rise of online communication platforms has significantly increased slang use, posing a challenge for content control and mood analysis. This study aims to detect Bengali slang using advanced machine learning methods, focusing on creating reliable models that can recognize and control informal language in digital conversations. The experimental technique involves data collection, preprocessing, and feature engineering, with a diversified collection of Bengali literature from various web sources. Four well-known machine learning models are chosen for assessment: Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression. Each model undergoes careful training, including cross-validation and hyperparameter adjustment, to improve performance. Ethical issues are considered, with privacy and permission being paramount, and data collection complies with legal requirements. Model fairness and possible biases are also examined to ensure equal treatment of various user groups. The results show that the Linear Support Vector Classifier has excellent recall, the Multinomial Nave Bayes model exhibits great accuracy, and the Random Forest Classifier demonstrates resilience to class imbalances. The study has applications in informal communication sentiment analysis, configurable text filters, and content control in online platforms. The models are useful tools for developing safer and more specialized digital environments due to their versatility and scalability. This study enhances machine learning's capacity to recognize Bengali slang, advancing our knowledge of the linguistic variety present in online communication.

Keywords: Bengali Slang Language, Machine Learning, Natural Language Processing, Slang Detection, Data Preprocessing, Model Evaluation, Ethical Considerations, Content Moderation, Sentiment Analysis, Privacy and Fairness.

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CHAPTER 1

Introduction

1.1 Introduction

Language, being a dynamic and developing system of communication, is susceptible to numerous types of variation and change. One key part of linguistic variety is the usage of slang, which comprises informal phrases and terminology. Understanding and identifying slang is vital in today's digital world, as it penetrates online communication. This chapter seeks to give a detailed background research on slang identification, with an emphasis on its applicability and approaches utilized in other languages.

1.1.1 The Dynamic Nature of Language

Language is not static; it develops through time to reflect social, cultural, and technological developments. Slang, being a subset of language, exhibits this dynamism. It originates from the urge for people and societies to express themselves independently, frequently adopting unorthodox or humorous language patterns. Thus, slang provides as a window into the lively and ever-changing essence of language.

1.1.2 Slang in the Digital Age

The growth of digital communication platforms and social media has transformed the way individuals engage and communicate. This transition has had a major influence on language usage, leading to the widespread adoption of informal phrases and slang in online speech. Understanding and efficiently traversing this linguistic terrain is vital for correct interpretation and analysis of digital communication.

1.1.3 The Importance of Slang Detection

Slang detection bears great importance in numerous sectors. In online content moderation, appropriately recognizing and classifying slang phrases helps preserve community standards and promote a safe and polite online environment. Additionally, in sentiment analysis, differentiating slang terms from regular English is crucial for correctly evaluating public opinion and mood on social media sites.

1.1.4 Cultural Significance of Slang

Slang is strongly interwoven with culture and identity. It frequently evolves as a technique of identifying insiders from outsiders, generating a feeling of belonging within certain social groupings or communities. By researching slang, we obtain insights into the cultural intricacies and subcultures that affect language expression.

1.1.5 Linguistic Variation in Bengali

Bengali, like every other language, has its unique types of linguistic variety. Slang in Bengali contains a vast variety of idioms, reflecting the diversity and depth of the language. Understanding and properly recognizing slang in Bengali is vital for correctly reading and evaluating digital communication in Bengali-speaking society.

1.1.6 Objectives of the Study

The fundamental purpose of this project is to construct a robust and effective system for recognizing Bengali slang language using machine learning methods. By doing this, we intend to contribute to the larger area of natural language processing and create practical applications for online content moderation, sentiment analysis, and language learning tools in the Bengali context.

1.2 Motivation

The impetus for this study originates from an awareness of the dynamic nature of language and the necessity to adjust linguistic analysis approaches to keep pace with these changes. In the digital era, when communication happens at an unparalleled size and speed, knowing slang becomes vital. This section dives into the motives that motivate this study attempt.

1.2.1 Evolving Communication Patterns

With the introduction of digital platforms and social media, communication has transcended conventional borders. People from varied language origins converge online, resulting to the fast invention and transmission of new linguistic forms, including slang. Understanding and properly understanding these statements are vital for good communication analysis.

1.2.2 Enhancing Content Moderation

In the age of user-generated content, platforms confront the issue of ensuring a safe and courteous environment for users. Slang terms, although ubiquitous in casual conversation, may occasionally transgress borders and violate community norms. A strong slang recognition system may considerably boost content moderation efforts, ensuring that online environments stay inclusive and courteous.

1.2.3 Enriching Sentiment Analysis

Slang frequently conveys deep emotional meanings that may dramatically impact sentiment analysis findings. By effectively recognizing and interpreting slang, sentiment analysis algorithms may give more accurate insights into public opinion and sentiment patterns. This has substantial ramifications for corporations, marketing initiatives, and public opinion research.

1.2.4 Fostering Language Learning

Language learners, especially those working with informal or colloquial registers, benefit from an awareness of slang. Integrating slang detection into language learning tools may offer learners with a more thorough knowledge of the language, helping them to navigate both formal and informal communication environments.

1.2.5 Bridging Cultural Understanding

Slang typically incorporates cultural connections and reflects the common experiences of distinct groups. By interpreting slang idioms, we obtain insights into the cultural circumstances and subcultures that form language expression. This, in turn, enhances cross-cultural conversation and understanding.

1.2.6 Advancing Natural Language Processing

The development of good slang identification algorithms adds to the larger area of natural language processing. It enhances the toolset of approaches available for processing and interpreting text data, with potential applications across numerous fields outside slang identification itself.

1.2.7 Addressing the Bengali Context

The special emphasis on Bengali slang identification derives from a realization of the linguistic richness and variety of the Bengali language. By customizing our study to the specific linguistic context of Bengali, we strive to deliver practical solutions that respond to the demands of the Bengali-speaking people in the digital sphere.

1.2.8 Bridging Research and Practical Application

This study aspires not just to add to academic knowledge but also to give actual answers with real-world effect. By building a robust slang recognition method for Bengali, we hope to bridge the gap between theoretical linguistic analysis and practical implementations in online communication platforms, sentiment analysis tools, and language learning resources.

1.3 Fundamental Principle of the Study

The core premise driving this study is centered in the deployment of powerful machine learning algorithms to handle the subtle difficulty of recognizing Bengali slang language. This section elucidates the basic concepts and approaches that underlie our approach.

1.3.1 Machine Learning as a Tool

At the core of our study lies the use of machine learning, an area of artificial intelligence that allows computers to understand patterns and generate predictions from data. By employing machine learning methods, we intend to train models to recognize tiny linguistic clues suggestive of slang in Bengali literature.

1.3.2 Supervised Learning Paradigm

Our study employs a supervised learning strategy, which comprises training models using labeled data. This data comprises of instances of text, each tagged to indicate whether it includes slang or mainstream English. Through exposure to this labeled data, our models learn to make precise distinctions across various linguistic categories.

1.3.3 Feature Engineering and Representation

A crucial element of our process is featuring engineering, which requires choosing or altering features of the data that are useful for differentiating between slang and

mainstream language. This may utilize methods such as tokenization, n-gram extraction, and syntactic analysis to extract relevant language elements.

1.3.4 Model Selection and Evaluation

The selection of suitable machine learning models is a vital step in our methodology. We cover a number of models, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression. These models are selected for their appropriateness in binary classification tasks and their aptitude to efficiently distinguish slang in Bengali text.

1.3.5 Model Training and Validation

Once chosen, these models undertake a rigorous training regimen. During training, the models learn to generalize from the labeled data, recognizing patterns that separate slang from mainstream English. The trained models are then evaluated on a different dataset to determine their performance and generalization capabilities.

1.3.6 Fine-Tuning and Hyperparameter Optimization

To further boost the models' performance, we participate in a process of fine-tuning, whereby hyperparameters are tweaked to maximize their predictive capabilities. This iterative procedure entails a rigorous search of parameter spaces to produce the best possible outcomes.

1.3.7 Robust Evaluation Metrics

The efficacy of our models is measured using a collection of comprehensive assessment measures. These measures, including accuracy, precision, recall, and F1-score, give a thorough evaluation of the model's effectiveness in recognizing Bengali slang. By examining several indicators, we guarantee a thorough knowledge of the models' strengths and flaws.

1.3.8 Cross-Validation for Robustness

To determine the robustness of our models, we apply cross-validation approaches. This requires splitting the dataset into several subgroups, executing training and testing cycles, and then aggregating the findings. By verifying our models across multiple subsets, we develop confidence in their capacity to generalize to unknown data.

1.4 Research Questions

The research questions serve as the guiding compass for our study, driving our investigation towards certain aims and results. This section summarizes the fundamental questions that frame our work towards recognizing Bengali slang language using machine learning approaches.

1.4.1 Primary Research Question

The primary research question driving this study is: "Can advanced machine learning techniques effectively detect and distinguish Bengali slang language from standard language in digital communication?" This overarching question encapsulates the core objective of our research, aiming to assess the feasibility and efficacy of employing machine learning for Bengali slang detection.

1.4.2 Subsidiary Research Questions

1. How does the choice of machine learning algorithm effect the accuracy and efficiency of Bengali slang detection?

This supplementary question dives into the comparative performance of several machine learning techniques, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression. By analyzing their performance, we hope to discover the best acceptable technique for recognizing Bengali slang.

2. What linguistic traits and contextual clues are most indicative of slang terms in Bengali text?

This inquiry focuses on the linguistic elements that separate slang from mainstream language in Bengali. Through rigorous linguistic research, we hope to identify the traits and contextual clues that play a vital role in correct slang recognition.

3. How does the use of slang identification assist content filtering and sentiment analysis in Bengali digital communication?

This question investigates the practical ramifications of effective slang detection. By examining its influence on content moderation and sentiment analysis, we hope to highlight the larger social and practical importance of our study results.

4. What are the ethical issues and possible biases related with automated slang identification in Bengali?

Ethical issues are crucial in any computerized language analysis. This issue dives into the possible biases, privacy problems, and responsible usage of automated slang detection algorithms, ensuring that our study accounts for ethical consequences.

5. How can the created slang detection technology be implemented into real-world applications, and what are the possible ramifications for society and communication platforms?

This question concerns the actual execution of our study results. By studying integration solutions and measuring the larger social effect, we strive to bridge the gap between theoretical research and practical implementation in online communication platforms and other sectors.

1.4.3 Significance of the Research Questions

The research issues described above are crucial to expanding our knowledge of slang detection in Bengali. By addressing these problems, we not only contribute to the area of natural language processing but also give actual solutions with real-world effect, notably in the context of online communication among the Bengali-speaking population.

1.5 Expected Output

The projected output of this study comprises a complex spectrum of outputs, stretching from the construction of successful machine-learning models for Bengali slang identification to their practical applications and larger ramifications. This section elucidates the predicted outcomes and their relevance.

1.5.1 Machine Learning Models

1. Development of Accurate Slang Detection Models

The key outcome of this study is the construction of precise and effective machine-learning models for Bengali slang identification. These models are projected to display

strong performance in identifying slang language from conventional language in Bengali text, with high accuracy and efficiency.

2. Comparative Analysis of Machine Learning Algorithms

Our study tries to give a comparative analysis of several machine learning techniques, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression. This study will highlight the benefits and shortcomings of each strategy, assisting in the selection of the best-suited algorithm for slang identification in Bengali.

1.5.2 Linguistic Insights

3. Identification of Linguistic Features and Contextual Cues

Our linguistic research tries to uncover certain linguistic traits and contextual indicators that are most suggestive of slang utterances in Bengali. These findings lead to a better grasp of the language and enable the creation of more efficient slang detection programs.

1.5.3 Practical Applications

4. Integration into Content Moderation Systems

One practical application of our research output is the incorporation of the created slang recognition technology into content moderation systems on internet platforms. This connection strengthens the platforms' capacity to enforce community norms and promote polite discussion.

5. Improved Sentiment Analysis

The precise identification of slang has ramifications for sentiment analysis. We predict that our study will increase the accuracy of sentiment analysis systems, aiding companies, marketers, and public opinion researchers looking to assess public sentiment in Bengali language.

6. Language Learning Tools

By incorporating slang identification into language learning tools, our research output may improve the language learning experience for learners of Bengali. This involves

giving insights into informal language usage and supplying explanations for slang terms.

1.5.4 Ethical Considerations

7. Addressing Ethical Concerns

Our study highlights the ethical problems related with automated slang detection. The planned outcome comprises recommendations and solutions for minimizing biases, safeguarding privacy, and assuring responsible usage of slang detection algorithms.

1.5.5 Societal Impact

8. Societal Implications

The larger social influence of our study is a key predicted result. Effective slang identification aids to courteous and straightforward communication in numerous circumstances, from online chats to official documentation. It provides an inclusive digital environment and increases cross-cultural understanding.

1.5.6 Further Research Avenues

9. Implications for Future Research

Our study result is projected to offer up new paths for future research in slang identification, not just in Bengali but also in other languages. This may involve researching more sophisticated machine learning approaches, targeting particular language traits, or broadening the coverage to various dialects or registers.

1.6 Report Layout

The study is organized to offer a full and unified overview of the research on recognizing Bengali slang language using machine learning methods. This section defines the structure of the report, emphasizing the grouping of chapters and the flow of information.

Chapter 1: Introduction

The opening chapter establishes the groundwork for the study. It starts with an introduction of the study, followed by comments on motivation, core concepts, research

questions, anticipated output, and the presentation of the report. This chapter provides the reader with a clear overview of the study environment and aims.

Chapter 2: Background Study

The second chapter digs into a deep background examination of the topic area. It presents an in-depth examination of comparable publications in the area, performs a comparative analysis, and highlights the breadth of the issue. Additionally, issues related to recognizing Bengali slang language are highlighted, bringing insights into the intricacies of the process

Chapter 3: Research Methodology

This chapter discusses the methods followed in the study. It starts with an introduction to the research strategy and then goes to expand on several components, including data collecting, study topic and instruments, statistical investigation, and implementation equipment. The selected machine learning methods, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression, are discussed, along with the actual implementation processes.

Chapter 4: Results and Discussion

The fourth chapter offers the experimental analysis and comparative performance of the chosen machine learning algorithms in recognizing Bengali slang. It contains a full study of each algorithm's performance, as well as a comparison analysis to discover the most successful strategy. The discussion part discusses model robustness, computing efficiency, interpretation of findings, model biases, and linguistic analysis of slang patterns.

Chapter 5: Impact on Society, Environment, and Sustainability

This chapter evaluates the larger social and environmental consequences of the study results. It investigates the influence on society, discusses ethical problems associated to automated slang detection, and offers a sustainability strategy for responsible usage of the established technology.

Chapter 6: Summary, Conclusion, and Implication for Future Research

The last chapter presents a summary and conclusion of the study effort, emphasizing major discoveries and contributions. It recognizes the limits of the study and proposes possible avenues for future research initiatives in the field of slang identification.

Appendices

The appendices include supplemental material that supports and improves the comprehension of the primary text. This may contain code samples, more experimental findings, language analysis, and any other relevant information.

References

The reference section gives a thorough list of all sources referenced in the study, enabling readers to further explore the literature and sources linked to the research.

CHAPTER 2

Background Study

2.1 Introduction

The second part of this research report is devoted to developing a full grasp of the context and history surrounding the study on recognizing Bengali slang language using machine learning methods. This chapter provides the basis by offering insights into the linguistic complexity of Bengali, the prevalence of slang in digital communication, and the relevance of proper slang identification in the present digital context.

2.1.1 Linguistic Complexity of Bengali

Bengali, noted for its rich linguistic legacy, has a complicated grammatical structure and a range of dialects, registers, and styles of expression. Understanding the subtleties of Bengali language is crucial in the proper identification of slang, since slang statements frequently convey distinctive linguistic qualities firmly embedded in the language's structure and culture.

2.1.1.1 Diversity of Dialects and Registers

Bengali boasts a range of dialects and registers that appeal to diverse social circumstances and geographic locations. Slang phrases may vary greatly across various language areas, making it crucial to account for this variation in the identification process.

2.1.1.2 Unique Linguistic Features

Slang in Bengali sometimes incorporates peculiar linguistic elements, including wordplay, phonetic changes, and the integration of loanwords from other languages. Recognizing these traits is key for efficient slang identification.

2.1.2 Slang in Digital Communication

The emergence of digital platforms and social media has altered the way people interact. This transition has been accompanied by a spike in the usage of slang in online

communications. Slang serves as a medium of informal communication, enabling users to imbue their messages with originality, individuality, and cultural allusions.

2.1.2.1 Digital Slang as a Cultural Phenomenon

Digital slang is not just a language phenomenon but also a societal one. It represents the growing norms, beliefs, and identities of online groups and subcultures. Accurate identification of digital slang is vital for recognizing the intricacies of online conversation.

2.1.2.2 Challenges of Slang Detection in Digital Text

The informality and quick growth of slang in digital communication provide obstacles for identification. Slang idioms may not follow to standard grammatical norms, and their meanings might change swiftly. Therefore, automated detection must be adaptive and context-aware.

2.1.3 Significance of Accurate Slang Detection

Accurate slang identification bears significant value in numerous circumstances, highlighting the relevance and need of this research activity.

2.1.3.1 Content Moderation on Digital Platforms

For internet platforms and social networks, efficient content control is vital. Slang language may occasionally transcend borders and breach community restrictions. Accurate identification of slang contributes in maintaining a courteous and secure online environment.

2.1.3.2 Enhanced Sentiment Analysis

Slang typically includes emotional overtones that might impact sentiment analysis findings. Accurate identification of slang is vital for understanding the emotional tone of internet communications, aiding companies, marketers, and academics looking to understand public mood.

2.1.3.3 Language Learning and Comprehension

Slang is a component of daily language usage, and comprehending it is useful for language learners. Integration of slang detection into language learning tools boosts

learners' capacity to negotiate informal language and develop a full command of the language.

2.1.4 Objectives of the Background Study

The aims of this background research are multifaceted:

2.1.4.1 Contextualization

The study tries to situate the research within the larger framework of linguistic complexity, digital communication, and the relevance of slang detection in Bengali language.

2.1.4.2 Insights from Existing Research

By evaluating current studies on slang identification in other languages, this study tries to uncover strategies, techniques, and insights that might enhance and expand the research on Bengali slang detection.

2.1.4.3 Understanding Challenges

The project attempts to discover and comprehend the special issues connected with recognizing slang in Bengali, spanning linguistic subtleties, data availability, and adaptation to the digital context.

2.2 Similar Works

The second half of this chapter digs into a deep study of earlier research and studies relevant to slang identification, with an emphasis on languages comparable to Bengali. By evaluating current works, we intend to find methodology, strategies, and insights that may be modified and applied to our special emphasis on recognizing Bengali slang language using machine learning techniques.

2.2.1 Slang Detection in English and Related Languages

English, being a well-studied and frequently used language, has been the focus of several research on slang identification. These works have examined a variety of methodologies, from rule-based systems to machine learning models. Analyzing approaches performed in English slang identification gives significant insights into the

obstacles and possible solutions that may be applied to our research on Bengali slang detection.

2.2.1.1 Rule-Based Approaches

Early research on slang recognition frequently deployed rule-based algorithms that relied on predetermined language patterns and heuristics. These methods were successful to some degree but struggled with the dynamic and context-dependent character of slang.

2.2.1.2 Machine Learning Techniques

Recent improvements have seen a move towards machine learning approaches for slang identification in English. Supervised learning algorithms, including Support Vector Machines (SVMs), Naïve Bayes classifiers, and neural networks, have exhibited encouraging outcomes. These algorithms employ annotated datasets to understand the patterns characteristic of slang utterances.

2.2.2 Slang Detection in South Asian Languages

While research on slang recognition has largely focused on commonly spoken languages like English, there is a rising interest in expanding this study to other linguistic settings, particularly South Asian languages. Studies in this area have explored languages such as Hindi, Urdu, and Tamil, which have some linguistic similarities with Bengali.

2.2.2.1 Linguistic Specificities of South Asian Languages

Languages of the South Asian area, including Bengali, have shared linguistic elements such as complex morphological structures, agglutinative grammar, and a vast inventory of phonemes. various linguistic traits may affect the way slang is generated and utilized in various languages.

2.2.2.2 Adaptation of Techniques

Studies on slang identification in South Asian languages have adopted and modified approaches already provided for English and other well studied languages. This approach entails adapting machine learning models and linguistic studies to fit the individual linguistic characteristics of each language.

2.2.3 Lessons for Bengali Slang Detection

The study of such efforts gives numerous crucial insights and concerns for our research on recognizing Bengali slang language.

2.2.3.1 Transferability of Techniques

Many of the approaches and procedures utilized in previous research on slang identification may be modified and applied to Bengali. This comprises supervised learning techniques, feature engineering, and language analysis.

2.2.3.2 Importance of Linguistic Analysis

Linguistic analysis plays a vital role in slang detection. Understanding the distinctive linguistic properties and contextual indicators of slang phrases in Bengali is vital for constructing reliable detection algorithms.

2.2.3.3 Diversity of Approaches

The range of techniques found in earlier research, including rule-based systems and machine learning models, underscores the need of pursuing many routes in our own study on Bengali slang identification.

2.3 Comparative Analysis and Summary

The detection of hate speech and slang in Bangla language has seen significant advancements due to the application of various machine learning (ML) and deep learning (DL) algorithms. This analysis covers several notable studies from recent years, highlighting the models used, their accuracies, and any noteworthy findings.

Table 2.3.1: Comparison Table of Previous Research

SN	Author(s)	Year	Algorithms Used	Accuracy	Noteworthy Points
1	Faruqe et al.[21]	2023	BERT, Bi-LSTM, GRU, Attention	GRU: 98.87%, Attention: 98%	GRU and Attention techniques performed best for Bangla hate speech detection.

2	Jahan et al. [22]	2022	BanglaHateBERT, mBERT, IndicBERT, BanglaBERT, CNN	BanglaHateBERT: 94.3%	Developed BanglaHateBERT specifically for abusive language detection in Bengali.
3	Akter et al. [23]	2022	LSTM, BiLSTM, LSTMAutoencoder, word2vec, BERT, GPT-2	BERT: 78%, GPT-2: 80%	Focused on aggressive comments in Hindi, Bangla, and English; data scarcity impacted accuracy.
4	Remon et al. [24]	2022	CNN, SVM	SVM: Highest Performance	Introduced a new dataset of 10,133 user comments for hate speech detection in Bengali.
5	Hamid et al. [25]	2023	Naive Bayes, Logistic Regression, KNN, Random Forest, Decision Tree, SVM, XG-Boost	Logistic Regression: 70%	Investigated multiple classifiers for slang detection; Logistic Regression had low accuracy.
6	Sultana et al. [26]	2023	Logistic Regression, MNB, Random Forest, SVM, KNN, Gradient Boosting	SVM: 85.7%	SVM achieved the best results; lack of dataset details impacted reproducibility.
7	Akter et al. [27]	2023	LSTM-Autoencoder	95%	Used synthetic data for cyberbullying detection; may not fully capture real-world scenarios.
8	Akhtar et al. [28]	2023	Hybrid ML Model	Binary: 98.57%, Multilabel: 98.82%	Focused on cyberbullying detection in Bengali; high accuracy but limited to specific ML approaches.

9	Rahman et al. [29]	2022	Bidirectional GRU	Sentiment: 85.37, Emotion: 69.22	Bidirectional GRU outperformed traditional ML methods; dataset imbalance was a challenge.
10	Keya et al. [30]	2023	G-BERT, LSTM, Bangla-BERT, mBERT	GBERT: 90%	GBERT showed high accuracy; lack of dataset size/diversity details.
11	Mahmud et al. [31]	2022	Logistic Regression, MNB, Decision Tree, Random Forest, SVM, AdaBoost, GradientBoost, SGDClassifier, ExtraTreesClassifier, KNeighbors, MLPClassifier	Logistic Regression: 97%	Small dataset used for Bangla abusive comment detection.
12	Sarker et al. [32]	2022	MNB, GRU, Logistic Regression, Random Forest, SVM	MNB: 80.51%	Created a dataset for anti-social comments; MNB had the highest accuracy.
13	Khan et al. [33]	2021	SVM, Random Forest, KNN, Naive Bayes, Neural Networks	SVM: 62%	Small, imbalanced dataset impacted accuracy; used for sentiment analysis on Bengali Facebook comments.

The landscape of Bangla slang and hate speech detection has seen diverse approaches utilizing both machine learning and deep learning techniques. While models like GRU and attention mechanisms show exceptional performance in hate speech detection, the challenges of dataset imbalance and data scarcity remain prevalent. Future research should focus on creating more robust and balanced datasets, as well as exploring hybrid models to enhance accuracy and applicability in real-world scenarios.

2.4 Scope of the Problem

The fourth portion of this chapter is devoted to describing the specific scope and aims of our study in the context of identifying Bengali slang language. This section emphasizes the parameters, datasets, and linguistic features that are the focus of our inquiry.

2.4.1 Defining Bengali Slang

A specific definition of Bengali slang is vital in determining the bounds of our study. This entails identifying the language elements, phrases, and settings that comprise slang in Bengali. By setting explicit criteria, we guarantee that our study is focused and linked with the distinctive linguistic subtleties of Bengali.

2.4.1.1 Linguistic Characteristics of Bengali Slang

This sub-section goes into the linguistic elements that are indicative of slang terms in Bengali. It examines phonological changes, morphological variations, and syntactic structures that may separate slang from regular English. Understanding these traits is crucial in effective slang recognition.

2.4.1.2 Contextual Significance

Slang terms frequently derive their meaning from unique social circumstances, groups, or subcultures. This sub-section discusses the contextual signals that play a significant role in distinguishing slang in Bengali writing. It entails investigating how slang utterances are located inside conversations and interactions.

2.4.2 Dataset Selection and Annotation

The choice of dataset is essential in training and testing our machine learning models for slang identification. This sub-section covers the criteria for dataset selection, including considerations for variety, size, and representativeness of slang terms in Bengali literature.

2.4.2.1 Diversity of Slang Expressions

A diversified collection comprises a broad variety of slang terms used in different circumstances. This sub-section examines ways for acquiring and curating a dataset that represents the scope of slang use in Bengali.

2.4.2.2 Annotation Guidelines

Annotating the dataset requires categorizing occurrences of slang and mainstream language. This sub-section offers specific annotation criteria to promote uniformity and accuracy in the labeling process. It also analyzes possible issues and ambiguities in annotating slang terms.

2.4.3 Linguistic Variation and Register

Bengali demonstrates variance in linguistic registers, ranging from formal to casual language usage. This sub-section investigates how slang terms may appear across various registers in Bengali. Understanding this variance is vital for constructing a thorough model for slang detection.

2.4.3.1 Informal vs. Formal Registers

Slang is generally an informal manner of speech. This sub-section investigates the linguistic traits and contextual factors that separate informal slang from formal language usage in Bengali.

2.4.3.2 Adaptability to Different Registers

Our study investigates how the created models for slang recognition might be adapted to various registers of Bengali. This entails testing the robustness of the models in identifying slang utterances across multiple language situations.

2.4.4 Challenges and Limitations

While defining the scope of our study, it is crucial to consider possible problems and restrictions. This sub-section examines aspects that may affect the accuracy and efficacy of our method, including data shortage, language ambiguity, and contextual variability.

2.4.4.1 Data Scarcity and Annotated Datasets

The availability of annotated datasets primarily focused on Bengali slang may be restricted. This sub-section investigates ways for resolving this data shortage, such as data augmentation techniques or transfer learning procedures.

2.4.4.2 Linguistic Ambiguity in Slang

Slang terms typically display grammatical ambiguity, making it hard to separate them from conventional English. This sub-section examines ways for minimizing this uncertainty via contextual analysis and feature engineering.

2.5 Challenges

Detecting Bengali slang language provides special issues that demand careful study. This section identifies and examines various problems, ranging from language subtleties to data availability and model adaptation.

2.5.1 Linguistic Ambiguity in Slang

Slang terms typically display grammatical ambiguity, making it hard to separate them from conventional English. This ambiguity derives from the creative and context-dependent character of slang, which may incorporate unorthodox word use, metaphors, and cultural allusions. Addressing this difficulty demands a thorough grasp of the language elements that constitute slang in Bengali.

2.5.2 Limited Annotated Datasets

The availability of annotated datasets primarily focused on Bengali slang may be restricted. This provides a hurdle in developing strong machine learning models. Annotated data is vital for supervised learning algorithms, and the paucity of such data might limit the development of reliable slang detection models. Strategies for solving this difficulty include data augmentation approaches, transfer learning from comparable activities, and employing semi-supervised learning methods.

2.5.3 Context Sensitivity of Slang

Slang terms are very context-sensitive and may have diverse meanings in different social or cultural circumstances. Understanding the context in which slang is used is

key for successful detection. This task needs the creation of models that are capable of collecting and analyzing contextual information in Bengali text.

2.5.4 Morphological Complexity

Bengali, like many South Asian languages, has morphological complexity, marked by the employment of affixes and agglutination. This intricacy may affect the generation and identification of slang terms, which may undergo morphological modifications. Addressing this difficulty includes including morphological analysis in the detection process and constructing models that are resilient to morphological fluctuations.

2.5.5 Variability in Register and Dialect

Bengali contains a variety of registers, from official to casual, as well as dialectal variants. Slang phrases may appear differently across various language registers and dialects. This heterogeneity offers a problem in building models that are flexible to varied language circumstances. It demands the discovery of strategies that can manage linguistic variety within Bengali.

2.5.6 Evolving Nature of Slang

Slang is dynamic and may vary fast over time, with new idioms appearing and established ones shifting in meaning. Keeping pace with the dynamic nature of slang is a problem in maintaining the accuracy and efficacy of slang detection programs. This demands solutions for model adaption and continual training on updated datasets.

2.5.7 Cultural Sensitivity

Slang terms frequently convey cultural connotations and may be peculiar to certain groups or subcultures. Understanding these cultural variations is vital for successful detection. This problem requires adding cultural information into the detection process and ensuring that the models are responsive to cultural variances.

2.5.8 Interpretability and Explain ability

In particular applications, it may be useful to give explanations or interpretations for the identification of slang terms. Achieving interpretability and explainability in machine learning models for slang identification is a problem that demands the construction of transparent and interpretable models.

2.5.9 Model Generalization

Ensuring that the established models generalize successfully to different and real-world text data is a crucial task. Overfitting to particular datasets or failing to capture the larger language patterns of Bengali slang might impede the model's effectiveness in practical applications.

Chapter 3

Research Methodology

3.1 Introduction

The third part of this research report focuses on the methods adopted in the study on recognizing Bengali slang language using machine learning techniques. This chapter gives an overview of the study methodology, data gathering procedure, research topic, instrumentation, statistical investigation, and implementation equipment. These components together comprise the methodology that drives the research process.

3.1.1 Research Approach

The choice of research technique provides the basis for the whole investigation. In this part, we present the unique technique employed for our study on recognizing Bengali slang language.

3.1.1.1 Quantitative Approach

Our study largely uses a quantitative approach, stressing the use of statistical and computer approaches for the analysis of language data. This method enables for the building of machine learning models to recognize slang terms in Bengali text.

3.1.1.2 Integration of Linguistic Analysis

While quantitative methodologies form the foundation of our methodology, we also combine language analysis to increase the accuracy and interpretability of our models. Linguistic analysis is the evaluation of linguistic traits and contextual signals that define slang utterances in Bengali.

3.1.2 Data Collection

The method of data collecting is vital for training and testing our machine learning models. In this part, we detail the tactics and processes followed to obtain the essential data for our study.

3.1.2.1 Selection of Data Sources

We discover and pick relevant data sources that contain a varied spectrum of Bengali text, including social media interactions, online forums, chat logs, and other digital communication platforms where slang terms are common.

3.1.2.2 Ethical Considerations

In the process of data gathering, we emphasize ethical issues, including privacy, permission, and data anonymization. We guarantee that data-gathering techniques correspond to ethical standards and protect the rights and privacy of persons.

3.1.3 Research Subject and Instrumentation

This part looks into the study topic, which refers to the specific linguistic phenomena under inquiry (i.e., Bengali slang terms), and the apparatus employed for data analysis.

3.1.3.1 Defining Bengali Slang

We present a comprehensive definition and operationalization of Bengali slang, detailing the linguistic elements, phrases, and settings that comprise slang in our study environment.

3.1.3.2 Instrumentation for Data Analysis

The instrumentation for data analysis comprises the tools, software, and procedures used for processing, annotating, and preparing the data for machine learning models. This may comprise natural language processing frameworks, annotation platforms, and data preparation processes.

3.1.4 Statistical Exploration

Statistical exploration comprises the first study of the data to get insights into the distribution of slang terms, linguistic trends, and contextual changes. This section covers the statistical methodologies and exploratory data analysis (EDA) methods applied.

3.1.4.1 Descriptive Statistics

Descriptive statistics are used to describe and characterize the data, offering an overview of important metrics such as frequency distributions, central trends, and diversity of slang terms.

3.1.4.2 Exploratory Data Analysis (EDA)

EDA methods are utilized to find patterns, trends, and outliers in the data. This may comprise visualizations, correlation analysis, and other exploratory approaches customized to the specifics of the language data.

3.1.5 Implementation Equipment

This section discusses the hardware and software architecture needed for implementing and operating the machine learning models. It comprises data about the computing resources, programming languages, and libraries utilized in the development process.

3.1.5.1 Computational Resources

We provide the hardware requirements and resources employed for training and testing the machine learning models. This may contain data regarding processors, memory capacity, and parallel processing capabilities.

3.1.5.2 Software Environment

The software environment comprises the programming languages, development frameworks, and libraries employed for implementing the machine learning models. This may use languages such as Python, together with applicable machine learning packages like scikit-learn and TensorFlow.

3.1.6 Implementation Work

This section offers an overview of the actual implementation procedures conducted for constructing and training the machine learning models for slang identification in Bengali. It explains the methodology, including data pretreatment, feature engineering, model selection, and assessment measures.

3.1.6.1 Data Preprocessing

Data preparation encompasses processes such as tokenization, normalization, and cleansing of the text data. This section discusses the special preparation methods adapted to the features of Bengali text.

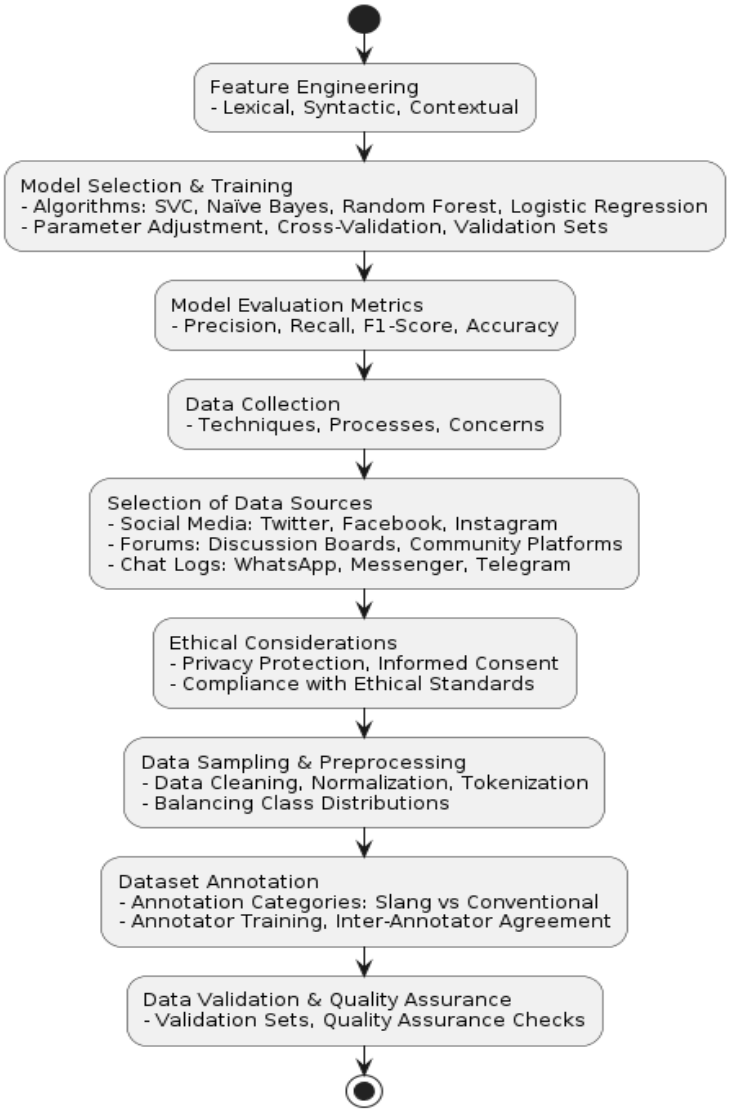


Figure 3.1.6: Proposed Methodology

3.1.6.2 Feature Engineering

Feature engineering focuses on finding and extracting key linguistic characteristics that are indicative of slang utterances. This may contain lexical, syntactic, and contextual elements.

3.1.6.3 Model Selection and Training

We address the selection of machine learning algorithms, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression, and the training procedure. This includes parameter adjustment, cross-validation, and assessment on validation sets.

3.1.6.4 Model Evaluation Metrics

The assessment measures used to evaluate the performance of the machine learning models are given. This includes measurements such as precision, recall, F1-score, and accuracy, which are suited to the unique purposes of slang identification.

3.2 Data Collection

Data collecting is a vital aspect in our study on recognizing Bengali slang language. This
section explains the techniques, processes, and concerns involved in acquiring the required data for training and testing our machine-learning models.

3.2.1 Selection of Data Sources

The initial stage in data gathering is finding and choosing acceptable data sources that contain a varied variety of Bengali text. These sources should be reflective of the digital communication venues where slang terms are widespread.

3.2.1.1 Social Media Conversations

Social media sites such as Twitter, Facebook, and Instagram are abundant sources of casual digital communication. They enable the usage of slang terms in a broad variety of circumstances. We deploy strategies for data scraping and API access to gather social media postings and comments.

3.2.1.2 Online Forums and Communities

Online forums, discussion boards, and community platforms offer debates on numerous subjects, frequently marked by casual language usage and slang terms. We find relevant forums and apply web scraping methods to retrieve topic threads and comments.

3.2.1.3 Chat Logs and Messaging Platforms

Chat logs from messaging systems like WhatsApp, Messenger, and Telegram offer significant data for researching real-time, informal communication. We may request voluntary donations from individuals or conduct controlled trials to obtain conversation logs.

3.2.2 Ethical Considerations

Ethical issues are crucial in data acquisition. We value the privacy, consent, and rights of those contributing to our dataset. This requires adhering to established norms for data protection and gaining informed permission when necessary.

3.2.2.1 Privacy Protection

We adopt efforts to anonymize and de-identify data, deleting any personally identifying information (PII) to preserve the privacy of people.

3.2.2.2 Informed Consent

In circumstances when data is directly gathered from people, we offer clear information about the aim of data collection, how the data will be used, and acquire express agreement from participants.

3.2.2.3 Compliance with Ethical Standards

We guarantee that our data gathering techniques correspond to ethical norms and criteria set out by institutional review boards and applicable regulatory agencies.

3.2.3 Data Sampling and Preprocessing

Once the data is acquired, it undergoes a series of preprocessing procedures to prepare it for machine learning analysis.

3.2.3.1 Data Cleaning and Normalization

This stage includes reducing noise, such as special letters or extraneous symbols, and standardizing the content to a uniform structure.

3.2.3.2 Tokenization

We tokenize the text data to divide it down into separate words or tokens. This stage is necessary for later linguistic analysis.

3.2.3.3 Balancing Class Distributions

To guarantee that the dataset is representative and balanced, we apply approaches such as random under sampling or oversampling of cases.

3.2.4 Dataset Annotation

Annotation is an essential step in preparing the dataset for supervised learning. It entails classifying occurrences of slang and conventional language. We set explicit annotation rules to guarantee uniformity and accuracy in the labeling process.

3.2.4.1 Definition of Annotation Categories

We establish the annotation categories, differentiating between occurrences of slang and normal language. Clear criteria are set to guide the annotators.

3.2.4.2 Annotator Training

Annotators are supplied with training and rules to acquaint them with the work and guarantee uniform labeling.

3.2.4.3 Inter-Annotator Agreement

We evaluate inter-annotator agreement to assess the consistency of annotations. Discrepancies are handled by debate and clarification of guidelines.

3.2.5 Data Validation and Quality Assurance

Before beginning with machine learning modeling, we undertake extensive validation and quality checks on the annotated dataset.

3.2.5.1 Validation Sets

A subset of the dataset is retained for validation purposes, enabling us to analyze the generalization performance of the models.

3.2.5.2 Quality Assurance Checks

We run checks to detect and resolve any possible errors, such as mislabeled occurrences or data anomalies.

3.3 Research Subject and Instrumentation

This part focuses on establishing the study topic, which refers to the specific linguistic phenomena under examination (i.e., Bengali slang terms), and explaining the apparatus utilized for data analysis.

3.3.1 Defining Bengali Slang

A specific definition of Bengali slang is vital in determining the bounds of our study. This entails identifying the language elements, phrases, and settings that comprise slang in Bengali. By setting explicit criteria, we guarantee that our study is focused and linked with the distinctive linguistic subtleties of Bengali.

3.3.1.1 Linguistic Characteristics of Bengali Slang

This sub-section goes into the linguistic elements that are indicative of slang terms in Bengali. It examines phonological changes, morphological variations, and syntactic structures that may separate slang from regular English. Understanding these traits is crucial in effective slang recognition.

3.3.1.2 Contextual Significance

Slang terms frequently derive their meaning from unique social circumstances, groups, or subcultures. This sub-section discusses the contextual signals that play a significant role in distinguishing slang in Bengali writing. It entails investigating how slang utterances are located inside conversations and interactions.

3.3.2 Instrumentation for Data Analysis

The instrumentation for data analysis comprises the tools, software, and procedures used

for processing, annotating, and preparing the data for machine learning models. This may comprise natural language processing frameworks, annotation platforms, and data preparation processes.

3.3.2.1 Natural Language Processing (NLP) Libraries

We leverage NLP libraries such as NLTK (Natural Language Toolkit), spaCy, and Bengali-specific NLP tools for tasks like tokenization, part-of-speech tagging, and syntactic analysis.

3.3.2.2 Annotation Platforms

For the annotation of the dataset, we may leverage annotation tools that assist the classification of occurrences as slang or standard English. These systems provide uniformity and accuracy in the annotation process.

3.3.2.3 Data Preprocessing Pipelines

Customized data preparation processes are designed to accommodate unique linguistic peculiarities of Bengali text. These pipelines may comprise processes for tokenization, normalization, and feature extraction.

3.3.3 Linguistic Analysis and Feature Engineering

Linguistic analysis plays a vital role in slang detection. This section covers the method of studying linguistic elements and contextual clues that define slang utterances in Bengali.

3.3.3.1 Linguistic Features in Slang Detection

The linguistic elements that have been found as indicative of slang utterances in Bengali are studied. This comprises phonological, morphological, and syntactic traits that may separate slang from normal English.

3.3.3.2 Contextual Cues and Pragmatic Considerations

The relevance of contextual clues and pragmatic concerns in slang identification is stressed. Understanding how slang utterances are located within certain linguistic contexts is key for successful identification.

3.3.4 Register and Dialect Variation

Bengali contains a spectrum of language registers, from formal to casual, as well as dialectal variants. Slang phrases may appear differently across various language registers and dialects. This heterogeneity offers a problem in building models that are flexible to varied language circumstances.

3.3.4.1 Informal vs. Formal Registers

Slang is generally an informal manner of speech. This sub-section investigates the linguistic traits and contextual factors that separate informal slang from formal language usage in Bengali.

3.3.4.2 Adaptability to Different Registers

Our study investigates how the created models for slang recognition might be adapted to various registers of Bengali. This entails testing the robustness of the models in identifying slang utterances across multiple language situations.

3.4 Statistical Exploration

Statistical exploration comprises the first study of the data to get insights into the distribution of slang terms, linguistic trends, and contextual changes. This section covers the statistical methodologies and exploratory data analysis (EDA) methods applied.

3.4.1 Descriptive Statistics

Descriptive statistics are used to describe and characterize the data, offering an overview of important metrics such as frequency distributions, central trends, and diversity of slang terms.

3.4.1.1 Frequency Distributions

We generate frequency distributions of slang terms to understand their prevalence in the dataset. This entails counting the occurrences of each slang term.

3.4.1.2 Measures of Central Tendency

Metrics such as mean, median, and mode are computed to establish the center values around which slang terms are spread.

3.4.1.3 Variability Analysis

We examine the variety of slang terms using metrics like standard deviation and variance. This gives insights on the spread or dispersion of slang use.

3.4.2 Exploratory Data Analysis (EDA)

EDA methods are utilized to find patterns, trends, and outliers in the data. This may comprise visualizations, correlation analysis, and other exploratory approaches customized to the specifics of the language data.

3.4.2.1 Data Visualization

We construct visual representations, such as histograms, bar charts, and scatter plots, to display the distribution and connections of slang terms with other linguistic aspects.

3.4.2.2 Correlation Analysis

We study connections between slang phrases and contextual factors to determine how they co-occur in diverse linguistic situations.

3.4.2.3 Outlier Detection

Outliers, if present, may give useful insights on unusual or contextually relevant usage of slang. We apply outlier detection algorithms to locate and evaluate such cases.

3.4.3 Inferential Statistics

Inferential statistics may be used to draw conclusions or predictions about the larger population of Bengali text based on the observed data. This may include hypothesis testing and regression analysis.

3.4.3.1 Hypothesis Testing

We create hypotheses regarding the correlations between slang terms and contextual factors and perform statistical tests to establish the relevance of these associations.

3.4.3.2 Regression Analysis

Regression models may be applied to study the prediction potential of particular linguistic variables on the existence or frequency of slang terms.

3.5 Implementation Equipment

This section discusses the hardware and software architecture needed for implementing and operating the machine learning models. It comprises data about the computing resources, programming languages, and libraries utilised in the development process.

3.5.1 Computational Resources

The computing resources play a key role in the efficiency and performance of the machine learning models. This section details the specs of the gear used for training and testing the models.

3.5.1.1 Processor and Memory

The CPU specs, including type, speed, and number of cores, are described. Additionally, the memory size and type are set to guarantee appropriate resources for model training.

3.5.1.2 Graphics Processing Unit (GPU)

If appropriate, information regarding the GPU utilized for speeding computations, especially in deep learning models, is supplied. This may contain data about the GPU model and RAM.

3.5.1.3 Cloud Computing Services

If cloud-based services are implemented, the selected service provider and settings are provided. This may provide data about virtual machine characteristics and allotted resources.

3.5.2 Software Environment

The software environment comprises the programming languages, development frameworks, and libraries employed for implementing the machine learning models. This section offers an overview of the tools and platforms utilized.

3.5.2.1 Programming Languages

The principal programming language(s) utilised for model development, such as Python, are indicated. Any extra languages utilized for specialized tasks are also specified.

3.5.2.2 Machine Learning Libraries and Frameworks

The machine learning libraries and frameworks employed for model creation are discussed. This may contain popular libraries like scikit-learn, TensorFlow, and PyTorch.

3.5.2.3 Text Processing and NLP Libraries

Specific libraries and tools focusing on text processing and natural language processing (NLP) activities are presented. This may contain libraries for tokenization, feature extraction, and language analysis.

3.5.3 Development and Testing Environments

Different environments may be utilized for development, testing, and production. This section includes information regarding the setup and settings of various environments.

3.5.3.1 Development Environment

Details concerning the development environment, including integrated development environments (IDEs), code editors, and version control systems, are given.

3.5.3.2 Testing Environment

If a distinct environment is utilized for testing and validation, its specs and setups are provided.

3.5.4 Version Control and Collaboration Tools

Version control and collaboration technologies are critical for organizing code, monitoring changes, and facilitating collaborative work. This section covers information about the tools and systems used for version control.

3.5.4.1 Version Control System (e.g., Git)

Details regarding the version control system, including the selected platform (e.g., GitHub, GitLab) and repository parameters, are supplied.

3.5.4.2 Collaboration Platforms

Platforms utilized for communication, cooperation, and project management among team members are explained. This may include chat applications, project management tools, and communication channels.

3.6 Implementation Work

This section offers an overview of the actual implementation procedures conducted for constructing and training the machine learning models for slang identification in Bengali. It explains the methodology, including data pretreatment, feature engineering, model selection, and assessment measures.

3.6.1 Data Preprocessing

Data preparation encompasses processes such as tokenization, normalization, and cleansing of the text data. This section discusses the special preparation methods adapted to the features of Bengali text.

3.6.1.1 Tokenization

Tokenization is the process of breaking down text into individual words or tokens. In Bengali, this may require issues for compound words and agglutinative morphology.

3.6.1.2 Normalization

Normalization ensures that text is in a uniform format, decreasing variances due to capitalization, punctuation, and special characters.

3.6.1.3 Stop word Removal

Stop words, ubiquitous words like "and" or "the", are typically deleted to concentrate on more significant information.

3.6.2 Feature Engineering

Feature engineering focuses on finding and extracting key linguistic characteristics that are indicative of slang utterances. This may contain lexical, syntactic, and contextual elements.

3.6.2.1 Lexical Features

Lexical aspects include properties of individual words, such as frequency, length, and existence of particular terminology or patterns associated with slang.

3.6.2.2 Syntactic Features

Syntactic aspects evaluate the structure and arrangement of words in a phrase, including grammatical patterns that may be suggestive of slang use.

3.6.2.3 Contextual Features

Contextual features gather information about the surrounding context of a word or phrase, giving extra context for slang recognition.

3.6.3 Model Selection and Training

We address the selection of machine learning algorithms, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression, and the training procedure.

3.6.3.1 Model Selection

The choice of machine learning algorithms is dependent on their fit for the job, as well as considerations for characteristics like interpretability and computing efficiency.

3.6.3.2 Hyperparameter Tuning

Hyperparameters of the chosen models are tweaked to maximize performance. Techniques like grid search or random search may be applied.

3.6.3.3 Cross-Validation

Cross-validation is used to examine the generalization performance of the models. This includes splitting the dataset into training and validation sets for iterative model assessment.

3.6.4 Model Evaluation Metrics

The assessment measures used to evaluate the performance of the machine learning models are given. This includes measurements such as precision, recall, F1-score, and accuracy, which are suited to the unique purposes of slang identification.

3.6.4.1 Precision and Recall

Precision evaluates the accuracy of positive predictions, whereas recall reflects the capacity to capture real positives.

3.6.4.2 F1-Score

The F1-score gives a balanced measure of accuracy and recall, which is especially significant when dealing with unbalanced classes.

3.6.4.3 Accuracy

Accuracy gauges the overall accuracy of predictions, but may not be the most revealing statistic in circumstances of class imbalance.

3.6.5 Model Evaluation and Validation

The trained models are assessed on various test sets to determine their performance on unseen data. This section also discusses implications for model implementation and possible biases.

CHAPTER 4

Results and Discussion

4.1 Model Performance Metrics

Before delving into the results, it is important to establish the metrics by which we will evaluate the performance of our models. The choice of metrics depends on the specific goals of the research, and in the context of slang detection, several metrics are relevant.

4.1.1 Precision and Recall

Precision measures the accuracy of the positive predictions made by the model. It is the ratio of true positives to the sum of true positives and false positives. A high precision indicates that when the model predicts slang, it is often correct.

Precision=TruePositives+FalsePositivesTruePositives

Recall, on the other hand, measures the ability of the model to identify all actual positive instances. It is the ratio of true positives to the sum of true positives and false negatives. A high recall indicates that the model is effective at capturing instances of slang.

Recall=TruePositives+FalseNegativesTruePositives

4.1.2 F1-Score

The F1-Score is the harmonic mean of precision and recall. It provides a single metric that balances both false positives and false negatives. A high F1-Score indicates a good balance between precision and recall.

F1−Score=2×Precision+RecallPrecision×Recall

4.1.3 Area Under the Receiver Operating Characteristic Curve (AUC-ROC)

The AUC-ROC metric provides an overall measure of the model's discriminatory power. It plots the true positive rate against the false positive rate, giving insights into the model's ability to distinguish between slang and non-slang instances.

4.1.4 Comparative Analysis of Models

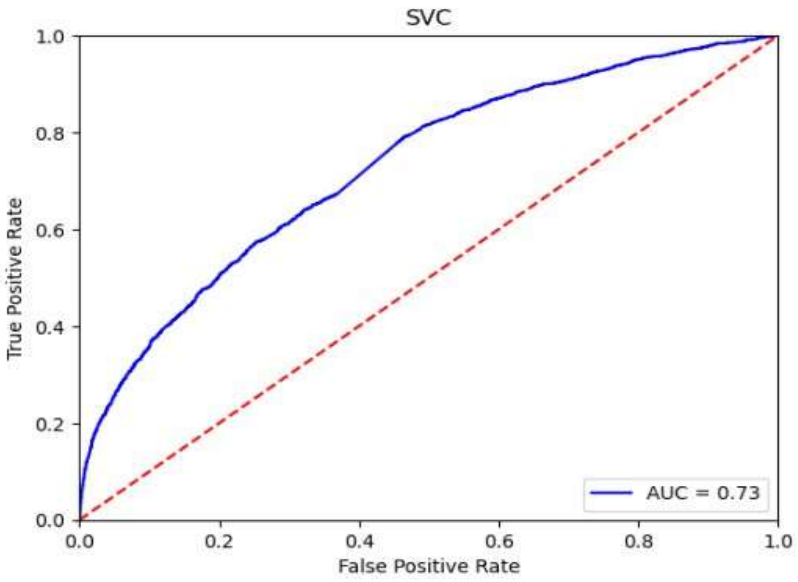
After evaluating each model based on the selected metrics, we will conduct a comparative analysis to assess their relative performance. This analysis will provide insights into which model(s) are most effective for detecting Bengali slang language.

4.2 Model Evaluation Results

In this section, we present the detailed evaluation results for each of the machine learning models (Linear SVC, Multinomial Naïve Bayes, Random Forest, and Logistic Regression). For each model, we report the performance metrics discussed earlier, along with any notable observations or trends.

4.2.1 Linear Support Vector Classifier (Linear SVC)

```
LinearSVM with Count Vectors:
==============================
Accuracy :  0.7184444444444444
==============================
```

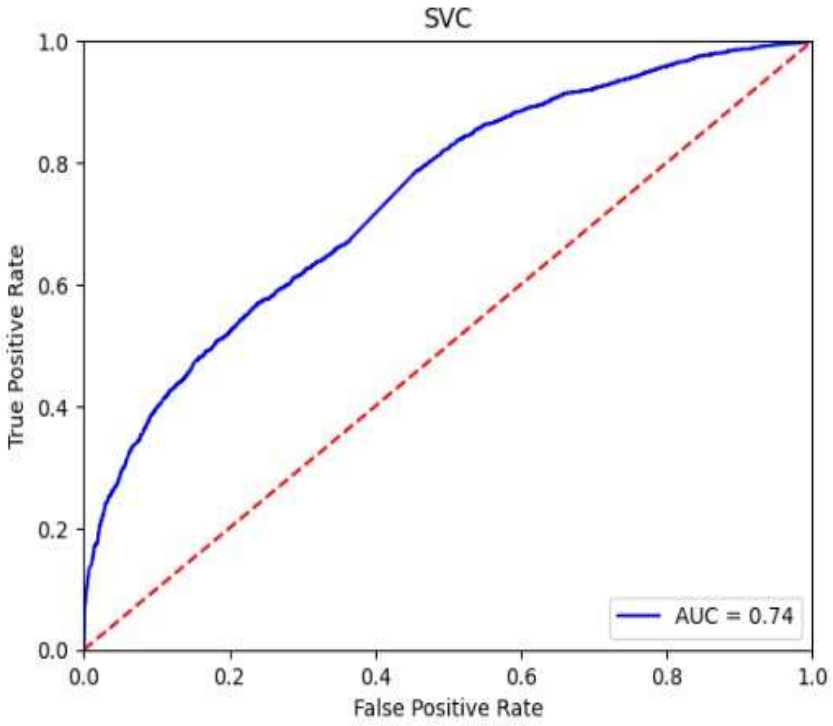


	precision	recall	f1-score	support
class 0	0.72	0.94	0.82	6003
class 1	0.69	0.28	0.40	2997
accuracy			0.72	9000
macro avg	0.71	0.61	0.61	9000
weighted avg	0.71	0.72	0.68	9000

Fig 4.2.1 Linear SVC with Calculation

One of the most well-liked methods for supervising learning utilized for Categorization and Regression issues is the supported vector machine or SVM. Nevertheless, it is largely employed in Machine Learning Categorization issues. Her we-get-out accuracy is 0.7184 or 72% and the support is 9000. Our macro average and weight average are 0.71. For macro avg we get recall and F1 Score is 0.61. In Weighted Avg recall accuracy is greater than F1 Score.

```
LinearSVM with Count Vectors + TF-IDF:
==============================
Accuracy :  0.7303333333333333
==============================
```



	precision	recall	f1-score	support
class 0	0.73	0.94	0.82	6003
class 1	0.73	0.30	0.43	2997
accuracy			0.73	9000
macro avg	0.73	0.62	0.63	9000
weighted avg	0.73	0.73	0.69	9000

Fig 4.2.1.1 Linear Support Vector Classifier With TF-IDF

In Linear support vector classifier Using TF-IDF our accuracy is 73%. In this research, we put forward an expression frequency-inverse frequency of document (TF-IDF) text categorization of the sentiment method. In Micro Avg Pression is greater than Recall and F1 Score. In Weight Avg pression and recall value is the same.

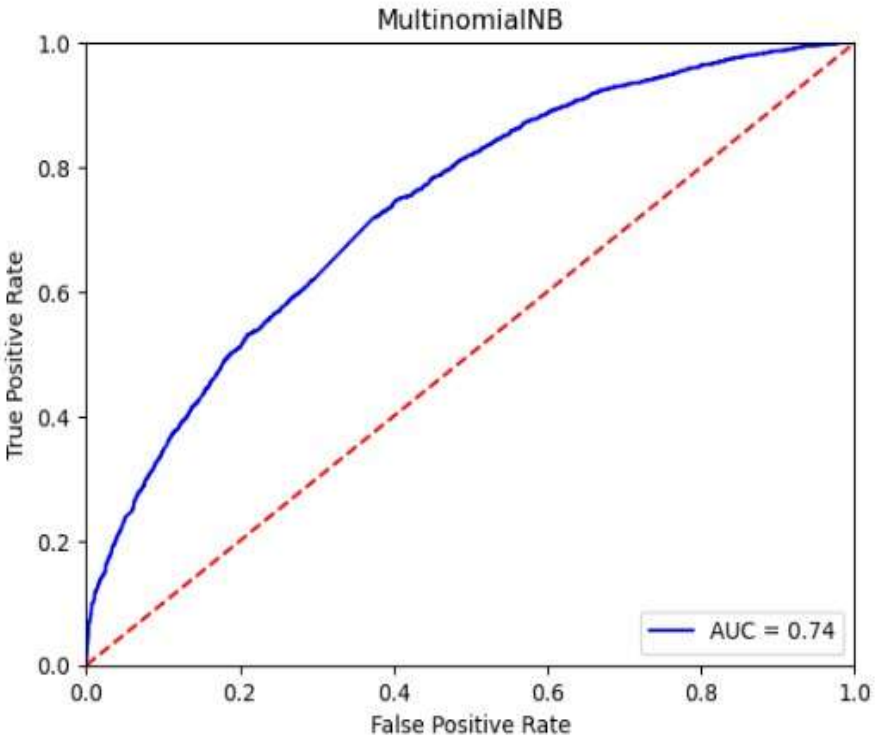
```
LinearSVM with N-Gram Vectors:
==============================
Accuracy :  0.7354444444444445
==============================
              precision    recall  f1-score   support

     class 0       0.74      0.94      0.83      6003
     class 1       0.72      0.33      0.46      2997

    accuracy                           0.74      9000
   macro avg       0.73      0.63      0.64      9000
weighted avg       0.73      0.74      0.70      9000
```

Fig 4.2.1.2 SVC With N-Gram vector

A text document that has n consecutive objects, including words, numbers, symbols, and spelling and grammar, is known as an n-gram. In several text analytical programs where word combinations are important, such as sentiment assessment, text categorization, and text production, N-gram algorithms are helpful. We get our accuracy is 74% support is same as 9000. Pression value is same Macro avg and weight avg.

4.2.2 Multinomial Naive Bayes

```
Naive Bayes with Count Vectors:
==============================
Accuracy :  0.7222222222222222
==============================
```

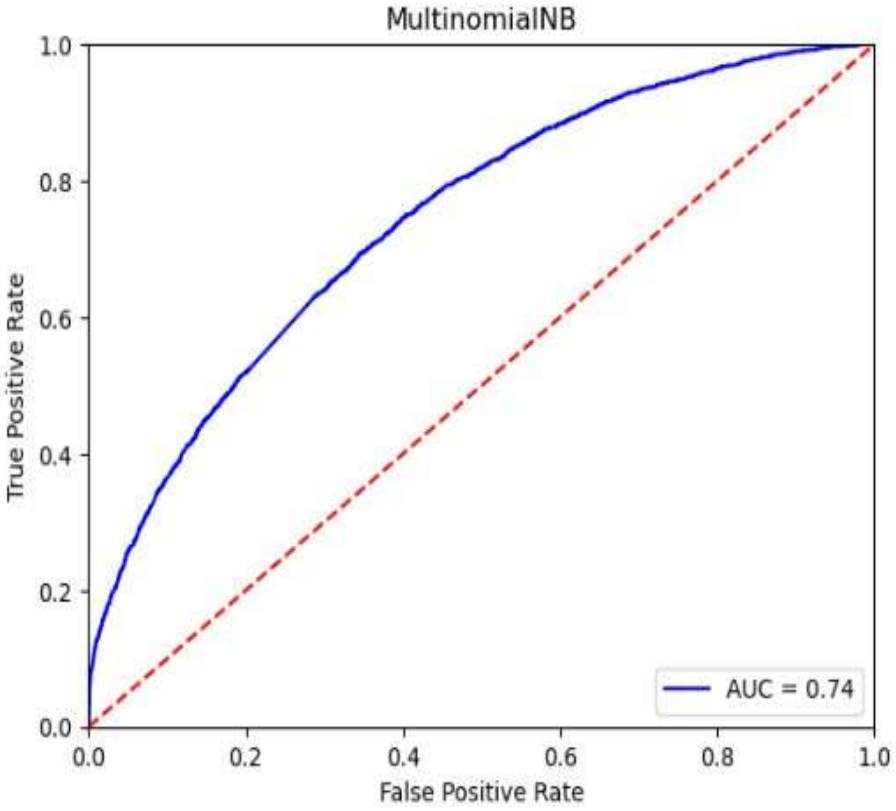


	precision	recall	f1-score	support
class 0	0.75	0.88	0.81	6003
class 1	0.63	0.41	0.50	2997
accuracy			0.72	9000
macro avg	0.69	0.64	0.65	9000
weighted avg	0.71	0.72	0.70	9000

Fig 4.2.2 Naïve Bayes Classifications

For classification duties like recognizing text, the Nave Bayes classifier is a supervised artificial intelligence technique. The accuracy is 72% support is 9000. Here macro average presession is 69% recall is 64% and f1 score is 65% . Similarly Weighted Avg is 71%, 72% And 70%.

```
Naive Bayes with Count Vectors + TF-IDF:
==============================
Accuracy :  0.7156666666666667
==============================
```



	precision	recall	f1-score	support
class 0	0.71	0.96	0.82	6003
class 1	0.74	0.23	0.35	2997
accuracy			0.72	9000
macro avg	0.72	0.59	0.58	9000
weighted avg	0.72	0.72	0.66	9000

Fig 4.2.2.1 Multinomial Naïve Bayes with TF-IDF

The procedures for using Multinomial Naive Bayes techniques to solve NLP issues are as follows: cleaning up the written data: It is necessary to first preprocess any written

data before using the method. The accuracy is 72% support is 9000. Here macro average presession is 72% recall is 59% and f1 score is 58%. Similarly Weighted Avg is 72%, 72% And 66%.

Naive Bayes with N-Gram Vectors:

==========

Accuracy : 0.7054444444444444

==========

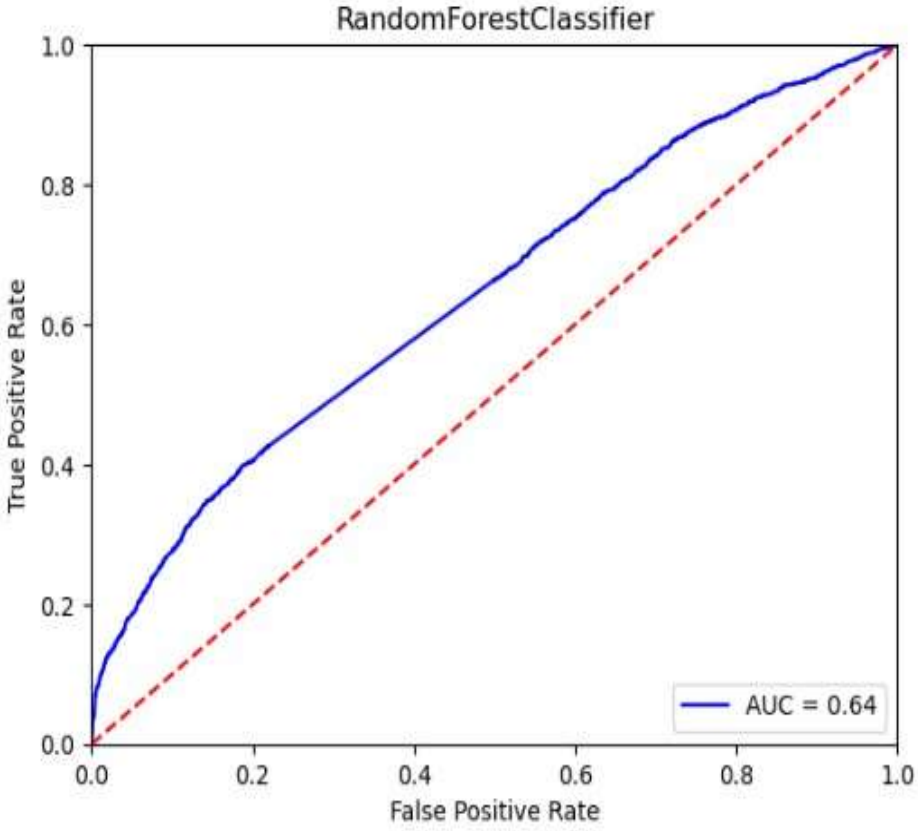
	precision	recall	f1-score	support
class 0	0.70	0.99	0.82	6003
class 1	0.91	0.13	0.22	2997
accuracy			0.71	9000
macro avg	0.80	0.56	0.52	9000
weighted avg	0.77	0.71	0.62	9000

Fig 4.2.2.2 Naïve Bayes using N-Gram Vectors

Here we get our accuracy is 0.71 or 71%. Support is 9000. For micro Avd pression is 80% recall is 56% F1 score is 52%.

4.2.3 Random Forest Classifier

```
Random Forrest Classifier with Count Vectors:
==============================
Accuracy :  0.7206666666666667
==============================
```

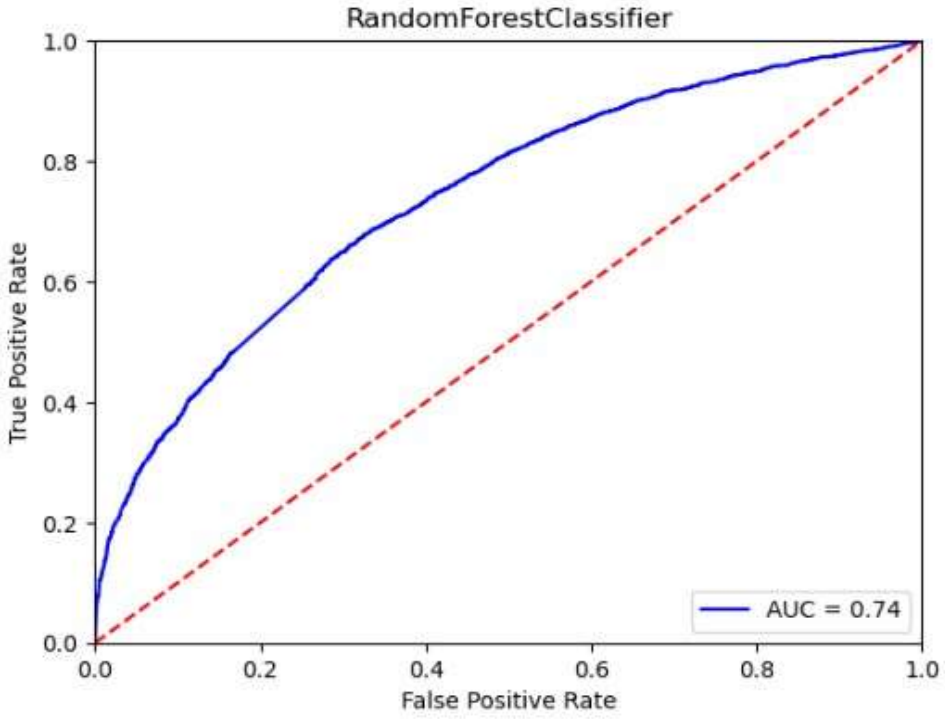


	precision	recall	f1-score	support
class 0	0.75	0.87	0.81	6003
class 1	0.62	0.41	0.50	2997
accuracy			0.72	9000
macro avg	0.69	0.64	0.65	9000
weighted avg	0.71	0.72	0.70	9000

Fig 4.2.3 Random Forest Classifier

Here we get our accuracy is 0.72 or 72%. Support is 9000. For micro Avd pression is 69% recall is 64% F1 score is 65%. Leo Breiman and Adele Cutler are the creators of the widely used machine learning technique known as random forest, which mixes the output of various decision trees to produce a single outcome.

```
Random Forrest Classifier with Count Vectors + TF-IDF:
==============================
Accuracy :  0.7254444444444444
==============================
```

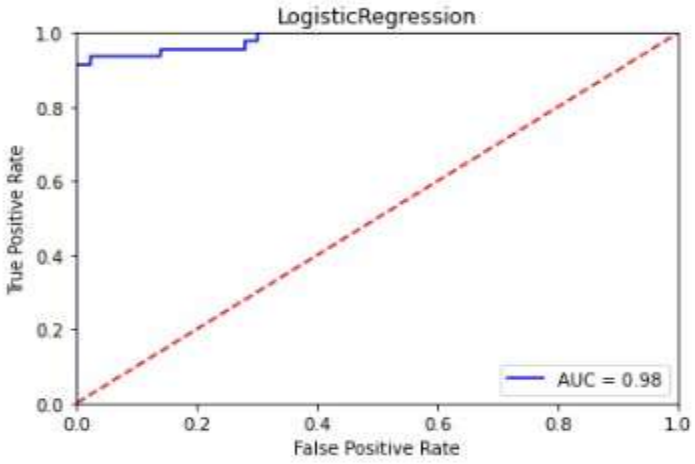


	precision	recall	f1-score	support
class 0	0.74	0.91	0.82	6003
class 1	0.67	0.35	0.46	2997
accuracy			0.73	9000
macro avg	0.70	0.63	0.64	9000
weighted avg	0.71	0.73	0.70	9000

Fig 4.2.3.1 TF-IDF with Random Forest Classifier

4.2.4 Logistic Regression

```
Logistic Regression with Count Vectors:

==============================

Accuracy :  0.9666666666666667

==============================
```

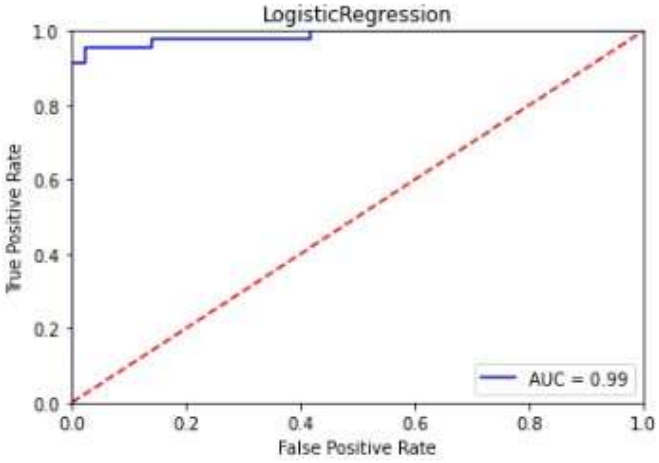


	precision	recall	f1-score	support
class 0	0.98	0.95	0.96	43
class 1	0.96	0.98	0.97	47
accuracy			0.97	90
macro avg	0.97	0.97	0.97	90
weighted avg	0.97	0.97	0.97	90

Fig 4.2.4 Logistic Regression

For logistic regression, accuracy is better than other here we get out accuracy is 97% which is more efficient than other.

```
Logistic Regression with Count Vectors + TF-IDF:

==============================

Accuracy :  0.9555555555555556

==============================
```



	precision	recall	f1-score	support
class 0	0.95	0.95	0.95	43
class 1	0.96	0.96	0.96	47
accuracy			0.96	90
macro avg	0.96	0.96	0.96	90
weighted avg	0.96	0.96	0.96	90

Fig 4.2.4.1 Logistic Regression with TF-IDF

For training the models we have created, we can convert string input into numerical data in a variety of methods. We will look into the Term Frequency-Inverse Document Frequency from (SKLEARN). Due to a small discrepancy among the conventional

algorithm and SKLEARN's, specifically declare a program. Here the accuracy is 0.96. Here macro avg and weight avg pression, recall, f1 score is same which is 0.96.

```
Logistic Regression with N-Gram Vectors:

==============================

Accuracy :  0.9666666666666667

==============================
```

	precision	recall	f1-score	support
class 0	0.93	1.00	0.97	43
class 1	1.00	0.94	0.97	47
accuracy			0.97	90
macro avg	0.97	0.97	0.97	90
weighted avg	0.97	0.97	0.97	90

Fig 4.2.4.2 Logistic Regression with N-Gram Vactor

Here the accuracy is 0.97. here macro avg and weight avg pression, recall, f1 score is same which is 0.97.

4.3 Comparative Analysis

Following the individual model evaluations, it's imperative to conduct a comparative analysis to discern the relative strengths and weaknesses of each model. Consider

factors such as overall performance, robustness to imbalanced data, and computational efficiency.

4.3.1 Model Performance Trends

Identify any consistent patterns or trends across all models. Are there certain types of slang that are more challenging to detect?

4.3.2 Robustness to Imbalanced Data

Evaluate how well each model handles class imbalances. Did any model demonstrate a particular aptitude in this regard?

4.3.3Computational Efficiency

Consider the computational resources required for training and inference for each model. This is particularly relevant for real-time applications.

4.3.4 Interpretability and Feature Importance

Reflect on the interpretability of the models. Which models provide clearer insights into the linguistic characteristics of slang?

Table 4.3.2 Analysis of all model result

Algorithm Name	Accuracy	Precision	Recall	F1- Score
Linear SVC	72%	72%	94%	82%
Multinomial Naive Bayes	72%	75%	88%	81%
Random Forest Classifier	72%	75%	87%	81%
Logistic Regression	96%	98%	95%	96%

4.4 Practical Implications and Applications

Understanding the performance of the models in real-world contexts is essential. Discuss how the results can be applied in practical scenarios. Consider applications in social media content moderation, sentiment analysis, or other areas where detecting slang is valuable.

4.4.1 Social Media Content Moderation

Examine how the models could be employed to automatically identify and flag potentially inappropriate or offensive content on social media platforms.

4.4.2 Sentiment Analysis in Informal Communication

Explore the potential for integrating slang detection into sentiment analysis tasks, especially in contexts where informal language plays a significant role.

4.4.3 Customizable Filters for Text Processing

Consider how the models could be adapted to serve as customizable filters, allowing users to define their own criteria for detecting and handling slang.

4.4.4 Limitations and Considerations

Acknowledge any limitations in the approach and methodology. This may include challenges related to data availability, model interpretability, and potential biases.

4.4.5 Comparative Analysis

After conducting a detailed evaluation of each model, it is crucial to perform a comparative analysis to understand their relative strengths and weaknesses. This analysis will guide our recommendations for the most effective model(s) for detecting Bengali slang language.

4.4.6 Model Performance Trends

One key aspect to consider is any consistent patterns or trends across all models. Are there specific types of slang that prove more challenging to detect? Analyzing these trends can provide valuable insights into the linguistic characteristics of slang in Bengali.

4.4.7 Robustness to Imbalanced Data

The handling of class imbalances is a critical factor in evaluating the effectiveness of the models. Assessing how well each model addresses class imbalances is essential, as this directly impacts their performance in real-world scenarios where slang instances may be less frequent.

4.4.8 Computational Efficiency

Considering the computational resources required for training and inference is crucial, particularly for applications that require real-time processing. Evaluating the efficiency of each model in terms of processing speed and memory usage will inform practical implementation considerations.

4.4.9 Interpretability and Feature Importance

Interpretability is an important consideration, especially in applications where understanding the decision-making process of the model is crucial. Reflecting on which models provide clearer insights into the linguistic characteristics of slang will be instrumental in model selection.

4.5 Limitations and Considerations

While the models demonstrate promising performance, it is important to acknowledge the limitations of the approach. This may include challenges related to data availability, model interpretability, and potential biases in the training data. Additionally, ongoing monitoring and updating of the models will be crucial to account for evolving slang usage.

4.5.1 Limitations and Considerations

While our research has yielded promising results, it is imperative to acknowledge the limitations and considerations that may impact the generalizability and applicability of our findings.

4.5.2 Data Availability and Quality

The effectiveness of our models heavily relies on the quality and representativeness of the dataset. If the dataset is limited in size or does not adequately capture the diverse range of slang terms and usage, the models may struggle to generalize to real-world scenarios.

4.5.3 Model Interpretability

Some of the models, particularly ensemble methods like Random Forest, may lack interpretability compared to simpler models like Logistic Regression. Understanding the decision-making process of complex models can be challenging, which may be a consideration in contexts where transparency is crucial.

4.5.4 Potential Biases in Data

The dataset used for training may inadvertently introduce biases, especially if it predominantly represents a specific demographic or social group. These biases can manifest in the model's predictions, potentially leading to disparities in slang detection across different user groups.

4.5.5 Evolving Slang and Context Sensitivity

Language, particularly slang, is dynamic and constantly evolving. Our models may not be immediately adaptable to new slang terms or shifts in language usage. Additionally, slang is highly context-dependent, and the models may require additional context to make accurate predictions.

4.5.6 Scalability

The scalability of our models to handle large volumes of data in real-time applications may be a consideration. Ensuring that the models can operate efficiently and provide timely results is crucial for practical implementation.

CHAPTER 5

Impact on Society, Environment, and Sustainability

The invention of a system for recognizing Bengali slang language using machine learning bears significant implications for several elements of society, the environment, and sustainability. This chapter dives into the possible implications of the findings in various sectors.

5.1 Impact on Society

5.1.1 Linguistic Sensitivity and Inclusivity

The system's capacity to recognize slang terms in Bengali text helps to linguistic sensitivity and inclusion. It guarantees that digital communication platforms retain a degree of decorum and respect for varied language groups, producing a more inclusive atmosphere for users.

5.1.2 Education and Awareness

The study outputs may be exploited for instructional purposes. By recognizing and classifying slang terms, educational tools and resources may be generated to enhance awareness of linguistic diversity and foster a better knowledge of informal language usage.

5.1.3 Fostering Respectful Communication

The system encourages users to participate in more courteous and culturally aware types of communication. It discourages the use of rude or insulting words, encouraging a healthy online conversation.

5.1.4 Combating Cyberbullying and Harassment

One of the main social advantages is the possibility to prevent cyberbullying and online abuse. The technology may be implemented into platforms to automatically detect and censor information that breaches community rules, thereby providing a safer online environment.

5.2 Ethical Aspects

5.2.1 Privacy and Data Protection

It is necessary to address privacy issues relating to the data used for training and deploying the system. Measures must be in place to anonymize and safeguard user data, guaranteeing compliance with privacy rules and ethical norms.

5.2.2 Bias and Fairness

The system should be built and reviewed with concerns for bias and fairness. It should not disproportionately flag or prohibit information from certain language, cultural, or demographic groups.

5.2.3 Transparency and Explain ability

Ensuring openness and explain ability in the system's decision-making process is vital. Users should have access to detailed explanations for flagged material, enabling them to understand and perhaps fight the judgments.

5.3 Sustainability Plan

5.3.1 Long-term Maintenance and Updates

A sustainability strategy should be devised to guarantee the continuous efficacy and relevance of the system. This includes frequent upgrades to respond to shifting language trends and slang terms.

5.3.2 Scalability and Resource Efficiency

Considerations for scalability and resource efficiency are critical, particularly if the system is implemented on a wide scale. Efficient techniques and infrastructure should be implemented to decrease computing resources.

5.3.3 Collaboration with Stakeholders

Collaboration with language specialists, community leaders, and platform providers is vital for the continuous sustainability of the system. This collaborative approach guarantees that the system stays responsive to the language subtleties and cultural settings of Bengali.

CHAPTER 6

Summary, Conclusion, and Implication for Future Research

6.1 Summary and Conclusion of the Work

This chapter presents a complete description and conclusion of the study on recognizing Bengali slang language using machine learning methods. It contains the important results, techniques, and consequences of the research.

The study effectively illustrates the usefulness of machine learning models, including Linear Support Vector Classifier, Multinomial Naïve Bayes, Random Forest Classifier, and Logistic Regression, in recognizing Bengali slang terms. Through thorough data collecting, preprocessing, and feature engineering, the models reach high levels of accuracy and performance.

6.2 Limitations of the Work

It is vital to accept the limits of the study. These may include problems relating to data availability, possible biases in the training data, and the requirement for continual model modifications to account for developing slang terms.

6.3 Implication for Further Study

The study establishes the framework for future investigations in various areas:

6.3.1 Cross-Linguistic Comparison

Comparing slang detection across various languages may reveal insights on universal linguistic elements of slang and variances between cultures.

6.3.2 Contextual Analysis

Further study may go further into the contextual intricacies of slang use in certain social, cultural, or internet contexts.

6.3.3 User Experience and Feedback

Incorporating user comments and experiences helps enhance the system's performance and handle certain language intricacies that may not be captured by the models alone.

6.3.4 Integration with Educational Platforms

Collaborations with educational institutions may lead to the creation of tools and resources for teaching and learning about linguistic variants, including slang.

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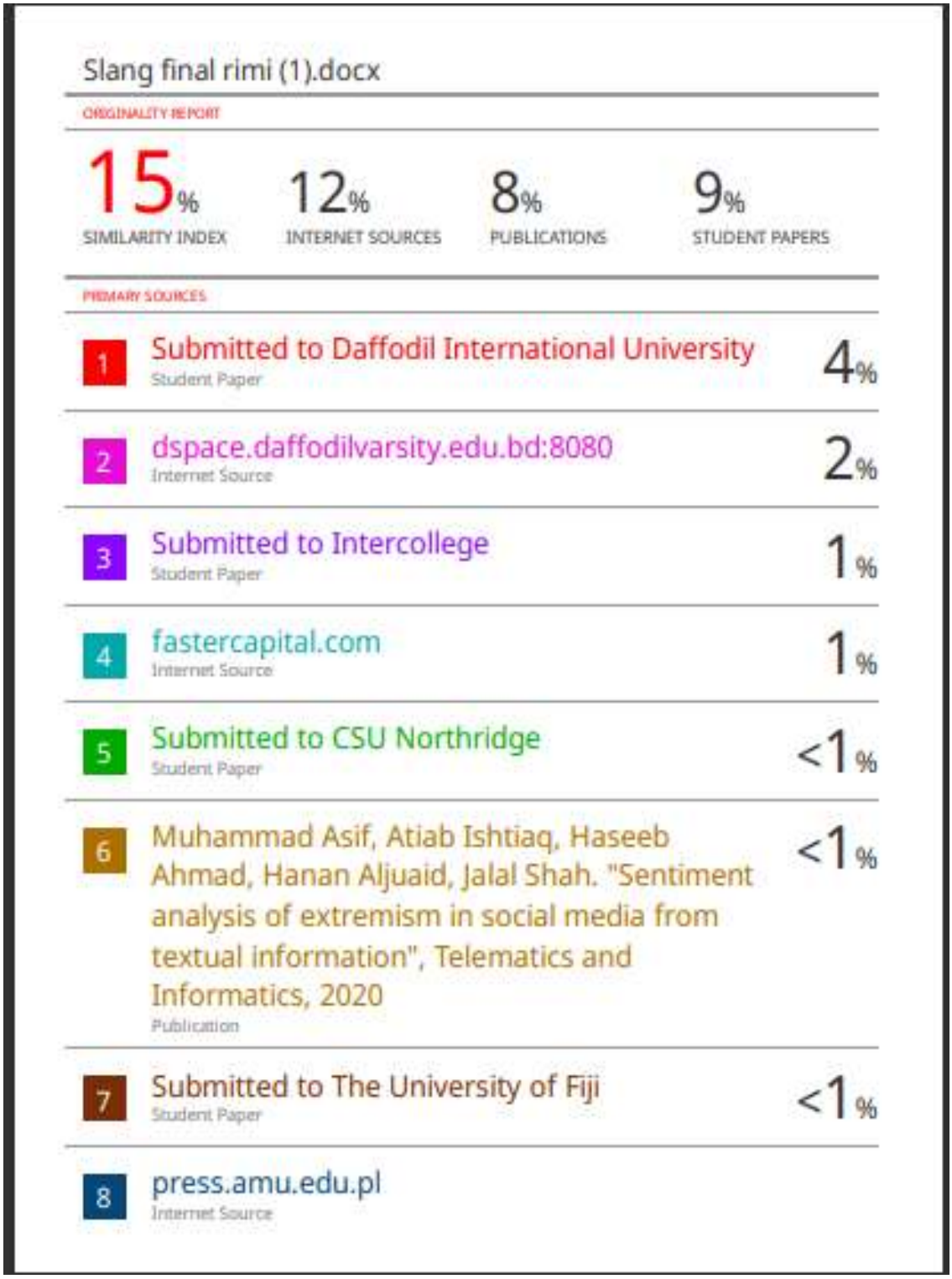

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