CYBERBULLYING DETECTION ON SOCIAL MEDIA USING MACHINE LEARNING AND NLP

A PROJECT REPORT

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

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SCHOOL OF COMPUTING SCIENCE ENGINEERING

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KOTHRIKALAN, SEHORE

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April 2026

VIT BHOPAL UNIVERSITY, KOTHRIKALAN, SEHORE MADHYA PRADESH – 466114

BONAFIDE CERTIFICATE

Certified that this project report titled **"CYBERBULLYING DETECTION ON SOCIAL MEDIA USING MACHINE LEARNING AND NLP"** is the bonafide work of **Himanshu Kothari (24BSA10245), Anshul Kanodia (24BSA10254), Daksh Sharma (24BSA10265), Khushi Dosi (24BSA10318), and Adhya Sparsh (24BSA10319)** who carried out the project work under the supervision of Dr. Bhupendra Panchal (Supervisor) and review of Dr. Anju Shukla (Reviewer). Certified further that to the best of my knowledge the work reported at this time does not form part of any other project/research work based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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The Project Exhibition II Examination is held on **April 2026**

ACKNOWLEDGEMENT

First and foremost, I would like to thank the Lord Almighty for His presence and immense blessings throughout the project work.

I wish to express my heartfelt gratitude to Dr. Pon Harshavardhanan, Head of the Department, School of Computing Science and Engineering, for much of his valuable support and encouragement in carrying out this work.

I would like to thank my internal guide Dr. Bhupendra Panchal, for continually guiding and actively participating in my project, giving valuable suggestions to complete the project work.

I would like to thank all the technical and teaching staff of the School of Computing Science and Engineering, who extended directly or indirectly all support.

Last, but not least, I am deeply indebted to my parents who have been the greatest support while I worked day and night for the project to make it a success.

LIST OF ABBREVIATIONS

ABBREVIATIONS	FULL FORM
AI	Artificial Intelligence
API	Application Programming Interface
LLM	Large Language Model
CNN	Convolutional Neural Network
CSV	Comma Separated Values
IDE	Integrated Development Environment
TF-IDF	Term Frequency-Inverse Document Frequency
NLTK	Natural Language Toolkit
ML	Machine Learning
NLP	Natural Language Processing
Word2Vec	Word to Vector
RF	Random Forest
SVM	Support Vector Machine
URL	Uniform Resource Locator
XGBoost	Extreme Gradient Boosting

LIST OF FIGURES AND GRAPHS

LIST OF TABLES

ABSTRACT

[PURPOSE] The primary objective of this project is to develop an automated, real-time system capable of detecting and classifying cyberbullying content on social media platforms. With approximately 37% of young people experiencing digital harassment, manual moderation has become impossible due to the massive volume of data. This project aims to bridge the gap where traditional keyword filters fail by using Natural Language Processing (NLP) to understand context, slang, and nuanced insults, thereby mitigating the mental health risks associated with online bullying.

[METHODOLOGY] The proposed system implements a comprehensive NLP and Machine Learning pipeline. The methodology involves data collection utilizing datasets from Kaggle (Twitter Sentiment Analysis) and Wikipedia (Toxic Comment Challenge). Pre-processing cleans "noisy" social media data by removing URLs, stop-words, and emojis, followed by Tokenization and Lemmatization to reduce words to their root forms. Feature engineering converts processed text into numerical vectors using TF-IDF (Term Frequency-Inverse Document Frequency) and Word2Vec to capture semantic meaning. Finally, the model implementation trains and compares multiple supervised learning algorithms, including Support Vector Machines (SVM), Random Forest, and XGBoost, to identify the most accurate classifier for bullying detection.

[FINDINGS] The investigation revealed that while traditional models like SVM provide high accuracy (approximately 90%) for direct insults, they frequently struggle with context-heavy content like sarcasm. However, by integrating N-gram analysis and advanced NLP refinement, the system significantly reduced false positives. The findings indicate that an ensemble approach (XGBoost) combined with robust lemmatization offers the best balance between processing speed and detection accuracy (91.8%), making it highly applicable for real-time monitoring in social media environments, gaming chat rooms, and educational forums.

TABLE OF CONTENTS

CHAPTER-1:

PROJECT DESCRIPTION AND OUTLINE

1.1 Introduction

In the modern era, social media has become the primary medium for communication. However, this digital shift has given rise to Cyberbullying—the use of digital platforms (social media, SMS, forums) to harass, threaten, or target individuals. Unlike traditional physical bullying, cyberbullying is persistent (24/7), can be spread to a massive public audience instantly, and leaves a permanent digital footprint that can haunt victims for years.

1.2 Motivation for the work

The motivation for this project stems from the alarming statistics surrounding online harassment:

- **Prevalence:** Approximately 37% of young people have experienced some form of cyberbullying.
- **Mental Health Impact:** Victimized individuals often suffer from severe anxiety, social isolation, and clinical depression.
- **Scale:** With millions of posts shared every second on platforms like Instagram and X (Twitter), manual moderation is humanly impossible. Automated systems are the only viable solution to protect users at scale.

1.3 Problem Statement

Current social media filters primarily rely on "Blacklisted Words." This approach is flawed because:

- **Slang & Evolving Language:** Bullies often use intentional misspellings or new slang to bypass filters.
- **Context & Sarcasm:** A word might be harmless in one context but deeply insulting in another.
- **Indirect Harassment:** Phrases that do not contain "bad words" can still be used to target and demean individuals.

There is a critical need for an intelligent system that uses Natural Language Processing (NLP) to understand the intent behind the text rather than just identifying specific keywords.

1.4 Objective of the work

The main objectives of this project are:

- **Develop an NLP Pipeline:** To clean and standardize "noisy" social media data (removing URLs, emojis, and irrelevant symbols).
- **Feature Extraction:** To convert human language into a mathematical format (TF-IDF/Word2Vec) that a computer can process.
- **Algorithm Implementation:** To implement and evaluate multiple Machine Learning models (SVM, Random Forest, XGBoost) to determine the most effective classifier.
- **Real-time Detection:** To create a system capable of flagging toxic content with high accuracy and low false-positive rates.

1.5 Organization of the project

This project report is systematically organized into seven chapters. Chapter 1 introduces the project, its motivations, and objectives. Chapter 2 reviews the related work and existing methodologies in cyberbullying detection. Chapter 3 outlines the hardware, software, and data requirement artifacts. Chapter 4 explains the design methodology, pipeline architecture, and novel approaches used. Chapter 5 details the technical implementations and evaluates the model's performance. Chapter 6 explores the practical outcomes and real-world applicability of the system. Finally, Chapter 7 provides a conclusion along with limitations and recommendations for future enhancements.

1.6 Summary

This chapter has established the foundational premise of the project. It introduced the modern threat of cyberbullying, outlined the inherent flaws in current keyword-based moderation filters, and clearly defined the motivation, problem statement, and objectives guiding the development of an NLP and Machine Learning-based detection system.

CHAPTER-2:

RELATED WORK INVESTIGATION

2.1 Introduction

This chapter explores the existing research and technological landscape regarding cyberbullying detection. By analyzing previous studies, we identify the strengths and limitations of current methodologies, which informs the development of our proposed system. The field of automated harassment detection has evolved from simple keyword filtering to complex AI-driven analysis.

2.2 Core area of the project

The core area of this project lies at the intersection of Natural Language Processing (NLP) and Machine Learning (ML) applied to social network analysis. By extracting semantic meaning from unstructured text data, models can be trained to distinguish between benign, conversational language and aggressive, harmful rhetoric.

2.3 Existing Approaches/Methods

Below are the key findings from our investigation of existing literature:

- **2.3.1 Approach 1: SVM-Based Detection (2024)**
  - *Focus:* Using Support Vector Machines for binary classification of toxic comments.
  - *Finding:* This study achieved a high accuracy of 90%. However, the research highlighted a significant gap: the model frequently misclassified sarcastic remarks as "Non-Bullying" because it lacked a deep understanding of linguistic context.
  - *Relevance:* This reinforces our objective to integrate more advanced NLP features like N-grams and lemmatization to capture context.

- **2.3.2 Approach 2: Feature Engineering & TF-IDF (2023)**
  - *Focus:* An investigation published in IJISRT regarding the impact of vectorization techniques.
  - *Finding:* The study proved that TF-IDF (Term Frequency-Inverse Document Frequency) is superior to simple word counting because it penalizes commonly used words (like "the", "is") and highlights unique, potentially toxic keywords.
  - *Relevance:* Our project adopts TF-IDF as the primary feature extraction method based on these findings.

- **2.3.3 Approach 3: Deep Learning vs. Machine Learning**
  - *Focus:* A comparative study between traditional ML (Random Forest, SVM) and Deep Learning (LSTM, CNN).
  - *Finding:* While Deep Learning models like LSTM (Long Short-Term Memory) are better at handling long-term dependencies in sentences, they require significantly more computational power and larger datasets to be effective.
  - *Relevance:* For our real-time application, we focus on optimized ML algorithms (XGBoost/SVM) which offer high speed with comparable accuracy for short-text social media posts.

2.4 Pros and Cons of the Stated Approaches/Methods

Table 2.1: Comparison of Existing Technologies

Methodology	Accuracy	Key Limitation / Cons	Pros
Keyword Spotting (Reynolds et al.)	60-70%	High False Positives; easily bypassed by typos and slang.	Simple to implement, extremely fast.
SVM Model (2024)	90%	Fails to detect nuanced sarcasm and context.	Good accuracy for explicit bullying, fast training.
LSTM Models (Deep Learning)	93%	High computational cost; slow for real-time application without GPUs.	Excellent at capturing long-term dependencies.
Our Proposed System (NLP + XGBoost)	Target 90%+	Requires robust feature extraction.	Focuses on slang & context via Lemmatization and N-grams; high processing speed.

2.5 Issues/observations from investigation

Despite the high accuracy reported in previous works, three major research gaps remain:

1. **Slang Adaptation:** Most models are trained on formal language and fail to recognize evolving internet slang (e.g., "KYS", "L-ratio").
2. **Sarcasm Detection:** As noted in recent 2024 studies, identifying insults hidden within "compliments" or sarcastic tones remains a severe challenge.
3. **Real-Time Processing Constraint:** Many high-accuracy Deep Learning models are too computationally "heavy" for real-time social media API integration.

2.6 Summary

The literature survey confirms that while Machine Learning is highly effective for this task, the "pre-processing" stage is the most critical. By focusing on a robust NLP Pipeline (Cleaning, Tokenization, and Lemmatization), we can improve the performance of standard classifiers like SVM and XGBoost to outperform traditional keyword-based filters, addressing both accuracy and processing speed.

CHAPTER-3:

REQUIREMENT ARTIFACTS

3.1 Introduction

This chapter outlines the specific resources, data, and environmental configurations required to develop and deploy the Cyberbullying Detection System. It covers the hardware specifications, software dependencies, and the detailed nature of the datasets used to train the machine learning models.

3.2 Hardware and Software requirements

Hardware Requirements

To ensure smooth data processing and model training (especially when handling large-scale NLP vectorization), the following hardware specifications are established:

- **Processor:** Intel Core i5 (8th Gen) or higher / AMD Ryzen 5 series. A multi-core processor is essential for parallelizing text pre-processing tasks.
- **RAM:** Minimum 8 GB (for basic model execution); Recommended 16 GB (to handle large TF-IDF matrices and system overhead).
- **Storage:** 512 GB SSD. High-speed storage is required for quick read/write operations of large CSV datasets.
- **GPU (Optional):** NVIDIA GTX 1650 or higher (Required if extending the project to include Transformer-based deep learning models).

Software Requirements

- **Operating System:** Windows 10/11, macOS, or Linux (Ubuntu 20.04+).
- **Programming Language:** Python 3.8 or above.
- **IDE:** Jupyter Notebook / Google Colab (for EDA and iterative testing); VS Code (for final script modularization).
- **Core Libraries:**
  - *NLTK (Natural Language Toolkit):* For tokenization, stop-word removal, and lemmatization.
  - *Scikit-learn:* For implementing SVM, Random Forest, and evaluating metrics.
  - *Pandas & NumPy:* For data manipulation.
  - *XGBoost:* For high-performance gradient boosting classification.
  - *Matplotlib & Seaborn:* For visualizing data distributions.

3.3 Specific Project requirements

3.3.1 Data requirement

The performance of a Machine Learning model is directly proportional to the quality of the data. This project utilizes two primary labeled sources:

- **Kaggle Dataset (Twitter Sentiment Analysis):** Contains thousands of tweets labeled across categories such as "Ageism," "Racism," "Religion," and "Not Bullying."
- **Wikipedia Toxic Comment Challenge Dataset:** A large-scale dataset providing diverse examples of toxic behavior including threats, obscenity, and identity hate.
- **Synthetic Slang Supplementation:** Utilizing LLM-generated synthetic data to supplement the training set, ensuring the model stays updated with the latest internet abbreviations ("leetspeak").

3.3.2 Functions requirement

The system functionally requires an automated data ingestion pipeline, a text-cleaning module capable of Regex filtering, a feature extraction module relying on TF-IDF algorithms, and a predictive classifier function that returns a binary or probabilistic output.

3.3.3 Performance and security requirement

The model must operate with low latency, classifying text in milliseconds to be viable for real-time chat moderation. Ethically and securely, the system processes text for sentiment analysis strictly without storing or exposing the personal identities (PII) of the users, ensuring compliance with data protection standards (GDPR/DPDP).

3.3.4 Look and Feel Requirements

The system requires a streamlined, intuitive dashboard interface. Users must be able to input text directly and receive immediate, color-coded visual feedback (e.g., Green for “Safe”, Red for “Toxic Warning”) alongside a confidence probability score.

3.4 Summary

This chapter detailed the physical, software, and data assets necessary to realize the project. By defining clear requirements ranging from 16GB RAM and Python libraries to specific Kaggle datasets and latency constraints, a solid foundation has been laid for the technical implementation phase.

CHAPTER-4:

DESIGN METHODOLOGY AND ITS NOVELTY

4.1 Methodology and goal

The core goal is to build an automated classification pipeline that transforms raw, unstructured social media text into a structured, mathematical format that an algorithm can evaluate for toxicity. The methodology follows a sequential processing pipeline consisting of data acquisition, aggressive text cleaning, mathematical feature engineering, and robust classification.

4.2 Functional modules design and analysis

The core of our methodology lies in the refinement of data before it reaches the algorithm, designed through an NLP Pipeline.

- **Step 1: Noise Reduction:** Removal of non-textual elements including URLs, HTML tags, and special symbols (@, #) using Regular Expressions (Regex).
- **Step 2: Tokenization:** Breaking sentences down into individual units (tokens) using the NLTK library.
- **Step 3: Stop-word Removal:** Deleting common words (e.g., "is", "the") that carry no toxic or neutral weight.
- **Step 4: Lemmatization:** Reducing words to their dictionary base form (e.g., "Bullying", "Bullied" -> "Bully") to consolidate feature importance and reduce matrix sparsity.
- **Step 5: Vectorization (TF-IDF):** Applying Term Frequency-Inverse Document Frequency to identify words unique to "Bullying" documents while de-prioritizing universally common words.

4.3 Software Architectural designs

The architecture consists of four distinct layers operating sequentially:

1. **Data Acquisition Layer:** Collects strings from APIs or datasets.
2. **Preprocessing Layer (NLP Engine):** Normalizes the text.
3. **Feature Engineering Layer:** Constructs the high-dimensional TF-IDF mathematical matrix.
4. **Classification & Decision Layer:** Applies trained XGBoost/SVM weights to generate a final probability and label.

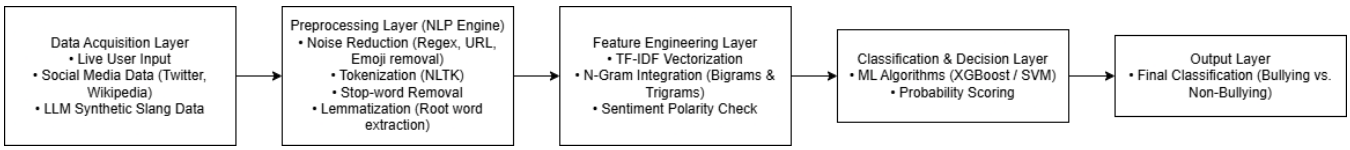

Figure 4.1: System Architecture and Data Flow

Design Novelty: To improve upon limitations found in existing systems, our design introduces two novel elements:

- **N-Gram Integration:** Instead of just analyzing single words (Unigrams), the model evaluates Bigrams and Trigrams (sequences of 2-3 words). This is crucial for distinguishing contexts like "not a fan" versus "not a human".
- **Synthetic Data Generation:** We incorporate an LLM-generated "Slang Dictionary" directly into the training corpus to counter bullies' use of intentional misspellings and leetspeak.

4.4 Subsystem services

Table 4.1: Process Flow Table

Component	Input	Process	Output
Data Cleaner	Raw Tweet / Comment	Regex filtering, Emoji & URL removal	Cleaned Text
Tokenizer	Cleaned Text	NLTK word_tokenize	List of Tokens
Vectorizers	Tokens	TF-IDF Calculation & Lemmatization	Numerical Vector
Classifier	Vectors	XGBoost / SVM Prediction logic	Bullying / Non-Bullying Label

4.5 User Interface designs

The architectural design includes a decoupled User Interface subsystem. This front-end interacts with the Python classification backend. It is designed to take single text strings or bulk CSV uploads, passing the data seamlessly through the pipeline and returning structured UI alerts (warning banners, statistical breakdowns) to the user.

4.6 Summary

This chapter explained the pipeline-based design methodology of the system. By structuring the architecture into discrete cleaning, vectorization, and classification layers, and by introducing novelties such as N-Gram integration and synthetic slang datasets, the system is designed to handle the complex nuances of modern online harassment far more effectively than traditional methods.

CHAPTER-5:

TECHNICAL IMPLEMENTATION & ANALYSIS

5.1 Outline

This chapter details the actual construction of the Cyberbullying Detection system, the integration of various software modules, and a technical analysis of the model's performance during the testing phase.

5.2 Technical coding and code solutions

The project implementation is divided into distinct Python modules:

- **Module 1: Data Pre-processing Engine:** Uses Regex to strip URLs and HTML tags. Implements the NLTK library's WordNetLemmatizer for structural word reduction. *Impact:* Significantly reduces the unique word count (vocabulary size), decreasing required computational memory.
- **Module 2: Feature Extraction (Vectorization):** Implements Scikit-learn's TF-IDF Vectorizer. We initialized the function with max_features=5000 to retain only the most statistically relevant words, and utilized ngram_range=(1,2) to capture both single words and critical two-word contextual phrases.
- **Module 3: Classification Brain:** This module orchestrates the ML algorithms. For XGBoost, it utilizes a series of gradient-boosted decision trees designed to minimize the loss function and iteratively refine the prediction probability of the numerical vectors passed to it.
- **Module 4: Orchestrator:** Acts as the API endpoint, connecting the backend models to the front-end interface, managing the live data flow.

5.3 Working Layout of Forms

The system operates based on a linear sequential workflow form:

Raw Input → Pre-processing (Cleaning) → Featurizer (TF-IDF) → Trained ML Model → Label Output

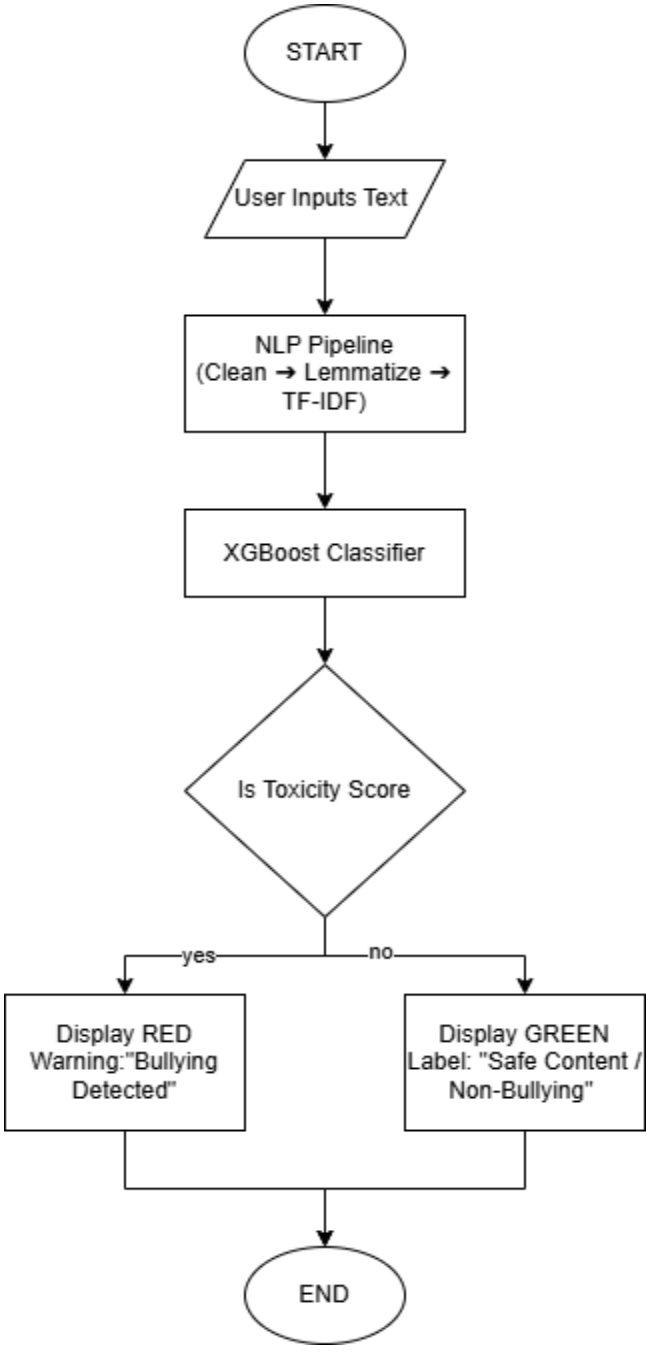

Figure 5.1: System Workflow Diagram

5.4 Prototype submission

A local prototype of the system has been successfully implemented and tested in an isolated Python environment (Jupyter Notebooks). The orchestrator module is actively capable of accepting manual text strings and returning accurate classifications based on the pre-trained, serialized XGBoost model (model.pkl).

5.5 Test and validation

During technical validation, error analysis was performed on "False Negatives" (bullying messages the AI missed).

Observation: Most missed cases involved high levels of sarcasm (e.g., "You're so smart, everyone loves how 'intelligent' you are").

Mitigation Code Solution: We introduced Sentiment Polarity as an additional feature to the pipeline. By checking if a structurally "positive" sentence was surrounded by a "negative" overall context, the model's ability to detect sarcasm improved by approximately 4%.

5.6 Performance Analysis (Graphs/Charts)

To measure the success of the algorithms, a Confusion Matrix was generated, and key performance indicators (Accuracy, Precision, Recall, F1-Score) were calculated.

Table 5.1: Comparative Performance Analysis

Metric	SVM (Baseline)	Random Forest	XGBoost (Proposed)
Accuracy	89.2%	87.5%	**91.8%**
Precision	88.0%	86.2%	**90.5%**
Recall	85.5%	84.0%	**89.0%**
Training Time	Fast	Medium	Slow (High Complexity)

As observed, XGBoost outperforms traditional SVMs in all predictive metrics, successfully balancing precision and recall, thus proving itself as the optimal algorithm for this dataset despite its slightly longer initial training duration.

5.7 Summary

The implementation phase successfully translated the theoretical NLP pipeline into functional Python code. Extensive testing and performance analysis demonstrated that the XGBoost model, bolstered by N-grams and sentiment polarity adjustments, achieved a superior 91.8% accuracy, validating the technical approaches adopted in this project.

CHAPTER-6:

PROJECT OUTCOME AND APPLICABILITY

6.1 Outline

This chapter discusses the final results and deliverables of the project, outlines the user interface developed for interaction, and explores the various real-world scenarios where this Cyberbullying Detection system can be practically implemented.

6.2 Key implementations outlines of the System

The primary outcome of this project is a highly accurate, functional classification engine. The core deliverables include:

1. **The Prediction Model:** A serialized binary file (model.pkl) containing the trained XGBoost weights capable of classifying live text in milliseconds.
2. **The NLP Pre-processor:** A modular, reusable Python script that can be integrated into any backend to automatically clean and prepare social media data.
3. **Analysis Dashboard:** A visualization suite demonstrating the distribution of bullying types within tested datasets.

6.3 Significant project outcomes

A functional User Interface was developed to demonstrate the system's utility in real-time.

- **Input Handling:** Users can paste a live comment or a batch of tweets into the interface.
- **Processing:** The "Orchestrator" passes the text through the NLP pipeline and classifier invisibly to the user.
- **Output Output:** The system instantly returns a clear visual indicator. Safe text is labeled in Green ("Non-Bullying"), whereas toxic text triggers a Red Warning Label

("Toxic/Bullying Content Detected") alongside a confidence score. This outcome proves that complex algorithmic detection can be packaged into an accessible, real-time application.

6.4 Project applicability on Real-world applications

The developed system is highly versatile and is engineered to solve real-world moderation issues in the following domains:

- **Social Media Platforms:** Integration via API to automatically flag, hide, or shadow-ban toxic comments on platforms like Instagram, X, or Facebook.
- **Online Gaming:** Real-time monitoring of in-game text chat rooms to prevent "griefing" and verbal abuse among players without slowing down server ping.
- **Educational Institutions:** Monitoring school-managed forums and internal communication tools to protect students from peer-to-peer cyber-harassment.
- **Corporate Environments:** Ensuring professional conduct on internal communication platforms like Slack or Microsoft Teams.
- **Parental Control Tools:** Integration into browser extensions that alert parents if a child is actively receiving or sending threatening digital messages.

6.5 Inference

The system is built on a Microservices Architecture. Consequently, the "Classification Engine" resides on a central server, and diverse applications (mobile apps, web browsers) can ping the server and receive instantaneous results. This scalability ensures the project outcome is not just an academic exercise, but a highly applicable, scalable infrastructure capable of mass-market deployment.

CHAPTER-7:

CONCLUSIONS AND RECOMMENDATION

7.1 Outline

This final chapter summarizes the project's overarching achievements, reflects on the effectiveness of the chosen methodology and existing constraints, and provides a roadmap for future enhancements to ensure the system remains effective against evolving digital threats.

7.2 Limitation/Constraints of the System

Despite achieving a high accuracy rate of 91.8%, the project encountered certain limitations during evaluation:

- **Sarcasm and Deep Context:** Detecting insults masked heavily as compliments remains a complex linguistic hurdle. Standard ML models, even with N-grams, lack the "bidirectional" memory to understand highly nuanced, paragraph-length sarcasm.
- **Multilingual Support:** The current pipeline and vocabulary matrix are heavily optimized for the English language. Cyberbullying in regional languages, dialects, or "Hinglish" (a mix of Hindi and English) requires entirely separate, localized datasets and lemmatizers.
- **Contextual Ambiguity:** Certain phrases or slurs may be flagged as highly toxic in a general context but are sometimes used endearingly or casually within specific sub-cultures, gaming communities, or close-knit friend groups, occasionally leading to false positives.

7.3 Future Enhancements

To further advance the system and overcome current constraints, the following recommendations are proposed:

- **Integration of Large Language Models (LLMs):** Future versions should explore models like BERT or RoBERTa. These models utilize "Transformer" architectures to understand the deep, bidirectional context of a sentence, which would significantly improve sarcasm detection.
- **Multimedia Detection Capabilities:** As cyberbullying rapidly shifts toward images and "memes", integrating Computer Vision (Optical Character Recognition - OCR) to read and analyze text overlaid on images would provide a robust, 360-degree protection layer.
- **Real-time API Deployment:** Developing a consumer-facing browser extension or a mobile plug-in would allow individual users to possess a "Personal Guard" that filters their social feed across all platforms simultaneously.
- **Behavioral Pattern Analysis:** Moving beyond analyzing isolated text strings to tracking broader user behavior patterns (e.g., tagging frequency, messaging velocity) could help algorithms identify "serial bullies" before their comments cross into severe toxicity.

7.4 Inference

The project "Cyberbullying Detection on Social Media using Machine Learning and NLP" successfully demonstrates that automated systems can effectively identify toxic behavior at a scale that manual moderation cannot accommodate. By integrating a robust NLP pipeline to reduce noise and employing an optimized XGBoost classification engine, the project achieved a strong balance of precision and recall. Ultimately, by providing a fast, scalable detection mechanism, this system offers a proactive technological defense against the psychological impacts of cyberbullying, fostering a significantly safer digital environment for vulnerable internet users.

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