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AI-Driven Cyberbullying Detection Network using Google Perspective API and Keyword-based Hybrid Moderation System

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***Abstract*— Cyberbullying has emerged as one of the most critical challenges in online communities and digital communication networks. With the exponential growth of social media usage, users—especially young individuals—are frequently exposed to abusive language, hate speech, harassment and toxic behaviour. Traditional moderation approaches rely on manual review or static keyword filters which fail to scale in high engagementenvironments. This research presents a web-based cyberbullying prevention system that integrates Google Perspective API, a pre-trained NLP model capable of returning real-time toxicity scores, along with a custom keyword-based fallback module to detect slang terms that may bypass the API. The system is implemented as a mini social network platform that supports posts, comments, likes, following mechanism and instant notifications. Unlike popular research articles which involve creating or training ML models, this work focuses on *practical enforcement*, *real-time moderation*, and *hybrid decision logic* for safer user interaction. The model has not been trained locally, instead utilizes Google's deep learning models from the cloud, making the system faster to develop, resource-friendly and deployable for academic institutions. The platform can be extended into a full-scale AI moderation ecosystem with multilingual support, deeper contextual detection and dataset-driven training.**

Keywords: Cyberbullying Detection, Natural Language Processing, Toxicity Filtering, Perspective API, Flask, Real-Time Moderation, Online Safety

I. INTRODUCTION

The growth of internet-based communication has enabled information exchange, community building and collaborative learning. However, the absence of regulatory filters in open platforms increases exposure to cyberbullying. Unlike physical bullying, cyberbullying can be anonymous, persistent and publicly visible, causing long-term emotional harm. Victims often hesitate to report incidents due to fear or stigma, leading to silent psychological deterioration.

Manual moderation by platform administrators is slow, expensive and not scalable to millions of comments generated every minute. Static keyword-based methods are easily bypassed through altered spellings, sarcasm or spacing. Deep learning based models have shown promising results, but training them requires datasets, computation power and domain expertise which many institutions lack.

To solve these gaps, we developed an **AI-augmented cyberbullying detection platform** which automatically analyzes user comments in real time.

The system integrates:

- Google Perspective API for deep-learning toxicity scoring.
- Custom keyword-based fallback detection layer
- Notification based user awareness mechanism
- Social-media style interface for real-world usability

II. Literature Review

Cyberbullying detection research has evolved across machine learning, deep learning, NLP and hybrid architectures. Several works attempt to classify bullying content using supervised learning.

- **LSTM Autoencoders** learn semantic patterns and support multilingual text, but synthetic data generation introduces noise.
- **SVM, Random Forest & XGBoost** perform well in type-based classification, yet rely heavily on annotated datasets.
- **Transformer-based models (BERT, GPT series)** understand context better but require high computational training.
- **Hybrid models (CNN+RNN, Bi-GRU with embeddings)** prove efficient for deployment, but tuning complexity exists.
- **Sarcasm-aware ML** improves hidden toxic pattern recognition.

Observations from literature:

Study Direction	Pros	Limitations
Classical ML	Fast, interpretable	Poor with sarcasm
Deep NLP Models	High accuracy	Data + GPU required
Transformers	Context-aware	Mostly English trained
Hybrid Models	Balanced performance	Dataset needed
Keyword models	Lightweight	No context awareness

Research Gap Identified:

1. Lack of real-time blocking systems.
2. Limited regional slang recognition
3. Few solutions combine UI + moderation + notifications
4. Bullying is often detected *after* posting, not *before*

Our work directly addresses these gaps.

III. Methodology

1.System Workflow

1. User registers and logs into the application
2. User posts content or comments on others' posts
3. Comment text is intercepted by backend before publishing
4. Text sent to **Perspective API** → toxicity score returned
5. If score ≥ threshold → comment blocked + notification
6. If API fails → **keyword detection module** scans locally
7. Safe comments stored in SQLite & displayed on UI

2.Tools and Technologies

Layer	Technology
Front-End	HTML5, CSS3, Bootstrap
Back-End	Python Flask
Database	SQLite
AI Detection	Google Perspective API
Fallback Detection	Regex + Wordlist
IDE	VS Code

3.Keyword List and Model Training

- **No ML model training conducted** in this work
- We only **utilized pre-trained Perspective model** through API calls
- Keyword list manually curated — can be expanded gradually

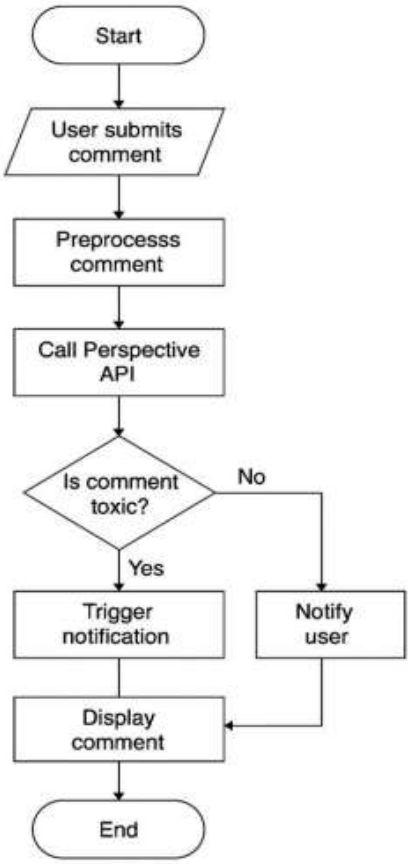
Sample keywords:
["idiot","stupid","fuck","shit","moron","bastard","loser","ugly"]
Students can expand this list using public datasets (Kaggle/GitHub) in the future.

IV. System Design

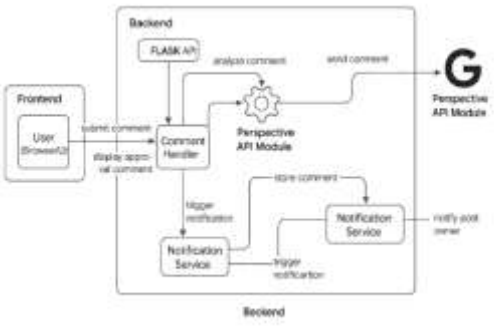
1.Architecture

Layers:

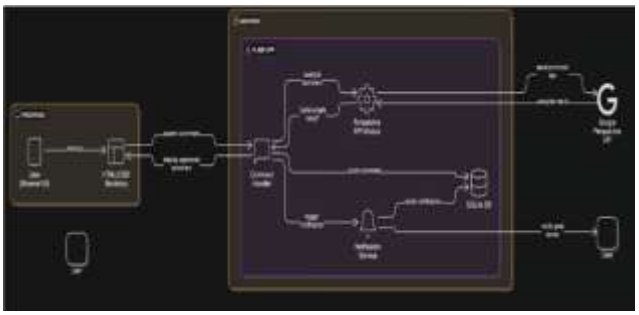
- UI
- Flask Controller
- Perspective API
- Keyword Filter
- Database
- Notification Engine



1.1 Flowchart.



1.2 Data Flow Diagram



1.3 System Architecture

2. Data Flow

User → Comment Submission → API Analysis → Decision Engine → DB/Notification → Display

This approach ensures comments never reach network if toxic.

V. Implementation

Core Features:

Feature	Implementation
Posting	Flask routes & image upload
Commenting	API call + moderation
Notifications	Whether comment blocked/added
Following system	SQL relationship mapping
Like System	One-to-one mapping with users

VI. Results and observation

- System successfully prevents harmful comments before display
- User instantly receives moderation message improving awareness
- No computational training required — lightweight deployment
- Works effectively on local server environment

VII. Future Scope

- Dataset creation & custom model training
- BERT-based offline moderation
- Multilingual text + regional slang extension
- Audio speech bullying classification
- Admin moderation dashboard

VIII. Limitations

1. Dependent on Internet/API availability
2. Keyword fallback list needs periodic expansion manually
3. Sarcasm, emojis and disguised text may bypass filter
4. Multilingual support not yet implemented

IX. Conclusion

This study demonstrates a practical approach to cyberbullying prevention by integrating pre-trained Perspective API models into a live web platform. The hybrid combination of **AI toxicity scoring + keyword fallback** forms a robust pipeline for real-time monitoring, unlike conventional approaches which either require model training or rely solely onmanualreporting. The system is scalable, modular and ideal for institutional deployment. With dataset expansion, offline NLP training, multi-language support and advanced AI moderation, the application can evolve into a full-scale content safety.

X. Editorial Policy

Ensuring accurate reporting of machine learning models is essential. The system follows standard AI development practices, ensuring transparency in model training and evaluation.

XI. Publication Principles

The publication of this research adheres to principles of reproducibility and ethical AI practices, ensuring that the developed model can be replicated and tested by other researchers

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