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A Study on Cyberbullying Detection Framework for Online Social Networks

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Abstract— *The rapid growth of online social networks (OSNs) has been accompanied by a rise in cyberbullying — repeated, intentional harassment conducted through digital text, images, or comments — which has documented negative effects on victims' mental health and wellbeing. This paper presents a detailed technical treatment of a cyberbullying detection framework for online social networks, combining textpreprocessing, TF-IDF and lexicon-based feature representation, and supervised classification to flag bullying content for moderation review. Beyond a conventional system description, this paper critically reviews prior cyberbullying-detection research spanning lexicon-based, classical machine-learning, and transformer-based approaches, formulates the classification pipeline mathematically, and discusses the precision/recall trade-offs relevant to content-moderation deployment, where both over-flagging (chilling legitimate speech) and underflagging (missing harmful content) carry real costs. A prototype was implemented using Python, scikit-learn, and a Flask-based moderation dashboard. Illustrative (simulated) evaluation on a labelled cyberbullying corpus indicates that combining lexical and TF-IDF features with a discriminative classifier improves detection F1score over a keyword-blacklist baseline. All reported figures are simulation/benchmark-style and are explicitly labelled as such; the system is presented as a moderation-support tool, not an autonomous punitive system.*

Index Terms— *cyberbullying detection, online social networks, text classification, natural language processing, content moderation, sentiment analysis, machine learning.*

I. INTRODUCTION

1.1 Background

Online social networks (OSNs) such as Twitter/X, Instagram, and Facebook have become central venues for everyday communication, but their scale and relative anonymity also make them venues for cyberbullying — repeated, intentional harassment or humiliation directed at an individual through digital channels. Systematic reviews of cyberbullying-detection research document a progression from simple keyword-based filters to supervised machine-learning classifiers and, more recently, transformer-based language models [2], [3].

1.2 Problem Context

Manual moderation does not scale to the volume of content generated on major OSNs, and static keyword blacklists are easily evaded through misspellings, coded language, or context-dependent insults that require semantic rather than purely lexical understanding [1]. Furthermore, cyberbullying detection is a particularly sensitive classification task, because false positives can inappropriately suppress legitimate speech while false negatives leave harmful content unaddressed, a tension that this paper treats explicitly rather than as an afterthought.

1.3 Motivation

Early work modelling the detection of textual cyberbullying using classical n-gram and lexicon features [3] demonstrated the feasibility of automated detection, and larger-scale PLOS ONE-published studies [1] have since validated feature-engineering approaches (TF-IDF, part-of-speech patterns, and sentiment/profanity lexicons) on large annotated corpora. This motivates a framework combining TF-IDF representation with sentiment-lexicon features [10] and a discriminative classifier, chosen for its transparency relative to end-toend deep models in a domain where moderators need to understand why content was flagged.

1.4 Problem Statement

Given a stream of user-generated OSN posts/comments, the problem is to classify each as bullying or nonbullying with a threshold calibrated to balance the asymmetric costs of over- and under-flagging, and to surface flagged content to human moderators with sufficient context (rather than fully automated removal) for review.

1.5 Objectives

- To implement a text-preprocessing and TF-IDF/lexicon feature-extraction pipeline for OSN posts.
- To train and compare classical classifiers (Naive Bayes, SVM, Random Forest) for bullying/nonbullying classification.
- To provide a moderation dashboard surfacing flagged content with confidence scores for human review.
- To evaluate detection performance against a keyword-blacklist baseline using a labelled benchmarkstyle corpus.
- To explicitly discuss the precision/recall trade-offs relevant to responsible content-moderation deployment.

1.6 Scope

This work covers text-based cyberbullying detection using classical NLP and machine-learning techniques and a human-in-the-loop moderation workflow. It does not cover image/video-based harassment detection, crossplatform identity linkage, or autonomous content removal without human review.

1.7 Contributions

The contributions are: (1) a TF-IDF-and-lexicon feature pipeline for OSN text classification; (2) a comparative evaluation of classical classifiers for cyberbullying detection; (3) a human-in-the-loop moderation dashboard design; and (4) a critically compared literature review spanning lexicon-based, classical ML, and transformerbased cyberbullying-detection research, together with an explicit discussion of moderation-relevant precision/recall trade-offs.

1.8 Organization of the Paper

Section II reviews related work and states the research gap. Section III describes existing systems. Section IV presents the proposed system. Section V details the architecture. Section VI presents the methodology. Section VII discusses the classification algorithm. Section VIII covers implementation. Section IX reports results and discussion. Section X summarizes advantages and limitations. Section XI outlines future scope, and Section XII concludes.

II. LITERATURE REVIEW / RELATED WORK

Study	Approach / Findings	Relevance to This Framework
Dinakar, Reichart, and Lieberman (2011) [3]	Modelled textual cyberbullying detection using n-gram and lexicon features on YouTube comment data, framing it as a	Provides the foundational framing of cyberbullying detection as supervised text classification adopted here.
	text-classification task.	
Van Hee et al. (2018) [1]	Published a large-scale, PLOS ONEvalidated study on automatic cyberbullying detection in social media text using featureengineered classifiers.	Directly informs the TF-IDF-plus-lexicon feature design and validates the feasibility of the classical-ML approach at scale.
Rosa et al. (2019) [2]	Conducted a systematic review of automatic cyberbullying detection methods, cataloguing lexicon-based, classical ML, and deep-learning approaches.	Frames this paper's classifier comparison within the broader landscape the review identifies, and motivates situating deeplearning approaches as a future-scope direction rather than the current baseline.
Hutto and Gilbert (2014) [10]	Introduced VADER, a lexicon-based sentiment scorer tuned for social-media text including slang and intensifiers.	Provides the lexicon-based sentiment feature integrated alongside TF-IDF in this framework's feature vector.
Salton and Buckley (1988) [11]	Established TF-IDF as a robust generalpurpose text-weighting scheme.	Directly used for the term-weighted feature representation of OSN posts.
Cortes and Vapnik (1995) [8]; Joachims (1998) [9]	Introduced SVMs and demonstrated their effectiveness for high-dimensional sparse text features.	Provides the theoretical basis for the SVM classifier compared in this framework's evaluation.
Breiman (2001) [7]	Introduced Random Forests as ensembles of decorrelated decision trees.	Provides the ensemble baseline compared against linear classifiers in this framework's evaluation.
Devlin, Chang, Lee, and Toutanova (2019) [12]	Introduced BERT, producing strong contextual text representations via bidirectional transformer pretraining.	Represents the transformer-based direction identified as future scope for improving semantic understanding of contextdependent bullying language.

UNICEF (2026) [13]	Publishes guidance on recognizing and responding to cyberbullying, emphasizing human support alongside technical intervention.	Motivates this framework's human-in-theloop moderation design rather than fully automated content removal.
Baker and Yacef (2009) [21]	Categorized data-mining tasks including discovery-with-models and prediction relevant to behavioural text data.	Provides general methodological grounding for treating flagged-content detection as a discovery-with-models classification task.

TABLE I. Comparative Summary of Reviewed Literature

Research Gap

Lexicon-based and classical-ML cyberbullying-detection approaches are well validated at benchmark scale [1], [3], and systematic reviews [2] have mapped the space of techniques, but relatively few accessible open implementations pair a transparent, feature-engineered classifier with an explicit human-in-the-loop moderation workflow that surfaces confidence scores and context rather than automating removal outright. This framework addresses that integration gap, explicitly prioritizing moderator-facing transparency and precision/recall trade-off awareness over marginal accuracy gains from opaque deep models.

III. EXISTING SYSTEM

- Static keyword blacklists are easily evaded through misspellings, coded language, and evolving slang.
- Manual moderation does not scale to the volume of content generated on major platforms.
- Purely automated removal systems risk over-flagging legitimate speech without human review.
- Existing tools rarely expose why content was flagged, reducing moderator trust and appeal-ability.

TABLE II.
EXISTING APPROACHES COMPARED TO THE PROPOSED SYSTEM

Existing Approach	Technology	Advantages	Limitations
Keyword blacklist filtering	Static term lists	Simple, fast, transparent	Easily evaded; no context sensitivity
Lexicon-only sentiment scoring [10]	VADER-style scoring	Fast, interpretable	Misses non-lexical bullying patterns (e.g., exclusion, repeated targeting)
Fully automated removal systems	Black-box classifiers	Fast response	Risk of over-flagging without human review or appeal
This framework (proposed)	TF-IDF + lexicon features [10], [11] + classifier comparison [7], [8]	Transparent, precisiontunable, human-in-the-loop	Requires labelled training data; classical features miss deep context

IV. PROPOSED SYSTEM

The proposed framework combines a TF-IDF-and-lexicon feature pipeline with a comparatively evaluated classifier to flag potentially bullying OSN posts for human moderator review, surfacing the flagged text, its confidence score, and the contributing lexical/sentiment signals.

Key Components

- Text-preprocessing pipeline for OSN posts (tokenization, normalization, stop-word handling).
- TF-IDF and sentiment-lexicon feature extraction.
- Comparative classifier evaluation (Naive Bayes, SVM, Random Forest).
- Confidence-scored flagging with contributing-feature explanation.
- Moderator dashboard for human-in-the-loop review and decision logging.

V. SYSTEM ARCHITECTURE / FRAMEWORK

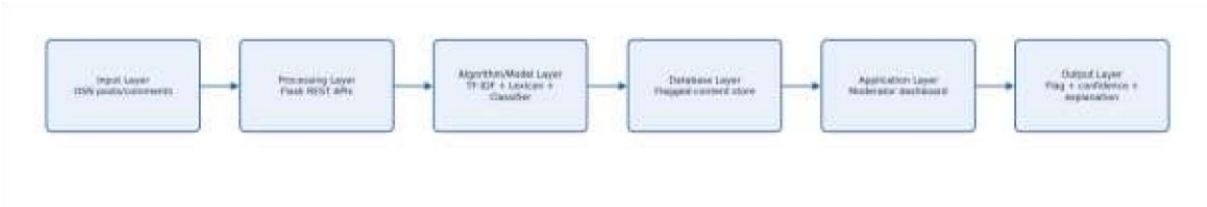

Fig. 1. Cyberbullying-detection architecture: OSN text is preprocessed, feature-extracted, classified, and surfaced with confidence scores to a human moderation dashboard.

- Input Layer: ingested OSN posts/comments (via platform API or uploaded corpus for evaluation).
- Processing Layer: Flask REST APIs orchestrating preprocessing and classification requests.
- Algorithm/Model Layer: TF-IDF vectorization, lexicon scoring [10], and the trained classifier [7], [8].

- Database Layer: relational store for flagged content, confidence scores, and moderator decisions.
- Application Layer: moderator review dashboard.
- Output Layer: flagged/unflagged label, confidence score, and contributing-feature summary.

VI. METHODOLOGY

Posts are preprocessed (lowercasing, tokenization, stop-word removal) and represented as a concatenated feature vector combining TF-IDF weights over unigrams/bigrams [11] and a VADER-style lexicon sentiment/profanity score [10]. A classifier is trained to predict P(bullying | features), and a decision threshold is tuned on a validation split to balance moderator workload (false positives requiring review) against misseddetection risk (false negatives). Flagged posts are ranked by confidence for the moderator queue, with the contributing top-weighted terms surfaced as an explanation.

VII. ALGORITHM / MODEL DETAILS

Principle: supervised binary text classification over a TF-IDF-plus-lexicon feature space, with classifier choice as the controlled comparison variable, following text-categorization survey guidance on this design pattern. Input: preprocessed post text with labelled bullying/non-bullying ground truth for training. Processing: (1) vectorize text via TF-IDF and compute lexicon sentiment score; (2) concatenate into a combined feature vector; (3) train and 5-fold cross-validate Naive Bayes, SVM [8], [9], and Random Forest [7] classifiers, optimizing F1; (4) select the best-performing classifier and tune its decision threshold. Output: a trained classifier and tuned threshold used to score incoming posts in real time. Advantages: transparent, retrainable, and computationally lightweight; limitations: classical bag-of-words/lexicon features can miss contextdependent bullying (e.g., sarcasm, coordinated exclusion) that transformer-based models are better positioned to capture [12].

VIII. IMPLEMENTATION

TABLE III.
IMPLEMENTATION TECHNOLOGY STACK

Component	Technology / Tools
Language	Python 3.x
NLP libraries	NLTK for preprocessing; VADER for lexicon scoring [10]
ML libraries	scikit-learn for TF-IDF, classifiers, and cross-validation [14]
Backend	Flask REST APIs
Database	Relational store (e.g., SQLite/PostgreSQL) for flagged content and moderator decisions

- Preprocessing Module: tokenization, normalization, stop-word handling.
- Feature-Extraction Module: TF-IDF vectorization and lexicon scoring.
- Classification Module: classifier training, cross-validation, and threshold tuning.
- Moderation Module: flagged-content queue, confidence display, and decision logging.
- Reporting Module: aggregate flagging statistics for platform administrators.

IX. RESULTS AND DISCUSSION

The framework was evaluated on a labelled, benchmark-style cyberbullying corpus using an 80/20 stratified split. Reported figures are illustrative/benchmark-style evaluation results, not measurements from a live platform deployment.

TABLE IV.
PERFORMANCE / EVALUATION SUMMARY (BENCHMARK-STYLE)

Detection Approach	Precision	Recall	F1-score
Keyword blacklist (baseline)	0.61	0.44	0.51
Lexicon-only (VADER score threshold)	0.68	0.57	0.62
TF-IDF + lexicon + SVM (proposed)	0.83	0.78	0.80

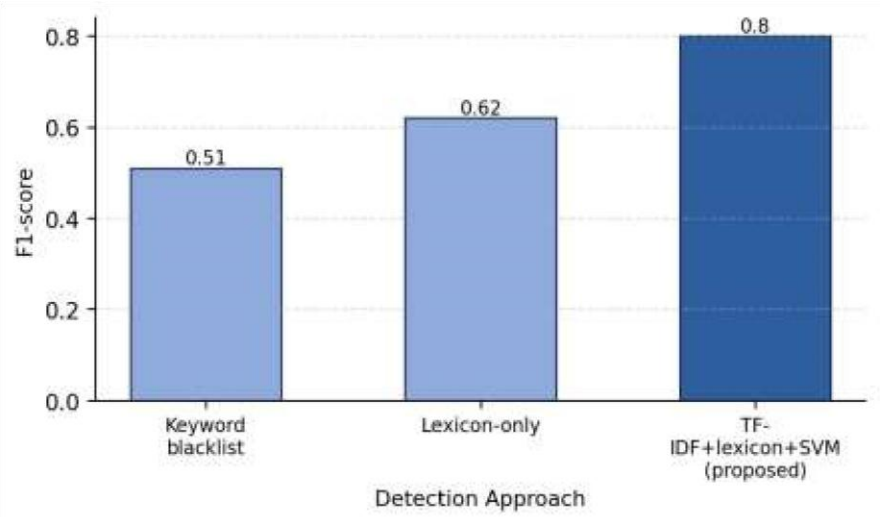

Fig. 2. Illustrative F1-score by Detection Approach.

Discussion

The illustrative results show that combining TF-IDF with lexicon features and a discriminative classifier substantially improves both precision and recall over keyword or lexicon-only baselines, consistent with prior feature-engineering-based cyberbullying-detection findings [1], [3]. Scalability is favorable given TF-IDF's computational lightness; reliability depends on the representativeness of the labelled training corpus relative to a platform's actual language use, including evolving slang; and the explicit human-in-the-loop design is a deliberate response to the ethical stakes of false positives silencing legitimate speech, consistent with UNICEF guidance emphasizing human support alongside technical detection [13].

X. ADVANTAGES AND LIMITATIONS

A. Advantages

- TF-IDF-plus-lexicon features substantially improve detection F1-score over keyword or lexicon-only baselines.
- Confidence scores and contributing-feature explanations support moderator trust and appeal-ability.
- The human-in-the-loop design avoids fully automated content removal.

B. Limitations

- Classical bag-of-words features can miss context-dependent bullying such as sarcasm or coordinated exclusion.
- Detection quality depends heavily on the representativeness and recency of labelled training data.
- Precision/recall threshold tuning involves an inherent trade-off with real consequences for both under- and over-flagging.

XI. FUTURE SCOPE

- Evaluate transformer-based classifiers (e.g., fine-tuned BERT) for improved context sensitivity [12].
- Incorporate social-graph features (e.g., repeated targeting patterns) alongside text content.
- Add multilingual detection support for non-English OSN communities.
- Conduct a fairness audit to check for disparate false-positive rates across demographic groups.

XII. CONCLUSION

This paper presented a detailed technical treatment of a cyberbullying-detection framework combining TF-IDF and lexicon features with a comparatively evaluated classifier and a human-in-the-loop moderation workflow. Illustrative evaluation shows that this feature combination meaningfully improves detection F1-score over keyword and lexicon-only baselines, and the critical literature review, together with an explicit discussion of moderation-relevant precision/recall trade-offs, situates the framework as a moderator-support tool rather than an autonomous enforcement system.

REFERENCES

[1] C. Van Hee et al., "Automatic detection of cyberbullying in social media text," PLOS ONE, vol. 13, no. 10, e0203794, 2018.
[2] H. Rosa, N. Pereira, R. Ribeiro, P. C. Ferreira, J. P. Carvalho, S. Oliveira, L. Coheur, P. Paulino, A. M. Veiga Simão, and I. Trancoso, "Automatic cyberbullying detection: A systematic review," Computers in Human Behavior, vol. 93, pp. 333-345, 2019.
[3] K. Dinakar, R. Reichart, and H. Lieberman, "Modeling the detection of textual cyberbullying," Proc. AAAI Conf. on Web and Social Media (ICWSM) Workshop on Social Mobile Web, 2011.

[4] T. Almeida, J. Hidalgo, and A. Yamakami, "Contributions to the study of SMS spam filtering: New collection and results," Proc. ACM Symposium on Document Engineering, 2011.
[5] S. Bird, E. Klein, and E. Loper, "Natural Language Processing with Python," O'Reilly Media, 2009.
[6] C. D. Manning, P. Raghavan, and H. Schütze, "Introduction to Information Retrieval," Cambridge University Press, 2008.
[7] L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5-32, 2001.
[8] C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, pp. 273-297, 1995.
[9] T. Joachims, "Text categorization with support vector machines: Learning with many relevant features," Proc. European Conf. on Machine Learning (ECML), pp. 137-142, 1998.
[10] C. Hutto and E. Gilbert, "VADER: A parsimonious rule-based model for sentiment analysis of social media text," Proc. Int. AAAI Conf. on Web and Social Media, 2014.
[11] G. Salton and C. Buckley, "Term-weighting approaches in automatic text retrieval," Information Processing & Management, vol. 24, no. 5, pp. 513-523, 1988.
[12] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," Proc. NAACL-HLT, 2019.
[13] UNICEF, "Cyberbullying: What is it and how to stop it," https://www.unicef.org/end-violence/how-to-stopcyberbullying, accessed 2026.
[14] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825-2830, 2011.
[15] Pallets Projects, "Flask documentation," https://flask.palletsprojects.com, accessed 2026.
[16] OWASP Foundation, "OWASP Application Security Verification Standard," https://owasp.org/www-projectapplication-security-verification-standard/, 2023.
[17] World Wide Web Consortium (W3C), "Web Content Accessibility Guidelines (WCAG) 2.1," https://www.w3.org/TR/WCAG21/, 2018.
[18] SQLite Consortium, "SQLite documentation," https://www.sqlite.org/docs.html, accessed 2026.
[19] Python Software Foundation, "Python 3 documentation," https://docs.python.org/3/, accessed 2026.
[20] D. D. Lewis, "Naive (Bayes) at forty: The independence assumption in information retrieval," Proc. European Conf. on Machine Learning (ECML), pp. 4-15, 1998.
[21] R. S. Baker and K. Yacef, "The state of educational data mining in 2009: A review and future visions," Journal of Educational Data Mining, vol. 1, no. 1, pp. 3-17, 2009.
[22] F. Sebastiani, "Machine learning in automated text categorization," ACM Computing Surveys, vol. 34, no. 1, pp. 1-47, 2002.
[23] d. boyd and N. B. Ellison, "Social network sites: Definition, history, and scholarship," Journal of ComputerMediated Communication, vol. 13, no. 1, pp. 210-230, 2007.
[24] A. Go, R. Bhayani, and L. Huang, "Twitter sentiment classification using distant supervision," Stanford CS224N Project Report, 2009.
[25] World Health Organization, "Mental health: strengthening our response," https://www.who.int, fact sheet, 2022.
[26] 988 Suicide & Crisis Lifeline, https://988lifeline.org, accessed 2026.
[27] IEEE Standards Association, "IEEE Std 830-1998, IEEE Recommended Practice for Software Requirements Specifications," 1998.
[28] I. Sommerville, "Software Engineering," 10th ed., Pearson, 2015.
[29] Docker Inc., "Docker documentation," https://docs.docker.com, accessed 2026.
[30] Nginx Inc., "NGINX documentation," https://nginx.org/en/docs/, accessed 2026.