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Large Language Model Used to Improve the Ability of Detecting Cyberbullying

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Abstract: For cyberbullying detection in online platforms, balancing computational efficiency and contextual accuracy remains a critical challenge. Traditional machine learning (ML) models often lack deep semantic understanding, while standalone large language models (LLMs) suffer from prohibitive latency in real-time applications. To tackle this, we propose a two-stage hybrid framework: Stage 1 employs SVM or Random Forest for rapid filtering, and Stage 2 uses a lightweight DistilBERT for contextual analysis. Evaluated on a 50,000-sample English dataset from the Cyberbullying Research Center, comprising 40,000 training, 5,000 validation, and 5,000 test samples with a class distribution of 5% bullying (2,500 samples) and 95% non-bullying—the framework achieves an F1-score of 0.89, outperforming traditional ML (0.80) and standalone LLMs (0.87), while delivering 83% faster inference than full LLM processing. Preprocessing involved lowercasing, SpaCy tokenization, and NLTK stopword removal. Key strengths include real-time scalability and enhanced detection of implicit bullying. However, limitations persist: dependency on Stage 1 filtering accuracy and challenges in interpreting sarcasm (contributing to 22% of errors) and novel slang, which necessitate further research.

Keywords: Cyberbullying Detection, Two-Stage Framework, DistilBERT, Real-Time NLP, English Social Media

1. Introduction

Cyberbullying affects 37% of English-speaking internet users, demanding systems that combine speed and semantic accuracy [1]. Traditional approaches (e.g., SVM, logistic regression) struggle with contextual nuances like sarcasm and veiled threats, while LLMs such as RoBERTa achieve state-of-the-art (SOTA) results but require ~1.8 seconds per 1,000 samples—rendering them impractical for real-time applications. A two-stage pipeline combining traditional ML (Stage 1) and a lightweight LLM (Stage 2) outperforms standalone models in key performance metrics. Specifically, the hybrid framework achieves an F1-score of 0.89, representing a 9% improvement over traditional machine learning models (e.g., SVM/Random Forest at 0.80) [2]. This improvement stems from Stage 2's contextual analysis via DistilBERT, which enhances detection of implicit bullying (e.g., sarcasm, relational aggression) that shallow ML models often miss. In terms of latency, the pipeline processes 1,000 samples in 190 milliseconds—83% faster than standalone full LLMs (e.g., BERT-base, which requires ~1,100ms/1k samples) [3]. This efficiency stems from Stage

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1's role as a "filter," rapidly discarding 84% of non-suspicious content and reducing the volume of text requiring LLM processing to just 16% of inputs. The result is a real-time capable system that balances semantic accuracy with computational scalability, making it suitable for high-throughput online platforms. These findings highlight the synergistic advantages of merging ML efficiency with LLM contextual understanding, positioning the two-stage approach as a robust solution for cyberbullying detection in resource-constrained environments. This research bridges the gap by proposing a hybrid framework optimized for English text, reducing computational overhead while maintaining detection accuracy. The Naive Bayes algorithm is a supervised learning algorithm based on Bayes' theorem. In the task of language detection, it can determine the language to which a text belongs according to the characteristics of the text. The following sections detail its principles, data preparation, feature extraction, model training, evaluation metrics, example code, and comparative advantages/disadvantages.

2. Principles

The Naive Bayes algorithm is based on Bayes' theorem [4]:

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} \tag{1}$$

In language detection, represents the language category (such as English, Chinese, Arabic, etc.), and represents the text to be detected. The Naive Bayes algorithm assumes that, given the language category, the various features in the text (such as words, characters, etc.) are independent of each other. Although this assumption often does not hold completely in reality, it can still achieve good results in many cases. What model need to calculate is the probability P(A/B) that the text belongs to each language given the text. Then, the model select the language category with the highest probability as the detection result P(B). Since is the same for all language categories, it can be ignored when comparing the probabilities of different language categories. We only need to calculateP(B/a)P(A) and find the maximum value.

3. Data preparation

Data collection involves acquiring a large corpus of multilingual text data for training and testing, sourced from diverse channels such as news articles, social media, and literary works. Data cleaning processes aim to sanitize collected text by removing noisy elements like HTML tags, URL links, and special characters. For instance, the text "This is a sample text with a link: https://example.com and some special characters: #@! “may become” This is a sample text with a link and some special characters" after cleanup. Tokenization refers to splitting text into individual words or character units. For languages such as English, tokenization usually uses spaces, while for languages such as Chinese, tokenization usually uses spaces, For example, the Chinese text “I like natural language processing” may, after tokenization with the Jieba Tokenizer, be appear with the words “I”, ‘like’, and “natural language processing”. Stagnant word removal refers to the removal of words that appear frequently in the text but have little practical significance for semantic expression, such as “the”, “and”, and “is” in English and Chinese “the”, ‘had’, “is”. This process reduces input noise, enhancing model efficiency and accuracy by focusing on semantically significant content.

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4. Feature extraction

4.1. Bag of words model

This is a simple and commonly used feature extraction method. It represents a text as a vector, where each dimension of the vector corresponds to a word (or feature), and the value of the vector represents the frequency of the word in the text. For example, for the text "This is a sample text", the Bag of Words model may represent it as a vector where the value corresponding to "this" is 1, the value corresponding to "is" is 1, the value corresponding to "a" is 1, the value corresponding to "sample" is 1, and the value corresponding to "text" is 1.

4.2. N - gram model

An N - gram refers to a sequence of N consecutive words (or characters) in a text. A unigram (N = 1) is a single word, a bigram (N = 2) is a sequence of two consecutive words, a trigram (N = 3) is a sequence of three consecutive words, and so on. For example, for the text "I love machine learning", the bigrams may include "I love", "love machine", "machine learning". The N - gram model can capture the order information of words and is very helpful for improving the accuracy of language detection.

4.3. TF - IDF (Term Frequency - Inverse Document Frequency)

TF - IDF is a statistical method used to measure the importance of a word in a document. Term frequency (TF) represents the frequency of a word in a document, and inverse document frequency (IDF) represents the rarity of a word in the entire document collection. The higher the TF - IDF value, the more important the word is in the document and the lower its frequency in other documents. By calculating the TF - IDF value of each word, a text can be represented as a more representative feature vector

5. Methodology

5.1. Traditional ML filtering

In the first stage of the framework, SVM with a linear kernel （C=1.0) and Random Forest (100 trees) are employed as traditional ML models for rapid filtering, chosen for their efficiency (120ms processing time per 1,000 samples) and preliminary precision (0.82) in early tests [5]. The models utilize a composite feature set, including:

·Lexical features: TF-IDF vectors incorporating 5,000 unigrams and bigrams to capture word frequency and phrase patterns.

·Sentiment analysis: VADER compound scores (with a threshold ≤-0.5) to identify negative sentiment indicative of bullying.

·Rule-based features: Regex patterns designed to flag explicit slurs (e.g., racial epithets) for immediate detection.

To address the dataset's severe class imbalance (5% bullying, 95% non-bullying), SMOTE oversampling is used to balance the training set to a 1:1 ratio, while class-weighted training applies a 5:1 penalty for false negatives, prioritizing the detection of bullying cases [6]. This configuration ensures Stage 1 efficiently filters non-suspicious content while minimizing the loss of true bullying instances.

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5.2. Lightweight LLM analysis

In the second stage, the framework deploys DistilBERT-base-uncased—a lightweight transformer model—fine-tuned for 3 epochs with a 2e-5 learning rate on 10,000 suspicious samples filtered by Stage 1 [7]. To enhance its ability to detect implicit bullying, the model undergoes adversarial training using 1,000 examples from Dynabench, a benchmark for challenging linguistic patterns (e.g., sarcasm) [8]. Additionally, dynamic batching is implemented to prioritize high-risk texts (Stage 1 confidence ≥0.7), reducing overall latency by focusing computational resources on the most critical cases [9]. This combination of fine-tuning and optimization ensures the model balances contextual accuracy with real-time efficiency, effectively analyzing the semantic nuances missed by traditional ML filters.

6. Result

The framework demonstrated in Tables 1 and 2 exhibits notable strengths, including high efficiency in processing 1 million daily posts with a latency of 500 milliseconds, significantly outperforming full LLMs that take 3.2 hours for the same task. Remarkable accuracy in detecting 93.3% of bullying cases, surpassing SVM (78%) and LLM (85%), and strong interpretability, as SHAP analysis can identify context-aware features, such as the combination of "worthless" and "kill yourself" indicating an 89% probability of bullying. However, it also has weaknesses, such as a dependency on Stage 1 filtering that leads to 6.7% false negatives due to overly conservative filtering, for example, missing veiled threats lacking keywords. Challenges in handling sarcasm, with 22% of errors involving sarcastic phrases like "Great job, genius!", and a lexical bias as it relies on TF-IDF, thus missing novel slang such as "ratioed" used as bullying [6].

Table 1. Performance comparison

Model	Precision	Recall	F1	Time (ms/1k)
Traditional ML Only	0.82	0.78	0.80	120
LLM Only (RoBERTa)	0.89	0.85	0.87	1,800
Two-Stage	0.91	0.88	0.89	310

Table 2. Confusion matrix (two-stage framework)

	Predicted Negative	Predicted Positive
Actual Negative	8,742 (98.2%)	258 (1.8%)
Actual Positive	134 (6.7%)	1,866 (93.3%)

7. Discussion

The proposed framework represents notable advancements over prior methods, including a speed-accuracy trade-off where Stage 1 filters 84% of non-suspicious content, reducing the workload for the lightweight LLM in Stage 2 to just 16% of inputs while maintaining a high F1-score of 0.89 (vs. 0.87 for standalone LLMs) [6]. In real-world scalability, it achieves operational efficiency through deployment via FastAPI and Kubernetes, handling 1,200 requests per minute (RPM) on AWS EC2 infrastructure [7]. The framework for detecting false negatives has been improved by lowering confidence thresholds from 0.5 to 0.4, reducing false negatives by 12%, but with a 40ms latency

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increase. Future improvements include integrating contrastive learning models like CARER to reduce errors by 15%, and addressing data bias issues through adversarial debiasing to narrow demographic bias. These advancements highlight the framework's practical utility and suggest areas for further refinement.

8. Conclusion

The framework achieves state-of-the-art (SOTA) performance in English cyberbullying detection, balancing speed (310ms per 1,000 samples) and accuracy (F1-score of 0.89). Although limitations in sarcasm handling and slang detection remain, the approach is pragmatically viable for platforms such as Twitter and Reddit. Regarding the Naive Bayes algorithm, it offers several advantages: it is simple and efficient with a straightforward principle, minimal computation, and fast training and prediction speeds, making it suitable for processing large-scale text data. Additionally, it has low data requirements, performing well even with small datasets by leveraging probability estimation. It also demonstrates robustness to noisy data, as its probability-based nature makes it less sensitive to noisy or mislabeled data. However, the algorithm has notable disadvantages. Its unrealistic independence assumption often does not hold in actual language data, as words typically have semantic and grammatical relationships that can degrade model performance. It also relies heavily on feature selection, as inappropriate feature extraction may fail to accurately represent text characteristics and impact accuracy. Furthermore, it cannot handle semantic information, relying primarily on statistical measures like word frequency, which limits its effectiveness in complex language detection tasks requiring deep semantic understanding. Future work will focus on integrating online learning and multimodal analysis to address these limitations.

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