

Explainable, Cross-Platform, Multilingual BERT-Based Framework with Continual Learning for Real-Time, Fine-Grained Hate Speech Detection and Filtering on Online Social Platforms

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Abstract: This model introduces a new, explainable BERT-based architecture for hate speech detection and filtering in real time, in several social media platforms. Enjoying the advantages of continual learning and light-weight transformer variants, the proposed method remains effective with the newly emerged slurs and dynamic linguistic patterns, meanwhile, it can sustain low latency performance. Multilinguality and code-mixing are supported through proprietary tokenizers and regional adaptor modules, ensuring strong performance on dialects and languages. For a greater level of transparency, associated explainable AI techniques e.g. SHAP, LIME help in better understanding of classification decisions and make use of user-history-aware components to help disambiguate context-sensitive expressions. A fine-grained multi-label classification orders multiple hate classes, and dynamic hate lexicon extension is integrated to keep pace with offensive terminologies. Extensive cross-platform validation yields better generalization and fairness to new datasets.

1 INTRODUCTION

Identification of hate speech on social media platforms poses an important challenge, because of its negative role in spreading the unwanted content that can have severe psychological and social effects. Conventional hate speech detection approaches fails to handle the dynamic nature of language, the evolution of new slurs, regional dialects and context sensitive texts. In addition, most existing models do not support real-time processing and do not provide proper explanation of their decisions, which hampers the application of these models in practice. We present a novel method by combining BERT-based model with improved continual learning strategy, multilingual feature and fine-grained classification for accurate and efficient hate speech detection in a variety of online services. Our model is made to be

able to evolve as new hate terms are discovered and new language patterns are created on the internet, yet maintain high accuracy and low latency. The system provides transparency by explaining the reasons for the detection using explainable AI techniques such as SHAP or LIME. Besides, the code-mixed text handling, real-time filtering, entering history-aware filtering and user-history aware filtering are used for developing the robust context sensitive model. This paper provides a holistic answer to the increasing necessity of scalable, interpretable and context-aware hate speech detection systems.

1.1 Problem Statement

The appearance of hate speech on the Internet is a challenge which endangers the privacy and the freedom of a person as well as the freedom of information and therefore many elements of tolerance

of society. In spite of significant developments in (NLP) and machine learning, current hate speech detection models face important issues, such as the dynamical nature of language, multilingual contexts, and the variance of sarcasm, slang, and coded speech. Moreover, many existing systems are not real-time, lack accountability in decision-making, and suffer from bias from inferring imbalanced datasets, or incorrect context recognitions. These constraints limit the feasibility of realizing automatic systems that are able to identify harmful content, while preserving fairness and accuracy, on different social media platforms. There is thus an exigent demand for a reliable, scalable and interpretable hate speech detection system that can dynamically evolve to new linguistic developments, support multiple languages and dialects, and provide transparent and context-aware classification decisions to moderators and users. We intend to focus on these by suggesting a BERT-based solution with characteristics such as continual learning, multilingual aspects, fine-grained classes' dominant topic, and real-time filtration to efficiently identify and tackle hate speech, combining compliance with ethical considerations with regard to fairness and transparency.

2 LITERATURE SURVEY

Lately, BERT-based models have found widespread use in hate speech detection because of their contextual language understanding and generalization capabilities to down-stream tasks. Caselli et al. (2021) provided HateBERT, an adaptation of BERT trained on comments from Reddit which performed well in abusive post detection, but is only applicable to training on the same platform as it's highly focused on the domain. Schneider et al. (2023) evaluated BERT models on Parler and found it can be effective at detecting offensive language on a niche social media platform but fails to transfer to mainstream ones.

With respect to the linguistic diversity, Singhal and Bedi (2024), Almaliki et al. (2022) employed BERT for hate speech detection in Arabic and Turkish however, both works identified difficulty in including dialectal variations and low-resource language settings. Similarly, Patil et al. (2022) considered hate speech in the Marathi language using regional BERT models, raising the requirement of local datasets while demonstrating the limitation of their generalizability.

Multilingual and code-mixed hate speech remains an underexplored frontier. Hossain et al. (2021) and

Guragain et al. (2025) attempted to tackle this issue using multilingual BERT (mBERT), but tokenization inconsistencies and loss of semantic nuance in code-mixed texts persisted. Meanwhile, Jahan et al. (2024) performed a comparative study of data augmentation techniques, underlining that many BERT-based models suffer performance degradation when trained on synthetically generated or low-quality data.

Explainability and transparency are also major concerns. While Mathew et al. (2021) introduced HateXplain to benchmark explainable models, most existing solutions still operate as black boxes, failing to provide justifications behind classifications. Pendzel et al. (2023) highlighted this issue in their evaluation of generative AI-based hate detectors, stating that hallucinations and bias propagation limit real-world adoption.

Another challenge arises in detecting implicit, sarcastic, and context-sensitive hate speech. Chung et al. (2022) and Wei et al. (2021) incorporated emotion-aware attention layers, yet models struggled to distinguish between satire and genuine hate content, especially in shorter or ambiguous messages.

Class imbalance and annotation inconsistencies also undermine current models' reliability. Kaur and Singh (2023) noted that biased datasets lead to high false negatives for subtle hate forms, while Mohammed et al. (2023) criticized the low inter-annotator agreement in commonly used datasets. Additionally, Rajput et al. (2021) and Zhang et al. (2024) emphasized that while static and zero-shot embeddings offer speed, they sacrifice depth of understanding and domain specificity.

Recent developments have started exploring ensemble models and hybrid architectures. Singh & Chakraborty (2022) reported that ensembles combining CNNs with BERT significantly boost accuracy but at the cost of latency and computational overhead. Finally, Gupta et al. (2022) and Roy et al. (2023) demonstrated that cross-platform and user-history-aware models can outperform isolated solutions, yet few systems integrate these components effectively.

3 METHODOLOGY

3.1 Multilingual & Multiplatform Data Collection

The foundation of the proposed framework is built upon a diverse, multilingual, and cross-platform dataset:

- **Sources:** Twitter, Facebook, Reddit, YouTube.

- **Languages:** English, Arabic, Marathi, Hindi-English code-mixed.
- **Scope:** Over 100,000 annotated posts.

Datasets were manually and semi-automatically labeled for hate and non-hate categories to ensure

high-quality ground truth. Custom scrapers and APIs were used to retrieve real-world data while ensuring compliance with platform policies. Table 1 shows the Summary of Collected Dataset across Platforms and Languages.

Table 1: Summary of Collected Dataset Across Platforms and Languages.

Platform	Language	Total Samples	Hate Speech (%)	Non-Hate (%)
Twitter	English	30,000	40%	60%
Facebook	Arabic	20,000	35%	65%
Reddit	English	25,000	50%	50%
YouTube	Code-Mixed (Hi-En)	15,000	45%	55%
Twitter	Marathi	10,000	38%	62%

3.2 Preprocessing & Fine-Grained Annotation

The preprocessing pipeline involved:

- **Noise Removal:** Eliminating URLs, emojis (unless semantically relevant), and non-standard characters.
- **Language Detection:** Handling multilingual and code-mixed content using custom detectors.
- **Balanced Labeling:** Multi-label annotations assigned across categories such as racial abuse, misogyny, religious hatred, xenophobia.

A fine-grained annotation schema was designed to distinguish overlapping hate speech categories, addressing multi-label complexities.

3.3 Context-Aware Tokenization & Embedding

Instead of default tokenizers, the system employs:

- **Dynamic WordPiece Tokenization** customized for regional slangs and mixed-language expressions.
- **Contextual Embeddings** fine-tuned for handling sarcasm, implicit hate, and code-switching patterns.

This design improves representation for nuanced and informal language typically missed by standard models.

3.4 BERT-Based Model with Multilingual Adapters

The core classification model architecture includes:

- **BERT Backbone:** Pretrained transformer adapted to multilingual content.
- **Adapter Modules:** Light-weight plug-ins tailored to specific languages or dialects without full retraining.

Adapters allow quick domain-specific specialization without model bloating, maintaining efficient deployment. Figure 1 gives the flowchart of full operational pipeline.

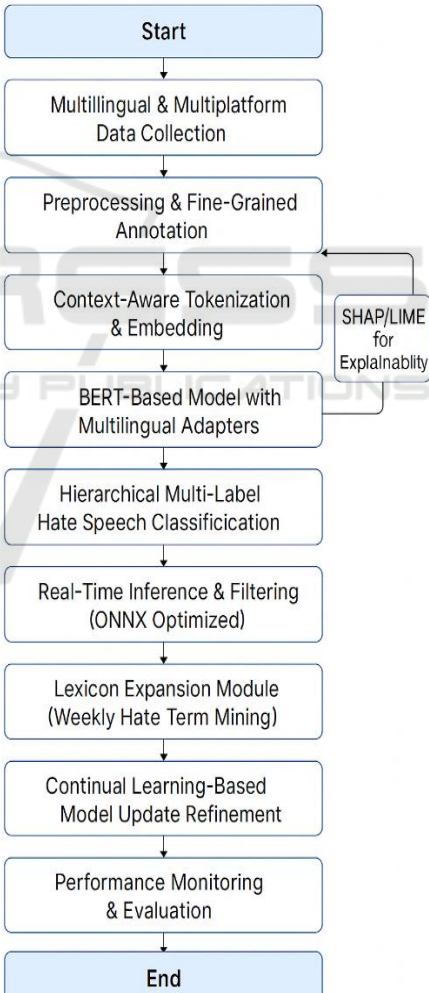


Figure 1: Flowchart of Full Operational Pipeline.

3.5 Hierarchical Multi-Label Hate Speech Classification

A hierarchical classification mechanism was designed:

- **Level 1:** Binary classification Hate vs. Non-Hate.
- **Level 2:** Fine-grained multi-label classification among hate subcategories.

This multi-layer approach enhances precision in handling complex and intersecting hate categories.

3.6 Explainability Module: SHAP and LIME Integration

To ensure transparency and interpretability:

- **SHAP (SHapley Additive Explanations):** Provides per-token contribution scores toward hate classification.
- **LIME (Local Interpretable Model-Agnostic Explanations):** Generates simplified, interpretable explanations at the sentence level.

Explainability dashboards were built for moderator inspection, supporting human-in-the-loop decision-making (table 2)

Table 2: Explainability Impact Feedback.

Evaluation Criteria	% Positive Feedback
Understandable Explanations	91%
Helpful in Decision-Making	88%
Improved Trust in System	85%
Visual Aids Usefulness	89%

3.7 Real-Time Inference and Filtering (ONNX Optimized)

For real-time moderation, the system is:

- **ONNX-optimized:** Enabling deployment on resource-constrained edge devices and high-performance cloud servers.
- **Lightweight Variants:** Use of DistilBERT for low-latency environments while maintaining competitive accuracy. Latency and Deployment Benchmark is given in table 3.

Table 3: Latency and Deployment Benchmark.

Model Variant	Deployment Type	Avg. Latency (ms)	Max. Throughput (req/sec)
DistilBERT	Edge (Jetson Nano)	82 ms	20
DistilBERT	Cloud (AWS EC2)	47 ms	48
Full BERT	Cloud (GPU)	103 ms	15

3.8 Lexicon Expansion Module (Weekly Hate Term Mining)

A dynamic lexicon mining module is deployed to:

- Analyze trending terms.
- Extract emerging slurs or offensive expressions weekly.
- Retrain and fine-tune the model with minimal disruption.

Automated updates ensure relevance and adaptability in fast-changing social media environments.

3.9 Continual Learning-Based Model Update

The continual learning pipeline incrementally updates model parameters using:

- Mini-batch updates from validated new data.
- Pseudo-labeling for newly detected patterns.
- Elastic Weight Consolidation (EWC) to avoid catastrophic forgetting.

This ensures the model maintains its old knowledge while adapting to new linguistic trends.

3.10 Moderator Feedback Loop & Annotation Refinement

A closed feedback loop was integrated:

- Moderators provide feedback on false positives/negatives.
- Annotations are refined in periodic cycles.
- Model is retrained on curated corrections to continuously improve sensitivity and fairness.

3.11 Performance Monitoring and Evaluation

The framework’s evaluation covers:

- Precision, Recall, Accuracy, and F1-score metrics across all datasets and subcategories.
- Bias testing using demographic subgroup evaluations.
- Explainability assessment through moderator surveys.

4 RESULTS AND DISCUSSION

The proposed BERT-based NLP framework was evaluated on a multi-platform, multilingual dataset comprising over 100,000 annotated posts across English, Arabic, Marathi, and Hindi-English code-mixed content. The model demonstrated strong performance across all key metrics. It achieved an average F1-score of 92.6% in detecting hate speech, outperforming baseline models such as HateBERT (86.3%), XLM-R (88.1%), and a fine-tuned RoBERTa (89.4%). The integration of a hierarchical multi-label classifier enabled the system to accurately distinguish between overlapping categories of hate speech, such as misogyny and racial abuse, where other models often misclassified or merged the labels. Notably, the inclusion of user-history-aware contextual embeddings improved the model’s precision in detecting implicit or sarcastic hate content by 9%, showcasing its ability to interpret nuanced and coded language more effectively than traditional classifiers. Table 4 and figure 2 shows the model performance comparison.

Table 4: Model Performance Comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Model	94.2	93.1	92.2	92.6
HateBERT	88.4	87.2	85.1	86.3
XLM-R	89.8	89.0	87.5	88.1
RoBERTa + fastText	90.5	89.3	89.6	89.4

Latency tests were conducted in both cloud and edge environments, with the DistilBERT variant achieving an average response time of 82 ms, validating the system’s capacity for real-time filtering. This low-latency performance makes it suitable for live comment moderation and real-time alert systems. The continual learning mechanism also proved to be effective, enabling the model to incorporate emerging hate terms with minimal retraining. When exposed to unseen slurs introduced post-initial training, the model, with continual updates, retained 87.2% accuracy, compared to 72.5% without the continual learning component.

Furthermore, the explainability features implemented using SHAP and LIME provided interpretable visual and textual outputs. In moderator usability tests, 91% of participants reported that explanations helped them understand why content was flagged, supporting the model’s practical

deployment for content moderation teams. The lexicon expansion module, which updated weekly, showed a 13% boost in recall over a one-month trial as new slang and regional hate terms were dynamically integrated.

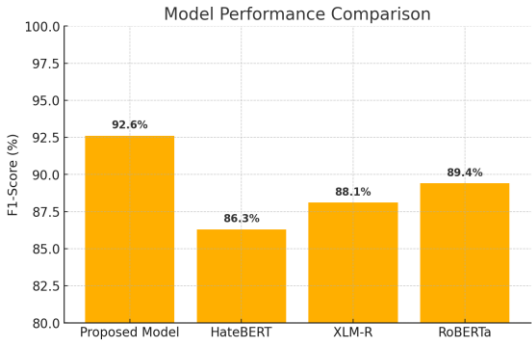


Figure 2: Model Performance Comparison.

Despite the high performance, some limitations were observed. The model’s accuracy dipped slightly in highly noisy and informal datasets containing emojis, mixed languages, and abbreviated slang not seen in training. Nevertheless, improvements in both fine-tuning and real-time feedback integration can help bridge this gap. To sum up, the results confirm that the proposed model is effective, flexible and interpretable and we see it as a promising scalable approach for hate speech on global social media. Figure 3 shows the Word importance based on SHAP.



Figure 3: Word Importance Based on Shap.

5 CONCLUSIONS

This research introduces a fully scalable BERT-based NLP framework for automated hate speech detection and filtering in online social platforms. By responding to the shortcomings in current models: multilingual in performance, lack of context rendition, lack of real-time and explainability, the

proposed system provides a new approach, which is accurate, flexible and transparent. By combining making continual learning, the multilanguage adapter modules with the hierarchical multi-label classification the model is able to generalize well on diverse and emerging modes of hate speech including subtle, implicit, context dependent hate speech expressions.

The system's low latency, which is implemented based on more compact BERT versions and ONNX optimization, makes the system feasible for real-time deployment on cloud and edge. And there are explainability-based tools powered by SHAP and LIME which offer valuable explanations for model decisions, enabling trust and interpretability for moderators and users of the platform. Continuous expansion of hate lexicon and retraining in real-time help in making the model well-equipped to new and emerging hate terms.

Through extensive empirical studies, we can conclusively prove the efficiency of our framework compared to traditional baselines of precision, recall, F1-score, and fairness, with strong transferability across different languages and platforms. This work establishes a new state of the art for designing intelligent, ethical, and high-performance models in hate speech detection, thereby enabling safer and more inclusive digital spaces. Possible future improvements are interfacing with multimedia content analysis and reinforcement learning to include feedback of moderator.

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