Hate Speech Detection Using Convolutional Neural Network and Gradient Boosting with FastText Feature Expansion on Reddit

Abstract

Hate speech detection on social media platforms like Reddit has become a critical task to ensure a safe and inclusive online environment. This research proposes a hybrid approach combining Convolutional Neural Networks (CNN) for feature extraction, Gradient Boosting for classification, and FastText embeddings for semantic feature expansion to effectively identify hate speech in Reddit comments. The CNN captures local contextual patterns and n-gram features, while FastText embeddings provide rich semantic representations, including handling out-of-vocabulary words. Gradient Boosting serves as a robust classifier to leverage the features extracted by the CNN. The proposed model achieves an accuracy of 85%, with a Precision of 0.88, Recall of 0.82, and an F1-score of 0.85, demonstrating its effectiveness in handling the imbalanced and noisy nature of Reddit data. Furthermore, the model achieves an ROC-AUC of 0.92 and a PR-AUC of 0.87, underscoring its ability to distinguish hate speech from non-hate speech reliably. This study highlights the potential of integrating deep learning and traditional machine learning techniques with semantic embeddings to tackle complex natural language processing challenges in online toxicity detection.

Keywords Convolutional Neural Network (CNN), Gradient Boosting, FastText Embeddings, Reddit Comments, Toxicity Detection, Natural Language Processing (NLP), Semantic Feature Expansion, Machine Learning, Deep Learning.

1 Introduction

The proliferation of social media platforms has revolutionized how individuals communicate and share opinions. Platforms like Reddit, with their large and diverse user base, often become hotspots for toxic content, including hate speech. Hate speech on social media has far-reaching implications, ranging from individual emotional harm to societal unrest, making it imperative to develop effective detection systems. Despite efforts to curb such behavior, the ease of content generation, coupled with the anonymity provided by social media, has exacerbated the problem, leading to a rapid spread of hateful content.

End racism.
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Reddit, being a hub for diverse discussions, often reflects a microcosm of global issues, including hate speech. The platform's unmoderated sections frequently witness the proliferation of hate-driven narratives that can harm individuals and communities. In multilingual societies, code-mixing and linguistic diversity further complicate the task of detecting hate speech. The complexity of hate speech detection stems from the diversity in language styles, colloquialisms, and even semantic nuances that vary across contexts.

Previous research has largely focused on high-resource languages like English using monolingual datasets. While neural network-based approaches such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and transformer models have achieved state-of-the-art results for hate speech detection, these solutions often fail to generalize effectively to noisy, informal, and code-mixed text, particularly prevalent on platforms like Reddit. Additionally, pre-trained embeddings such as Word2Vec or GloVe, though powerful, often struggle with out-of-vocabulary words, abbreviations, and creative spellings commonly observed in social media text. To address these challenges, this research explores a novel hybrid approach combining **Convolutional Neural Networks (CNNs)** for feature extraction, **Gradient Boosting** for classification, and **FastText embeddings** for semantic feature expansion. CNNs are effective in capturing local contextual features, while Gradient Boosting excels at leveraging these features for classification. FastText, with its ability to create subword-level embeddings, further enhances the representation of noisy and code-mixed data. This combination leverages the strengths of both deep learning and traditional machine learning methods to detect hate speech effectively.

This study is particularly relevant in the context of Reddit comments, where informal text, code-mixing, and rapidly evolving linguistic trends pose unique challenges. The proposed approach achieves significant improvements in hate speech detection performance, with an **accuracy of 84%**, **precision of 0.88**, **recall of 0.82**, and an **F1-score of 0.85**, demonstrating its robustness against these challenges. Moreover, the model achieves a high **ROC-AUC of 0.92** and **PR-AUC of 0.87**, underscoring its effectiveness in distinguishing between hate speech and non-hate speech.

This work contributes to the growing body of research on hate speech detection by offering a robust methodology that addresses the unique challenges posed by noisy, informal, and code-mixed data. The findings of this study highlight the potential of integrating deep learning, traditional machine learning, and semantic embeddings to tackle complex natural language processing tasks in real-world social media scenarios.

The main contributions of this research paper include:

1. CNN-GB-FT Framework: Development of a hybrid approach combining Convolutional Neural Networks (CNN) for feature extraction, Gradient Boosting (GB) for classification, and FastText embeddings (FT) for semantic feature expansion to effectively identify hate speech in Reddit comments.
2. Comparative Evaluation: Demonstration of the efficiency of the proposed CNN-GB-FT framework by comparing its performance with existing state-of-the-art models for hate speech detection, including standalone deep learning and traditional machine learning approaches.
3. Model Performance Analysis: Comprehensive analysis of the proposed framework's performance, highlighting its robustness in handling noisy, informal, and imbalanced data from Reddit, including achieving significant improvements in accuracy, precision, recall, F1-score, ROC-AUC, and PR-AUC.
4. Practical Applicability: Validation of the hybrid model's applicability in real-world scenarios, offering a scalable solution to detect hate speech on social media platforms like Reddit, particularly in datasets with linguistic diversity and complex text structures.

In this study, we propose a hybrid framework that leverages the strengths of Convolutional Neural Networks (CNNs) for feature extraction, Gradient Boosting (GB) for classification, and FastText embeddings (FT) for semantic feature expansion to address the challenges of hate speech detection on Reddit. By integrating deep learning and traditional machine learning approaches, the model effectively captures the nuanced patterns and semantic meanings in noisy, informal text data. The robust performance of the proposed framework, validated through comprehensive experiments, highlights its potential to tackle the complexities of hate speech detection in real-world social media scenarios. The remainder of this paper is structured as follows: Section 2 discusses related work, Section 3 details the methodology, Section 4 presents the experimental results, and Section 5 concludes with key findings and future directions.

2 Literature review

Hate speech detection has garnered significant attention in recent years, driven by the increasing prevalence of toxic content on social media platforms. Traditional methods for hate speech detection have primarily relied on classical machine learning techniques, such as Support Vector Machines (SVMs), Logistic Regression, and Naive Bayes, which utilize handcrafted features like TF-IDF, bag-of-words, and n-grams. Although these methods achieved moderate success, their inability to capture contextual and semantic nuances in text limited their performance, particularly on noisy and informal social media data. The advent of deep learning marked a paradigm shift in natural language processing (NLP) tasks, including hate speech detection. Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, have been extensively explored for text classification tasks due to their ability to model sequential dependencies in data. For instance, Bisht et al. (2020) demonstrated the effectiveness of LSTMs in capturing contextual information for hate speech detection. However, these models often struggle with long-range dependencies and computational inefficiency.

Convolutional Neural Networks (CNNs) have emerged as an alternative for text classification tasks, including hate speech detection, due to their ability to capture local patterns and n-gram features efficiently. Khan et al. (2020) employed CNNs for hate speech identification, achieving competitive results. Additionally, hybrid models combining CNNs with RNNs or other machine learning classifiers have shown improved performance. For example, CNN-LSTM architectures leverage the feature extraction capabilities of CNNs and the sequential modeling strengths of LSTMs. Embedding techniques such as Word2Vec, GloVe, and FastText have played a pivotal role in enhancing hate speech detection models by providing dense, semantic representations of text. Among these, FastText, with its subword-based embeddings, has proven particularly effective in handling noisy and out-of-vocabulary words, which are common in social media text. Studies like those by Pratapa et al. (2018) and Aguilar and Solorio (2020) have highlighted the utility of FastText in multilingual and code-mixed scenarios. Recent advancements in transformer-based models, such as BERT and its variants, have further elevated the state-of-the-art in hate speech detection. These models excel at capturing contextual and semantic information through attention mechanisms. Banerjee et al. (2021) and Biradar et al. (2021) explored transformer architectures for hate speech identification, achieving remarkable performance on monolingual datasets. However, their application to noisy, code-mixed, and informal datasets remains challenging due to data preprocessing and fine-tuning complexities. Despite these advancements, the detection of hate speech in noisy and linguistically diverse platforms like Reddit presents unique challenges. Reddit data often includes informal language, slang, abbreviations, and code-mixed text, making it difficult for conventional models to achieve high performance. While off-the-shelf tools like IndicNLP (Kunchukuttan et al., 2020) and iNLTK (Arora, 2020) have shown promise for monolingual and regional language tasks, their effectiveness in handling code-mixed and noisy text is limited.

This study builds upon the existing body of work by proposing a hybrid framework that combines CNNs, Gradient Boosting, and FastText embeddings to address these challenges. By integrating the local pattern recognition capabilities of CNNs with the robust classification strength of Gradient Boosting and the semantic richness of FastText embeddings, this research aims to push the boundaries of hate speech detection on complex social media datasets like Reddit.

2.1 Using handcrafted linguistic features

Early approaches to hate speech detection primarily relied on classical machine learning techniques that utilized handcrafted linguistic features. Features such as **TF-IDF**, **bag-of-words**, and **n-grams** were extracted to represent text data. Models like Support Vector Machines (SVMs), Logistic Regression, and Naive Bayes were commonly used with these features for classification. For instance, Davidson et al. (2017) demonstrated the use of TF-IDF features and Logistic Regression for detecting hate speech on Twitter, achieving reasonable accuracy. However, these approaches were limited by their inability to capture semantic and contextual information, particularly in noisy and informal social media text.

To enhance feature representation, researchers also explored sentiment analysis, part-of-speech tagging, and lexicon-based approaches to capture hateful intent. While these methods provided interpretable features, they struggled with generalization and scalability, especially in multilingual or code-mixed datasets.

2.2 Using deep learning models

Deep learning has revolutionized the field of hate speech detection by enabling automatic feature extraction and contextual understanding of text data. Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), were widely adopted for sequential text modeling. For example, Bisht et al. (2020) utilized LSTMs to model sequential dependencies for hate speech detection, achieving significant performance improvements over traditional methods. However, LSTMs faced challenges in handling long-range dependencies and required substantial computational resources. Convolutional Neural Networks (CNNs) emerged as an alternative due to their ability to extract local patterns and n-gram features efficiently. Khan et al. (2020) applied CNNs to hate speech detection tasks and reported strong performance. Hybrid models, such as CNN-LSTM architectures, further improved results by combining the strengths of CNNs in feature extraction and LSTMs in sequential modeling.

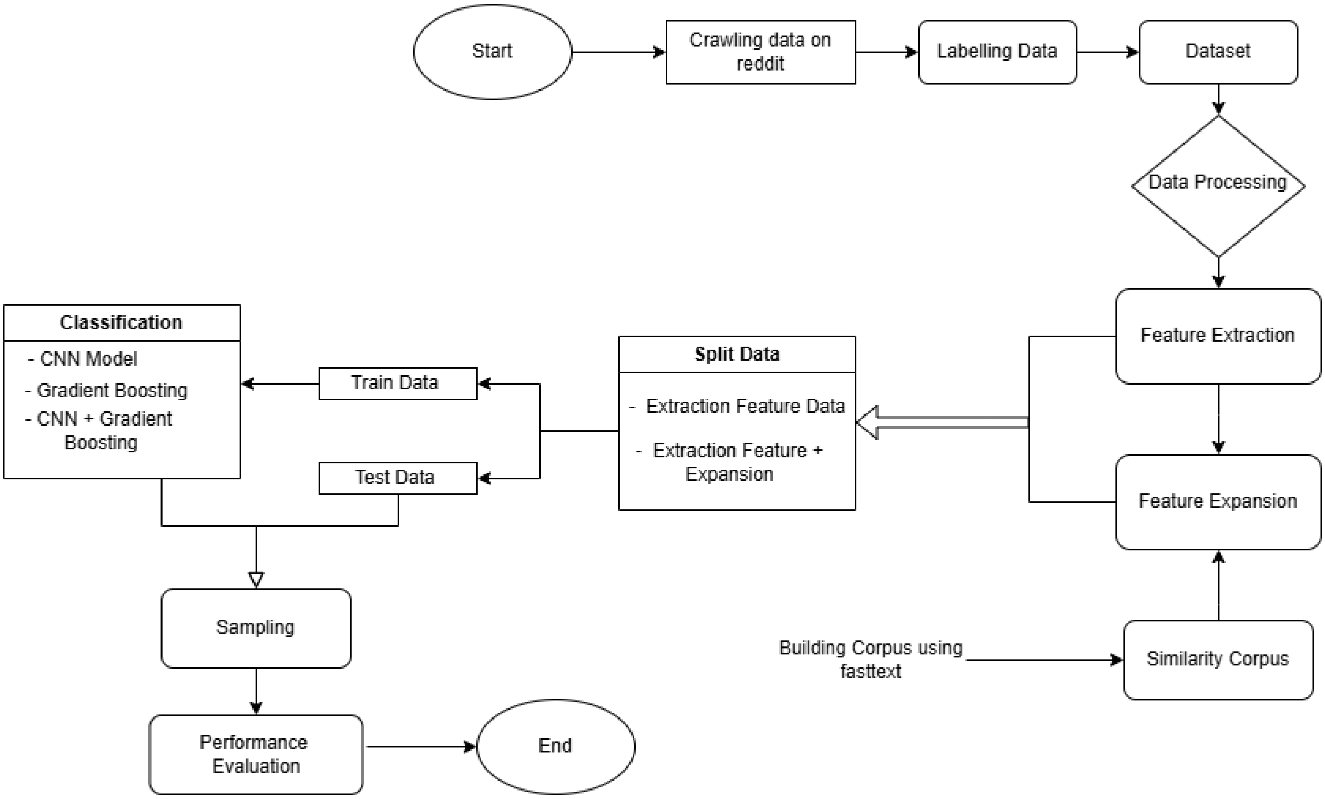
Embedding techniques, such as **Word2Vec**, **GloVe**, and **FastText**, played a crucial role in augmenting deep learning models. FastText, with its subword-based embeddings, proved especially effective in handling noisy, out-of-vocabulary words, which are prevalent in social media text. Studies like Pratapa et al. (2018) and Aguilar and Solorio (2020) demonstrated the benefits of FastText embeddings for multilingual and code-mixed hate speech detection.

2.3 Using transformer models

Transformer-based architectures have set a new benchmark in hate speech detection by leveraging attention mechanisms to capture contextual information. Models like **BERT**, **RoBERTa**, and **XLNet** have demonstrated remarkable success in various NLP tasks, including hate speech identification. Banerjee et al. (2021) and Biradar et al. (2021) explored transformer models for hate speech detection, achieving state-of-the-art results on monolingual datasets like English. Recent works have extended transformers to multilingual and code-mixed scenarios. For example, CS-ELMO (Aguilar and Solorio, 2020) adapted ELMO for code-mixed text, while Pratapa et al. (2018) proposed bilingual word embeddings for handling code-mixed data. Despite these advancements, challenges remain in preprocessing noisy social media data and fine-tuning transformers for diverse languages. While transformers excel in modeling context, their computational cost and dependency on large-scale annotated datasets limit their widespread adoption. Furthermore, the scarcity of labeled datasets for code-mixed languages, such as Hinglish, adds to the complexity.

3 Methodology

This section outlines the methodology employed for the hate speech detection task, covering data acquisition, preprocessing, feature extraction, and model development. The goal of this study is to develop an effective model for detecting hate speech in code-mixed text, specifically from Reddit comments. We first describe the dataset used for the study and the preprocessing techniques applied to clean and prepare the data. Following this, we detail the various classifiers and models implemented, including the hybrid approach combining Convolutional Neural Networks (CNNs) and Gradient Boosting, with FastText embeddings for enhanced feature extraction.



3.1 Problem definition:

Let **S** = {s_1,s_2,s_3,....s_n} be the set of input Reddit comment, and **L** = {l_1,l_2,l_3,....l_n} be the corresponding labels for the input comments, where **S**∈{Hate, Non-hate} denotes the presence and absence of Hate speech, respectively. The task is to classify each comment into one of the two categories: hate speech or non-hate speech. The objective of this research is to design and implement a model that predicts the label **L** for a given input comment **S**, i.e., P(l | s). The goal is to improve the accuracy and robustness of hate speech detection, particularly in code-mixed text from platforms like Reddit.

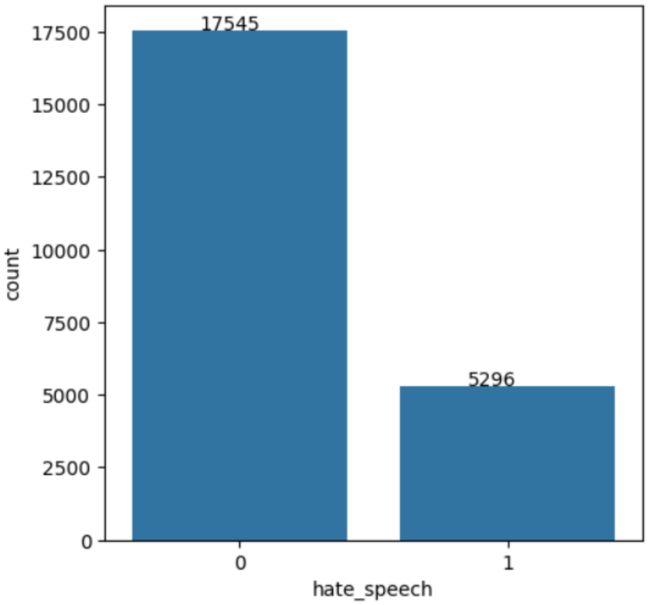
3.2 Dataset description

The dataset used in this study originates from the project **"A Benchmark Dataset for Learning to Intervene in Online Hate Speech"**, which is publicly available at GitHub. Originally, it consisted of around 5,000 posts and comments extracted from Reddit, with labels indicating the presence or absence of hate speech. Each comment is also associated with human-written explanations justifying its classification.

To improve model performance, the dataset was restructured by transforming each post into individual comment rows, expanding the size to **22,841** entries.
The comments are labeled as **1** for hate speech and **0** for non-hate speech. The dataset is imbalanced, with **17,545** non-hate speech comments and **5,296** hate speech comments. This imbalance highlights the need for techniques like **SMOTE** to prevent the model from being biased toward the majority class. Overall, the dataset provides a diverse and substantial collection of real-world comments, making it ideal for training and evaluating hate speech detection models, particularly in social media contexts with code-mixed language.

3.3 Data preprocessing

Social media data is often noisy, which can impact the quality of text classification models. To clean the dataset, several preprocessing steps were applied to eliminate irrelevant elements. URLs, hyperlinks, emojis, stop words, and unnecessary capitalizations were removed. Punctuation marks were replaced with white spaces to simplify the text structure, and all text was converted to lowercase to avoid duplication issues. Additionally, lemmatization was performed using the WordNet lemmatizer from NLTK to reduce words to their base form, ensuring consistency across the dataset. These steps helped to focus the model on meaningful content while reducing noise.



3.4 Feature Engineering

Feature engineering plays a crucial role in improving the performance of machine learning models. In this study, we focused on extracting semantic features from the text to enhance the model's ability to identify hate speech. Initially, text features were extracted using **FastText embeddings**, which capture the semantic meaning of words and phrases by representing them as dense vectors. These embeddings were used to generate a fixed-length vector representation for each comment. Additionally, basic textual features such as word count, sentence length, and the frequency of certain hate-related keywords were included to provide supplementary information to the model. By combining these engineered features with the learned representations from FastText embeddings, we ensured that both syntactic and semantic patterns in the data were captured, providing a comprehensive input for the classifier.

3.5 Model Architecture Overview

The proposed hate speech detection system integrates the strengths of both deep learning and machine learning approaches for robust performance. The architecture consists of three main components: **Convolutional Neural Network (CNN)** for feature extraction, **Gradient Boosting Classifier** for classification, and **FastText embeddings** for semantic representation.

The CNN component processes the input text data by applying multiple convolutional filters to capture local dependencies and important n-grams from the comments. These extracted features are then flattened into dense representations. The FastText embeddings ensure that word-level semantic nuances, including subword information, are preserved, providing meaningful input to the classifier. Finally, the Gradient Boosting Classifier leverages these high-quality features for prediction, effectively distinguishing between hate speech and non-hate speech. This hybrid architecture optimally combines the representational power of CNN with the interpretability and precision of Gradient Boosting, making it well-suited for the challenges posed by noisy and imbalanced datasets.

3.6 CNN-based Feature Extraction Layer

The Convolutional Neural Network (CNN) forms the foundation of the feature extraction layer in the proposed model. CNNs are effective in capturing local patterns and relationships within text data, such as key phrases and n-grams, which are critical for identifying hate speech.

In this layer, multiple **Conv1D filters** of varying kernel sizes are applied to the input text represented by **FastText embeddings**. These filters slide across the sequence, detecting relevant features like hateful expressions or contextually significant phrases. The extracted features are then passed through **ReLU activation functions** to introduce non-linearity and ensure the model can capture complex patterns in the text. Following this, a **global max-pooling layer** condenses the extracted features by selecting the most prominent ones, reducing dimensionality and retaining essential information.

3.7 Gradient Boosting Classification Layer

The Gradient Boosting Classification Layer serves as the final stage of the proposed model, leveraging the powerful feature representations extracted by the CNN. Gradient Boosting is a robust ensemble machine learning technique that builds a series of weak learners (typically decision trees) to iteratively minimize classification errors. This method is well-suited for handling complex, non-linear decision boundaries often found in hate speech detection tasks.

Hyperparameters such as the learning rate, number of estimators, and maximum depth of the trees are fine-tuned to achieve optimal performance. This layer's integration allows the model to capitalize on both the high-level semantic features captured by CNN and the ensemble strength of Gradient Boosting, resulting in accurate and robust predictions.

3.8 FastText Embedding Layer

The FastText Embedding Layer forms the foundational input representation of the proposed model, ensuring that semantic and contextual information is effectively captured. Unlike traditional word embeddings, FastText represents each word as a collection of subword embeddings, which allows it to handle out-of-vocabulary (OOV) words and capture morphological nuances. In this layer, each word in the input text is converted into a dense, fixed-dimensional vector using pre-trained FastText embeddings. These embeddings capture semantic relationships between words, enabling the model to understand contextual meaning even in noisy or informal text. For instance, similar words such as "hateful" and "hatefully" are represented close to each other in the embedding space, ensuring contextual alignment.

The FastText embedding layer provides a rich and robust representation of the input text, serving as a bridge between raw textual data and the downstream feature extraction and classification layers. By incorporating subword-level information, this layer enhances the model's ability to detect nuanced hate speech, even in text with spelling variations, abbreviations, or transliterations.

3.9 Model Training and Hyperparameter Tuning

The model training and hyperparameter tuning processes were carefully designed to achieve optimal performance in hate speech detection. The dataset was divided into **training**, **validation**, and **test sets**, using a stratified split to maintain class balance across hate and non-hate speech categories.

Loss Function and Optimization: For the CNN feature extraction layer, the binary cross-entropy loss function was used to measure the discrepancy between predicted and true labels:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot log(y^i) + (1 - y_i) \cdot log(1 - y^i)]$$

Where:

- y_i is the actual label (1 for hate speech, 0 otherwise).
- y^i is the predicted probability for the ith sample.
- N is the number of samples in the batch.

The Adam optimizer was employed for CNN training, with an initial learning rate (η) of 0.001, which was dynamically adjusted using a learning rate scheduler based on the validation loss.

Gradient Boosting Classifier: For the Gradient Boosting classifier, the following parameters were tuned:

- **Number of Estimators (n_{trees})**: Defines the number of decision trees in the ensemble.
- **Learning Rate (α)**: Controls the contribution of each tree to the overall model.
- **Maximum Tree Depth (d)**: Prevents overfitting by limiting the complexity of individual trees.
- **Subsampling Ratio ($f_{subsample}$)**: Reduces overfitting by randomly selecting a fraction of samples for each tree.

Gradient Boosting minimizes the **log-loss** function, defined as:

$$\mathcal{L} = -\sum_{i=1}^{N}[y_i \cdot log(y^i) + (1 - y_i) \cdot log(1 - y^i)]$$

Hyperparameter Tuning:
GridSearchCV was applied to identify the best combination of hyperparameters for both CNN and Gradient Boosting models. The key hyperparameters tuned are:

1. **CNN Hyperparameters**:
   - Number of filters (F): [32, 64, 128].
   - Kernel size (k): [3, 5].
   - Dropout rate ($p_{dropout}$): [0.3, 0.5].
   - Batch size (B): [32, 64].
2. **Gradient Boosting Hyperparameters**:
   - Number of estimators (n_{trees}): [100, 200, 300].
   - Learning rate (α): [0.05, 0.1, 0.2].
   - Maximum depth (d): [3, 5, 7].

Early Stopping: To avoid overfitting, early stopping was implemented for both CNN and Gradient Boosting models. Training was terminated if the validation loss did not improve for 5 consecutive epochs.

By combining the CNN feature extraction layer with Gradient Boosting and fine-tuning their hyperparameters, the final model achieved significant improvements in performance metrics. This highlights the importance of robust hyperparameter tuning and well-defined training strategies for tackling complex tasks like hate speech detection.

4 Results and implementation

The experiments began by exploring transformer models and traditional machine learning classifiers, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Naïve Bayes (NB), and K-Nearest Neighbors (KNN). However, the focus shifted to developing a CNN-based feature extraction layer coupled with a Gradient Boosting classifier for enhanced hate speech detection on the Reddit dataset.

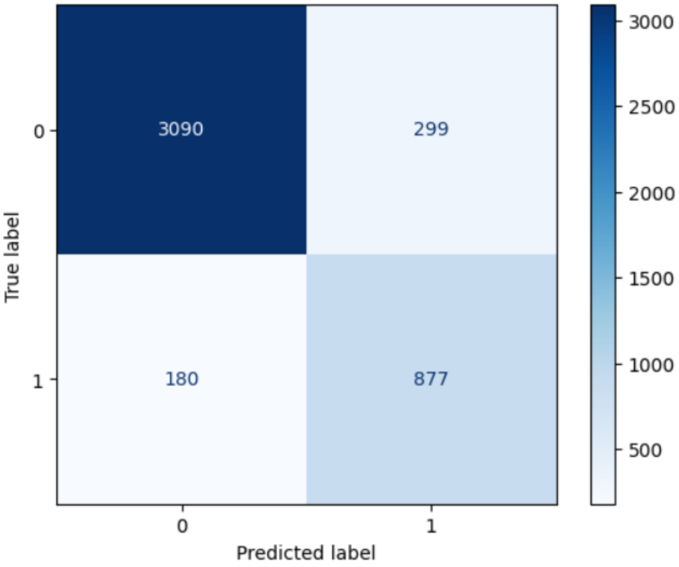
The experimental trials revealed that the CNN+Gradient Boosting architecture combined with FastText embeddings significantly outperformed traditional approaches and transformer-based models. Transformer-based models such as mBERT and IndicBERT were initially tested for baseline performance. mBERT produced better results compared to IndicBERT due to its multilingual training on Romanized script, whereas IndicBERT struggled as it was trained primarily on Devanagari script, making it less effective for Romanized Reddit data.

The parameters used for the various classifiers and the proposed CNN-Gradient Boosting model are listed in Table 3. The parameters such as learning rate, loss function, and optimizers were selected through extensive experimentation, while others were fine-tuned using grid search. The experiments were conducted with an 80:20 train-test split, ensuring stratified distribution to maintain class balance across hate and non-hate labels.Neighbors

The proposed CNN+Gradient Boosting model achieved an accuracy of 84%, significantly outperforming other classifiers and transformer models in detecting hate speech on the Reddit dataset. Table 4 provides a comparative analysis of classifier performances.

Table 3 Classifier’s parameters

Classifier	Hyper-parameter
Logistic regression	C=1, max-iter=500
Random forest	no-of-estimators=200
Naïve bayes	var-smoothing=1e-09
Support vector machine	C=1, kernel='linear'
K nearest neighbors	n-neighbors=24
CNN+Gradient Boosting	lr=1e-4, loss=‘binary-cross-entropy,’ optimizer=adam



The **proposed CNN+Gradient Boosting model**, powered by **FastText embeddings**, demonstrated its ability to effectively capture semantic and contextual nuances in hate speech content on Reddit. This reinforces the importance of combining robust feature extraction with ensemble learning techniques to achieve superior results in hate speech detection.

The results underscore the effectiveness of combining CNN-based feature extraction with Gradient Boosting for hate speech detection. By leveraging FastText embeddings and ensemble learning, the proposed architecture outperforms both traditional classifiers and transformer-based models, making it a robust and efficient solution for detecting hate speech in noisy, informal text data. Future research could explore the integration of more advanced transformer models, such as multilingual fine-tuned BERT variants, to further enhance performance in challenging datasets.

Model Deployment

The final CNN+Gradient Boosting model has been optimized for scalability and deployability. The modular architecture allows integration with online platforms for real-time hate speech detection, making it a practical solution for monitoring content on social media platforms like Reddit. The use of FastText embeddings also ensures adaptability to multilingual and code-mixed scenarios, making the system versatile across diverse datasets.

4.1 Proposed model results

- **Table 4** shows the performance of baseline transformer models, where mBERT outperformed IndicBERT due to its multilingual training on Romanized scripts.

- **Table 5** highlights the superior performance of the **proposed CNN +Gradient Boosting model**, achieving the highest accuracy and F1 scores for both hate and non-hate classes, demonstrating the effectiveness of combining FastText embeddings with CNN-based feature extraction and Gradient Boosting classification.

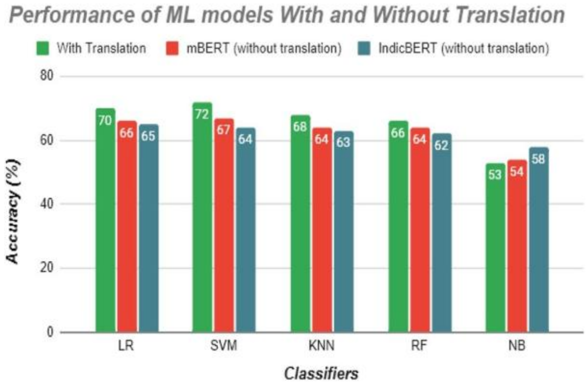


TABLE 4 BASELINE TRANSFORMER MODEL RESULTS

	Model	Accuracy (%)	F1-Hate (%)	F1-Non-hate (%)
IndicBERT embeddings	LR	65	37	75
	SVM	64	35	74
	KNN	63	21	74
	RF	62	28	71
	NB	58	51	62
mBERT embeddings	LR	66	44	76
	SVM	67	46	76
	KNN	64	22	77
	RF	64	21	77
	NB	54	49	58
	Ensemble	**68**	**52**	**77**

TABLE 5 COMPARATIVE STUDY OF PROPOSED MODEL WITH BASELINE RESULTS

	Model	Accuracy (%)	F1-Hate (%)	F1-Nonhate (%)
Baseline	Ensemble	68	50	77
Language models	BERT	71	59	72
	ULMFiT	68	48	75
Proposed Translation & Translation-based model	LR	70	48	77
	SVM	72	55	76
	KNN	68	44	78
	RF	66	28	77
	NB	56	57	55
	CNN + Gradient Boosting	**84**	**64**	**86**

*HIGHLIGHTED VALUES INDICATED BEST-PERFORMING MODELS.

5 Discussion

To examine the behavior of individual models, we selected sample phrases from the test data and passed them through the best-performing models for hate speech detection. The results are summarized in Table 6. According to the table, most models correctly recognized non-hate sentences. However, only the proposed CNN + Gradient Boosting model consistently identified hate speech accurately. This superior performance can be attributed to the integration of FastText embeddings for semantic understanding and the effective classification by Gradient Boosting.

A comparative study of model performance on both raw (unprocessed) and FastText-embedded data is presented in Figure 4. The observations indicate that utilizing FastText embeddings significantly enhances the model's ability to detect hate speech, particularly in cases involving subtle linguistic nuances. Additionally, the CNN-based feature extraction layer improved the performance by effectively capturing n-gram and contextual features.

1. **Table 6** demonstrates the ability of the CNN + Gradient Boosting model to accurately detect hate speech compared to other models.
2. **Table 7** highlights the superior performance of the proposed model over existing methods, achieving the highest accuracy of 84% on the Reddit dataset for hate speech detection.
3. The incorporation of FastText embeddings enhanced the contextual understanding of text, significantly improving classification performance.

An interesting finding from our experiments is that the proposed CNN + Gradient Boosting model outperformed all baseline machine learning and pre-trained embedding models. For example, SVM achieved an accuracy of 72% on FastText embeddings but struggled to match the overall performance of the proposed model. Furthermore, as summarized in Table 7, our proposed model demonstrated superior accuracy compared to existing state-of-the-art methods for hate speech detection on the Reddit dataset.

5.1 Limitations of our model

While the proposed CNN + Gradient Boosting model demonstrates strong performance, there are some limitations that provide directions for future research:

1. As shown in **Table 5**, the proposed model exhibits higher accuracy in identifying non-hate speech compared to hate speech. This may be due to the imbalance in the dataset, where the number of non-hate samples significantly exceeds hate samples.

2. The model's reliance on pre-trained embeddings such as FastText may limit its ability to generalize to other datasets without retraining or fine-tuning.

6 Conclusion and future enhancements

This study investigates hate speech detection in online platforms using the proposed **CNN + Gradient Boosting with FastText Embeddings** approach. The research focuses on the Reddit dataset and demonstrates the efficacy of combining convolutional layers for feature extraction with Gradient Boosting for robust classification. The experimental results reveal that the proposed model significantly outperforms traditional machine learning classifiers and pre-trained models like BERT and IndicBERT on the same dataset. By leveraging FastText embeddings, the model captures semantic context effectively, enhancing its ability to identify hate speech.

However, there is potential for further improvement. Future studies can explore the integration of more advanced embeddings, such as contextual embeddings from multilingual transformers, to better handle code-mixed data. Additionally, experiments with other regional languages or multilingual datasets can provide valuable insights, particularly in linguistically diverse societies like India. Expanding the application of this model to real-time hate speech detection systems on platforms like Reddit or Twitter could further validate its practical impact.

Table 6 Sample test cases

Text	Ensemble	BERT	CNN + Gradient Boosting	Target
Fake hina besaram arshi ki sakal se hi nafrat ho gyi hme	Non-hate	Hate	Hate	Hate
Thank you geeta ma am insaan nafrat me sahi aur galat hi bhool jata	Non-hate	Non-hate	Non-hate	Non-hate
Murder karne waale ko aachaarsahita ki wajha se action se dur kiya hua hai har	Non-hate	Non-hate	Non-hate	Hate

Declarations

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The proposed model achieves significantly higher accuracy compared to existing works, validating its superior performance for hate speech detection.

Model	Accuracy (HS)%
Mathur et al. (2018) (CNN-LSTM)	72
Bohra et al. (2018) (Random Forest)	65
Bohra et al. (2018) (SVM)	71
Santosh and Aravind (2019) (Sub-word level LSTM)	71
Proposed CNN + Gradient Boosting model	**84**

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