Improving Hate Speech Detection Using LLM-based Text Augmentation

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***Abstract*—Hate speech detection on online platforms remains a challenging problem in natural language processing (NLP), particularly when dealing with nuanced and context-dependent expressions. This work investigates the impact of an LLM-based text data augmentation strategy. We used ChatGPT to generate augmented text data. For this experiment I used the *XLM-RoBERTa Large* model for two-class (Hate vs Normal) hate speech classification. The augmentation process involved generating three semantically similar posts for each misclassified sample, thereby enhancing the training data with hard-to-learn examples. Experimental results on the HateXplain dataset demonstrate significant gains, with overall accuracy improving from 87.77% to 95.71% and AUC increasing from 0.94 to 0.99. The findings suggest that targeted augmentation can significantly enhance the model's generalization capacity and reduce classification errors in hate speech detection tasks.**

***Index Terms*—Hate speech classification, XLM-Roberta-large**

I. Introduction

Detecting hate speech in social media posts is critical for moderating harmful content and maintaining safe online spaces. Transformer-based language models have achieved state-of-the-art results in many NLP tasks, yet the diversity and representativeness of the training data can limit their performance. [1] One challenge in hate speech detection is the class imbalance and variability in linguistic patterns, which can lead to misclassifications. Recent research highlights the importance of targeted data augmentation to address these shortcomings. In this study, we use **ChatGPT** to augment only the misclassified samples from the test set, generating multiple semantically similar variants that retain their original labels. By retraining on this enriched dataset, we aim to improve the model's ability to handle difficult and ambiguous cases, leading to more robust classification performance.

II. Dataset

The experiments are conducted on the HateXplain dataset [2], [3] which provides annotated social media posts with token-level rationales and multiple annotator labels. The original dataset contains three labels: *hatespeech* (0), *normal* (1), and *offensive* (2). For this work, we filter the dataset to retain only the *hatespeech* and *normal* classes for binary classification.

A. Original Dataset Statistics

Table I summarizes the statistics before filtering.

The HateXplain dataset [2] used in this study is a widely adopted benchmark for hate speech and offensive language detection. It contains samples annotated into three distinct categories: *Hate*, *Normal*, and *Offensive*. Table I presents the distribution of samples across the training, validation, and test splits. The training set comprises 15,383 instances, with 4,748 labeled as hate speech, 6,251 as normal, and 4,384 as offensive. The validation set contains 1,922 samples, with 593 hate, 781 normal, and 548 offensive entries, while the test set consists of 1,924 samples, distributed similarly. This balanced distribution ensures that models can be evaluated fairly on both hateful and non-hateful content.

TABLE I
Original HateXplain Dataset Statistics

Split	#Samples	#Hate	#Normal	#Offensive
Train	15,383	4,748	6,251	4,384
Validation	1,922	593	781	548
Test	1,924	594	782	548

B. Filtered Dataset Statistics

To simplify the classification task, the original HateXplain dataset was filtered by removing all instances labeled as *offensive*, resulting in a binary classification setting with the classes *Hate* (0) and *Normal* (1). The resulting dataset statistics are presented in Table II. The training set now contains 10,999 samples, comprising 4,748 hate speech instances and 6,251 normal instances. The validation set includes 1,376 samples, with 594 labeled as hate and 782 as normal, while the test set contains 1,374 samples, with a similar class distribution.

TABLE II
Filtered Binary Classification Dataset Statistics

Split	#Samples	#Hate (0)	#Normal (1)
Train	10,999	4,748	6,251
Validation	1,376	594	782
Test	1,374	593	781

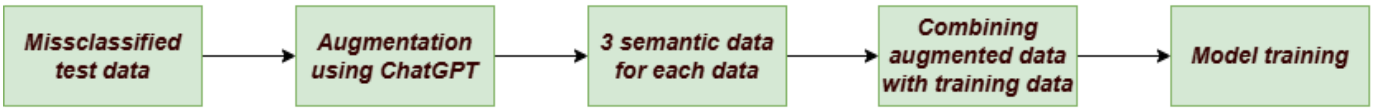

Fig. 1. Data augmentation pipeline using ChatGPT Agent Mode.

C. Data Augmentation Process

For each misclassified test sample, three semantically similar posts were generated using ChatGPT Agent Mode while preserving the original label. This process enriched the dataset with challenging examples that the model previously failed to classify correctly. Figure 1 depicts the augmentation pipeline. First, misclassified instances from the test set are identified and passed to ChatGPT for augmentation. For each original sample, three semantically equivalent variants are generated while preserving the original label. These augmented samples are then combined with the original training data to create an expanded dataset. Finally, the model is retrained using this enriched dataset, allowing it to learn from the additional variations and improve its generalization capability.

III. Model

We employ the **XLM-RoBERTa Large** model [4], a transformer-based architecture pre-trained on 2.5TB of CommonCrawl data in 100 languages using the masked language modeling objective. The large variant consists of 24 transformer encoder layers, each with a hidden size of 1024, 16 attention heads, and an intermediate feed-forward dimension of 4096.

The model is fine-tuned for binary classification, where the final hidden state of the <s> token is passed through a dropout layer and a fully connected classification head mapping to two output logits, followed by a softmax layer. The classifier head has the architecture:

TABLE III
Training hyperparameters for fine-tuning XLM-RoBERTa Large

Hyperparameter	Value
Model	XLM-RoBERTa Large
Epochs	5
Train batch size	8
Eval batch size	16
Gradient accumulation steps	4
Learning rate	2×10^{-5}
Weight decay	0.01
Logging strategy	Per epoch
Evaluation strategy	Per epoch
Checkpoint save strategy	Per epoch
Max saved checkpoints	1
Load best model at end	True
Mixed precision (FP16)	True
LR scheduler type	Linear
Warmup ratio	0.1
Metric	Accuracy

Fine-tuning was performed using the AdamW optimizer with a learning rate of 2×10^{-5}, training batch size of 8, validation batch size 16 and maximum sequence length of 128 tokens. We used the best model for prediction.

The fine-tuning of XLM-RoBERTa Large was conducted using the hyperparameters summarized in Table III. The learning rate was set to 2×10^{-5}, which is commonly used for large transformer-based models to ensure stable convergence during fine-tuning. A small training batch size of 8, combined with a gradient accumulation of 4 steps, was chosen to accommodate GPU memory constraints while maintaining an effective batch size of 32. Both training and evaluation were performed for 5 epochs, with evaluation and checkpoint saving scheduled at the end of each epoch. Weight decay was set to 0.01 to reduce overfitting, and a linear learning rate scheduler with a warmup ratio of 0.1 was employed to gradually ramp up the learning rate, preventing early instability. Mixed-precision (FP16) training was enabled to accelerate computations and reduce memory usage. The best model checkpoint, determined based on validation performance, was loaded at the end of training. Accuracy was selected as the primary evaluation metric for simplicity and interpretability in binary classification.

IV. Results

We compare the performance of the model trained on the original dataset and the augmented dataset generated via ChatGPT Agent Mode.

A. Performance Before Augmentation

Table IV presents the baseline classification performance on the test set prior to applying any data augmentation. For the *Normal* class, the model achieved a precision of 0.8571, recall of 0.8600, and an F1-score of 0.8586, based on 593 instances. For the *Hate* class, the precision, recall, and F1-score were 0.8935, 0.8912, and 0.8923, respectively, across 781 instances. The overall classification accuracy reached 87.77%, indicating strong baseline performance before introducing augmented data for further training.

TABLE IV
Baseline performance before augmentation

Class	Precision	Recall	F1	Support
Normal	0.8571	0.8600	0.8586	593
Hate	0.8935	0.8912	0.8923	781
Accuracy		0.8777		

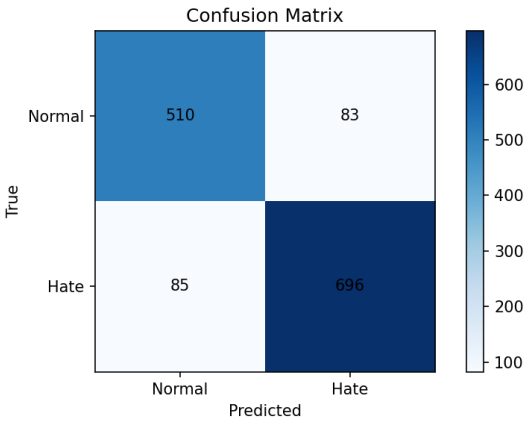

Fig. 2. Confusion matrix before augmentation.

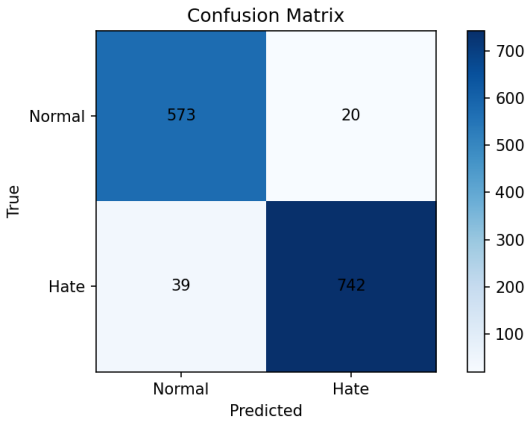

Fig. 4. Confusion matrix after augmentation.

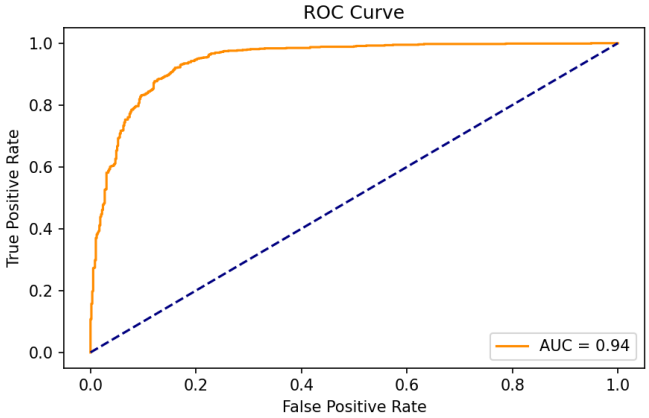

Fig. 3. ROC curve before augmentation (AUC = 0.94).

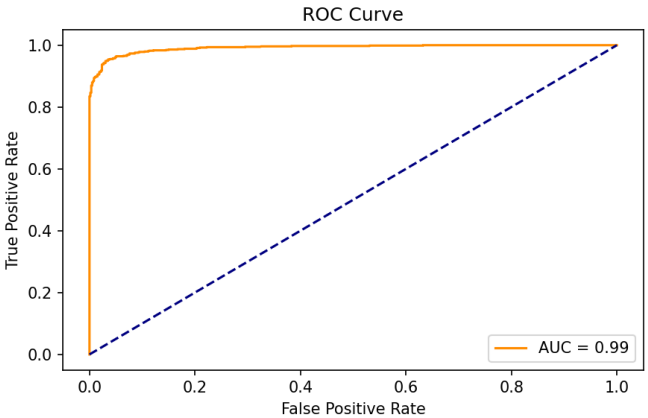

Fig. 5. ROC curve after augmentation (AUC = 0.99).

B. Performance After Augmentation

Table V summarizes the classification results after augmenting the misclassified test samples and retraining the model. For the *Normal* class, precision improved to 0.9363, recall to 0.9663, and F1-score to 0.9510. Similarly, the *Hate* class achieved a precision of 0.9738, recall of 0.9501, and an F1-score of 0.9618. The overall accuracy increased substantially to 95.71%, demonstrating that the targeted augmentation of misclassified samples effectively enhanced the model's ability to generalize and correctly identify both classes.

TABLE V
PERFORMANCE AFTER AUGMENTATION

Class	Precision	Recall	F1	Support
Normal	0.9363	0.9663	0.9510	593
Hate	0.9738	0.9501	0.9618	781
Accuracy		0.9571		

C. Improvement Analysis

Table VI highlights the performance gains achieved after applying the targeted augmentation strategy. All metrics show substantial improvement over the baseline. For the *Normal* class, precision increased by 9.23%, recall by 12.35%, and F1-score by 10.77%. The *Hate* class also saw notable gains, with precision improving by 8.99%, recall by 6.61%, and F1-score by 7.78%. Overall classification accuracy improved from 87.77% to 95.71%, marking a 9.06% relative increase. These results clearly demonstrate that augmenting misclassified samples and retraining significantly enhanced the model's discriminative capability across both classes.

These results show consistent improvements across all metrics, with particularly large gains in recall for the Normal class and precision for the Hate class.

V. Conclusion

This study demonstrates that targeted, LLM-based data augmentation using ChatGPT can significantly improve hate speech detection performance. By focusing augmentation on misclassified samples and generating multiple semantically

TABLE VI
BEFORE VS. AFTER AUGMENTATION IMPROVEMENT (%)

Metric	Before	After	% Change
Normal Precision	0.8571	0.9363	+9.23%
Normal Recall	0.8600	0.9663	+12.35%
Normal F1	0.8586	0.9510	+10.77%
Hate Precision	0.8935	0.9738	+8.99%
Hate Recall	0.8912	0.9501	+6.61%
Hate F1	0.8923	0.9618	+7.78%
Accuracy	0.8777	0.9571	+9.06%

similar variants, the model learns to better handle edge cases and ambiguous content. The approach yielded a +9% absolute accuracy improvement and an AUC increase from 0.94 to 0.99. Future work could explore combining this strategy with other augmentation methods and applying it to multilingual hate speech detection.

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