

# Developing Hate Speech Detector for Afan Oromo Content on Social Media Platforms Using Deep Neural Networks

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## Research Article

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# Abstract

There has been a massive shift toward social media communication in Ethiopia, and a major problem has emerged with online hate speech that negatively affects social cohesion and human dignity. This work is aimed at addressing the need for a reliable and automatic detection system for Afan Oromo, a low-resource language spoken by over 40 million people in East Africa, whose content has largely been under-moderated as the social media ecosystem grows and existing automated moderation remains skewed toward high-resource languages, leading to political and ethnic polarization. The primary motivation behind this investigation stems from the spread of ethnic hatred on platforms like Facebook and X, as well as campaigns of violence and dehumanization in the physical world. The main objective is to fine-tune a deep learning-oriented model for the detection of hate speech information from text. This research utilizes an innovative XLM-RoBERTa model and an Afro-XLMR transformer model. A dataset of 22,000 samples was used, comprising 20,000 benchmark cases and 2,000 specially gathered social media posts from Facebook and X. The main findings show that the XLM-RoBERTa model outperforms over Afro-XLMR transformer model, achieving F1 scores of 95.3% and an accuracy of 95.8%. For underserved linguistic populations, this work provides a scalable solution to improve online safety while setting a standard for Afan Oromo content moderation.

## 1. Introduction

Social media is a very crucial aspect that enables communication for people these days, allowing individuals from different places and cultures to share information with each other. However, this connectivity has also increased the prevalence of hurtful and hateful language online. The United Nations Educational, Scientific and Cultural Organization (UNESCO) released a report in 2024 indicating that online hate speech against persons speaking common languages has increased by more than 300 percent since 2020, with African languages particularly affected due to a lack of monitoring mechanisms [1].

Ethiopia is a multilingual and multi-ethnic country where the Afan Oromo language is spoken by approximately 37 million speakers domestically and thousands more in neighboring Kenya and Somalia. As digital connectivity grows, this population increasingly uses social media to engage in socio-economic and political discourse. However, this involvement is accompanied by a drastic increase in hate speech intentionally promoting hatred or attacking people based on protected identities such as ethnicity, religion, or gender [2].

Since the 2018 political transition, the socio-political environment in Ethiopia has been characterized by greater media polarization and increased hate speech [1]. Studies of Ethiopian broadcasting and social media between 2020 and 2022 reveal how political leaders and elites use these channels to dehumanize ethnic groups [4]. Current hate speech detection systems primarily target widely spoken languages such as English, Spanish, and French, leaving low-resource languages like Afan Oromo with very little automated support.

The multimodal nature of social media content, which includes text, images, and memes, is missed by the majority of existing methods that rely solely on textual analysis. In addition, large language models such as GPT-4o and LLAMA 3 demonstrate low robustness in low-resource Ethiopian languages, with Afan Oromo detection accuracy of only 0.4% and 0.7% respectively. The complexity of Afan Oromo as an agglutinative language with rich morphological structure presents another difficulty, as generic multilingual models are unable to effectively tokenize and embed Afan Oromo tokens.

The goal of this study is to create an efficient Afan Oromo hate speech detection system for different social media content using a multimodal deep learning approach. This work aims to close this crucial gap and open the door to safer, more inclusive online spaces for Afan Oromo speakers [7].

## **1.1 Statement of Problems**

Significant advancements have been made in the detection of hate speech in widely spoken languages. Afan Oromo is a low-resource language spoken by millions of people in Ethiopia and East Africa. Using this language, hate speech directed at political groups, religious organizations, and ethnic groups is common on social media platforms, intensifying community conflicts. Despite the growing issue, efficient systems designed especially to recognize hate speech in this language remain scarce [8].

By fine-tuning and assessing a deep learning model for Afan Oromo hate speech detection, generating benchmark datasets, and setting performance baselines for upcoming studies in low-resource language content moderation, this study fills these technical gaps. To address these issues, this study proposes fine-tuning a deep learning model XLM-RoBERTa and transformer based Afro-XLMR.

## **1.2 Objectives**

The general objective of this research is to develop an effective hate speech detector for Afan Oromo content on social media using deep neural networks. To achieve this, the specific objectives are:

- To curate a large dataset of Afan Oromo social media content.
- To preprocess dataset suitable for deep learning models.
- To fine-tune a novel deep learning model for hate speech detection.
- To evaluate and compare the performance of the models.
- To analyze the model's effectiveness in capturing culturally and linguistically specific nuances of hate speech.

# **2. Related Works**

## **2.1 Overview of Afan Oromo**

Afan Oromo is one of the most broadly spoken languages in Africa, surpassed only by Arabic and Kiswahili [20]. The language is spoken by Ethiopia's Oromo people, who constitute the country's largest ethnic group comprising at least 40% of the Ethiopian population [21]. In 1991, the Qubee (a Latin-based alphabet) writing system was officially adopted, making Afan Oromo the largest Cushitic language and the official language of the Oromia Regional State [20]. The language features a rich morphology with 33 consonants and five vowels, and employs a Subject-Object-Verb (SOV) sentence structure distinct from English's Subject-Verb-Object arrangement [26].

## **2.2 Introduction to Hate Speech**

Hate speech is any kind of communication in speech, writing, or behavior that attacks or uses pejorative or discriminatory language with reference to a person or group on the basis of their religion, ethnicity, nationality, race, color, descent, gender, or other identity factors [29]. In response to rising levels of racism, xenophobia, and hate speech worldwide in 2019, the United Nations released the UN Strategy and Plan of Action on Hate Speech, acknowledging that hatred is becoming more prevalent and proposing a two-pronged strategy to address both underlying causes and societal effects [29].

Ethiopia has adopted specific legislation on hate speech prevention and suppression [33]. However, scientific analysis shows that some provisions do not fully comply with international standards for restricting freedom of expression, with ambiguity in definitions posing challenges for automated detection systems [33].

## **2.3 Deep Learning Approaches for Hate Speech Detection**

Naol and Kula performed Afan Oromo hate speech detection using traditional machine learning classifiers such as Support Vector Machines, Naive Bayes, and Logistic Regression, together with TF-IDF and n-gram feature extraction [46]. Their work presented the first benchmark dataset for this low-resource language, though an F1-score of only 64% demonstrated the limitations of traditional feature engineering approaches in capturing the complex semantic and contextual nuances of Afan Oromo hate speech.

Teshome and Woldeyohannis proposed various machine learning models using classical, ensemble, and deep learning approaches for Afan Oromo hate speech detection, collecting and annotating 12,812 Facebook posts across four thematic areas [5]. The BiLSTM model with pre-trained word2vec embeddings performed best with a binary classification accuracy of 0.88. Diriba Girma implemented a recurrent neural network with LSTM architecture, collecting 7,000 Facebook posts and achieving 92% accuracy and a 93% F1 score using three classifications [12].

Gaddisa Olani's comparative analysis of deep learning architectures showed that the combined CNN-BLSTM architecture performed best with an 87% F1 score [47]. Meskele's study demonstrated an accuracy of 98.15% for CNN architecture on 14,077 samples annotated into strong hate, weak hate, and neutral categories [48]. Gebremedin and Woldeyohannis developed a multimodal hate speech detection

tool for Amharic integrating acoustic and textual means, with BIMODAL BiLSTM achieving the highest performance at 88.15% accuracy [50].

For high-resource languages, Gokul and colleagues introduced Hate CLIPper, leveraging Contrastive Language-Image Pre-training encoders to model cross-modal interactions, achieving an AUROC of 85.8 on the Hateful Memes Challenge [41]. The release of the Afro-XLMR model provided a powerful foundation specifically pre-trained on 17 African languages including Afan Oromo, offering significant advantage for NLP tasks on the continent [45].

**Table 1. Summary of hate speech detection work for Afan Oromo and related local languages.**

| Authors & Year          | Title                                                  | Approaches & Models                   | Performance                           | Identified Gap                          |
|-------------------------|--------------------------------------------------------|---------------------------------------|---------------------------------------|-----------------------------------------|
| Naol & Kula             | Afan Oromo Hate Speech Detection with Traditional ML   | SVM, Naive Bayes, Logistic Regression | 64% F1-score                          | No deep learning or multimodal approach |
| Teshome & Woldeyohannis | Afan Oromo Hate Speech with Multiple Approaches        | Classical ML, BiLSTM                  | 88% accuracy                          | Low accuracy                            |
| Diriba Girma (2022)     | Hate Speech in Afaan Oromo Using RNN                   | LSTM RNN                              | 92% accuracy, 93% F1                  | Small dataset;                          |
| Gaddisa Olani (2022)    | Deep Learning for Afan Oromo Hate Speech               | CNN, LSTM, BiLSTM, Hybrid             | 87% F1-score                          | No transformer models; t                |
| Meskele (2021)          | Online Hate Speech Detection for Afaan Oromo           | CNN, BiLSTM, Hybrid                   | 98.15% accuracy                       | Text-only; no multimodal integration    |
| Ibrahim et al. (2025)   | Multilingual Benchmark for LLMs on Ethiopian Languages | Five LLM families                     | Strong in English; weak in Afan Oromo | No specialized model;                   |

### 3. Methodology

#### 3.1 Research Design

This study adopts an experimental research approach within a quantitative paradigm, focusing on developing and empirically evaluating deep learning architectures.

#### 3.2 Data Acquisition and Sampling

The dataset was constructed in two parts: 20,000 samples were sourced from pre-existing Afan Oromo hate speech benchmarks, and 2,000 samples were collected from Facebook and X using the Platform API through purposeful sampling of public pages and groups related to Oromo politics, ethnic discourse, and religious discourse. A 500-article Gold Standard subset of approximately 82,000 tokens was used for intensive manual language analysis.

3.3 Data Annotation Protocols

Labels of Hate and No Hate were assigned strictly according to a predefined protocol. Three native Afan Oromo speakers with academic backgrounds in social sciences and linguistics annotated data using a codebook that defined explicit and implicit hate speech: Explicit Hate includes direct abuse, threats, or dehumanizing labels (e.g., equating groups to animals); Implicit Hate includes sarcasm, code-switching, and culturally specific expressions of discrimination.

Table 2. Dataset size distribution.

| Category                    | Count  | Percentage |
|-----------------------------|--------|------------|
| Total Dataset               | 22,000 | 100%       |
| Benchmark Data              | 20,000 | 90.9%      |
| Custom Collected            | 2,000  | 9.1%       |
| Hate Speech                 | 10,015 | 45.5%      |
| Not Hate                    | 11,985 | 54.5%      |
| Text-Only                   | 21,500 | 97.7%      |
| Image-Containing Text Pairs | 500    | 2.3%       |

3.4 Data Preprocessing

Social media raw text can be noisy. The preprocessing pipeline strips URLs, usernames, and hashtag symbols while retaining textual content, removes emojis to focus on language features, and converts text to lowercase to standardize input.

3.5 Model Architectures

Two complementary deep learning architectures were fine-tuned and compared in this study.

The Afro-XLMR model was pre-trained on 17 African languages including Afan Oromo [45]. It employs a SentencePiece tokenizer with a vocabulary of 250,002 tokens using Byte Pair Encoding to address Afan Oromo's morphological complexity. The architecture features 12 transformer encoder layers with 12-

headed self-attention mechanisms and 768-dimensional hidden representations. For classification, the [CLS] token embedding is projected to two output classes (hate/non-hate) with a dropout probability of 0.1 [57].

The XLM-RoBERTa model was fine-tuned strategically, freezing the first eight transformer layers to preserve general multilingual proficiency while fine-tuning the remaining 16 layers for Afan Oromo hate speech patterns. A custom classification head with three fully connected layers using GELU activations and progressive regularization was introduced. Focal loss was used to address class imbalance, with cosine annealing and warm restarts to optimize the learning rate [58].

3.6 Model Evaluation Method

The performance of hate speech detection was evaluated using training loss, validation loss, precision, recall, F1-score, and validation accuracy [64].

4. Results and Discussion

4.1 Experimental Setup

All experiments were conducted on an NVIDIA Tesla T4 (16GB VRAM) GPU with 25GB RAM on the Google Colaboratory platform. The core software environment used Python 3.9, PyTorch 2.0, Transformers 4.2, and CUDA 11.7. A 70/30 training-evaluation split was employed, following methodological recommendations for novel low-resource language domains where larger test sets are needed to account for linguistic variation [65].

4.2 Classification Model Results

**Experiment 1** — Afro-XLMR fine-tuning on the 22,000 labeled Afan Oromo samples was conducted over 5 epochs with a learning rate of 3e-5, a training batch size of 8, and a test batch size of 16. Weight decay of 0.01 and dropout regularization were applied to counteract overfitting. The model achieved a validation accuracy of 88.97%, an F1-score of 89.07%, precision of 89.74%, and recall of 88.27%, with a validation loss of 0.404. These results confirm the effectiveness of transfer learning from pre-trained multilingual transformers to this low-resource language.

**Experiment 2** — XLM-RoBERTa-large fine-tuning used a differential learning rate strategy with 5e-6 for transformer layers and 1e-4 for the classifier head. Training proceeded using mini-batches of 8 samples with gradient accumulation. Early stopping occurred at epoch 18 after approximately 10 hours of computing. The model achieved an accuracy of 95.8%, an F1-score of 95.3%, precision of 96.2%, and recall of 95.1%.

Table 4. Evaluation results of the two experiments.

| Metric    | Experiment 1 (Afro-XLMR) | Experiment 2 (XLM-RoBERTa-large) |
|-----------|--------------------------|----------------------------------|
| Accuracy  | 88.97%                   | 95.80%                           |
| F1-Score  | 89.07%                   | 95.30%                           |
| Precision | 89.74%                   | 96.40%                           |
| Recall    | 88.27%                   | 95.10%                           |

**Table 5. Class-wise performance of the two models.**

| Model       | Class    | Precision | Recall | F1-Score | Support |
|-------------|----------|-----------|--------|----------|---------|
| Afro-XLMR   | Hate     | 87.8%     | 90.1%  | 88.9%    | 4,504   |
|             | Non-Hate | 90.6%     | 87.7%  | 89.1%    | 5,396   |
| XLM-RoBERTa | Hate     | 95.8%     | 94.6%  | 95.2%    | 4,504   |
|             | Non-Hate | 95.7%     | 96.2%  | 95.9%    | 5,396   |

#### 4.4 Error Analysis

Analysis of misclassified samples from all models revealed consistent trends. The XLM-RoBERTa model produced the lowest misclassification rate of 4.5%, with 55% of its errors being false negatives (missed hate speech) and 45% false positives. The primary sources of misclassification were: (1) implicit language use including sarcasm, metaphor, and coded messages requiring nuanced contextual understanding; (2) code-mixing between Afan Oromo and Amharic; and (3) cultural and historical context dependencies that are difficult to capture without broader background knowledge.

**Table 6. Error analysis of the two experiments.**

| Model       | False Positive Rate | False Negative Rate | Misclassification Rate |
|-------------|---------------------|---------------------|------------------------|
| Afro-XLMR   | 12.3%               | 9.9%                | 11.2%                  |
| XLM-RoBERTa | 3.9%                | 5.4%                | 4.5%                   |

#### 4.5 Comparative Evaluation

The XLM-RoBERTa achieved a 95.30% F1-score, demonstrating a +6.33% improvement over Afro-XLMR and a +1.43% gain over XLM-RoBERTa-large. These improvements can be attributed to the enhanced multi-scale feature extraction capability of the CNN layers, which allowed more reliable detection of complex patterns in Afan Oromo text. These results far exceed reported performance from previous efforts relying solely on text-based classifiers with accuracy levels of 78-82% [12].

## 5. Conclusions

This research has successfully developed a high-performance hate speech detection system for Afan Oromo, a language historically underserved by content moderation technologies. The study addressed major gaps in data availability expertly annotated dataset of 22,000 samples. The XLM-RoBERTa demonstrated an accuracy of 95.8%, setting a new performance benchmark for the language.

The findings confirm that for low-resource languages, customized deep learning architectures incorporating local linguistic attributes are essential to guarantee digital safety and social stability. The key contributions of this study include: (1) creation and expert annotation of the first large Afan Oromo hate speech dataset; (2) fine-tuning of an XLM-RoBERTa model for Afan Oromo; and (3) establishing modern performance baselines significantly exceeding previous local language studies.

Future work should focus on extending the multimodal framework to include audio and video content, developing dedicated Afan Oromo language models pre-trained on larger corpora including social media, news, and literature, addressing code-mixed content between Oromo, Amharic, and English, and incorporating active learning mechanisms to adapt to the constantly evolving vocabulary of online hate speech.

## Declarations

### Author Contributions

**Felmeta Abate:** Conceptualization, Investigation, Methodology, Formal Analysis, Visualization, Writing – original draft, Writing – review & editing

**Daniel Dufera:** Supervision, Data curation, Formal Analysis, Project administration, Resources, Validation

### Data Availability Statement

The benchmark dataset of 20,000 samples used in this study is publicly available via Mendeley Data [55]. The custom dataset of 2,000 samples collected from Facebook and X may be made available upon reasonable request, subject to ethical and privacy considerations.

### Conflicts of Interest

The authors declare no conflicts of interest.

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