Abstract

Social media platforms allow users to freely share their opinions about issues or anything they feel like. However, they also make it easier to spread hate and abusive content. The Fulani ethnic group has been the victim of this unfortunate phenomenon. This paper introduces the HERDPhobia—the first annotated hate speech dataset on Fulani herders in Nigeria—in three languages: English, Nigerian-Pidgin, and Hausa. We present a benchmark experiment using pre-trained languages models to classify the tweets as either hateful or non-hateful. Our experiment shows that the XML-T model provides better performance with 99.83% weighted F1. We released the dataset for further research.

1 Introduction

Hate speech is any form of communication that promotes hatred against an individual or a group based on religion, sexual orientation, race, ethnicity, gender, nationality, age, and disability (Schmidt and Wiegand, 2017). Recently, the Natural Language Processing (NLP) community has seen an increase in research related to the task of detecting hate speech (Alkomah and Ma, 2022; Poletto et al., 2021; Celli et al., 2021; Moy et al., 2021).

The Fulani herdsmen in Nigeria are known for their migration, along with their herds from one location to another for grazing purposes (Enor et al., 2019). Recently, there has been an exponential increase in hate rhetoric against the Fulani tribe (Udanor and Anyanwu, 2019). Hence, there is a need to develop an automatic system for the detection of hate speech.

In this paper, we present HERDPhobia, a Twitter dataset for hate speech detection against Fulani herdsmen. To our knowledge, this is the first dataset created for the detection of hate speech against Fulani herdsmen in Nigeria.

2 Related work

Some of the work done to create hate dataset for automatic detection includes: a corpus of 16,914 English tweets to detect sexist or racial slur by Waseem and Hovy (2016); Davidson et al. (2017) collected 85.5 million tweets from Twitter using a hate speech lexicon by Hatebase.org, manually annotating a random 25,000; Poletto et al. (2017) created a corpus of hate against immigrants, Muslims, and Roma; Ibrohim and Budi (2018) developed a dataset to detect abusive language in Indonesian tweets using a machine learning approach; Ousidhoum et al. (2019) annotated multilingual hate corpus in English, French, and Arabic. and del Arco et al. (2021) created a corpus of comments from Twitter, YouTube, and Instagram for offensive language detection in Spanish.

3 Data Collection and Annotation

Following a similar approach for tweet collection used in (Muhammad et al., 2022), we collected tweets using three keywords: Fulani, cow and herdsmen from Nigeria in three languages: English (97.2%), Hausa (1.8%) and Nigerian-Pidgin (1%).

For data annotation, we adopted the guidelines from (Warner and Hirschberg, 2012), and we annotated tweets into three categories: Hate (HT), Not-Hate (NHT), and Indeterminate (IND). A tweet was labelled as hate if it contains words that attack or disparage an individual or group that belongs to the Fulani tribe. All factual and non-sentimental tweets were classified as Not-Hate. Tweets that are sarcastic or ambiguous were classified as indeterminate. After the annotation, we obtained 1, 131 HT, 5, 007 NHT, and 36 IND tweets, with a Fleiss kappa inter-annotator agreement score of 57%.

Three annotators annotated each tweet, and we used a simple majority vote to select the tweet to train our model from two classes (HT and NHT). Table 1 provides examples of annotated the tweets.
Table 1: Hate Tweets Examples, A1 = Annotator1, A2 = Annotator2, A3 = annotator3

| S/N | Tweet                                                                 | A1 | A2 | A3 |
|-----|------------------------------------------------------------------------|----|----|----|
| 1   | @user it’s true that all **fulani herdsmen** are **terrorist** think wisely b4 answer | HT | HT | HT |
| 2   | @user how much for the whole **cow** boss                            | NH | NH | NH |
| 3   | @user na so all for fulani **malu**                                 | IND | HT | NH |

Table 1: Hate Tweets Examples, A1 = Annotator1, A2 = Annotator2, A3 = annotator3

Figure 1: Distribution of hateful tweets by states. 12 states have less than 10 tweets and are grouped as Others.

The first two were straightforward cases where the three annotators unanimously agree on their labels as **Hate** and **Not Hate** respectively. The last is a hard-case annotation scenario where the three annotators could not agree due to its ambiguity. Figure 1 shows distribution of hateful tweets, with Lagos having the highest. Overall, hateful tweets are more prevalent in the southern part of Nigerian states, as also reported in (Udanor and Anyanwu, 2019).

4 Baseline Model

To prepare the training and validation data, we removed all tweets that are partially or completely annotated as indeterminate. This resulted in 892 Hate and 3,523 Not Hate tweets. We splitted the dataset as shown in Table 2.

| Data      | Train | Dev | Test |
|-----------|-------|-----|------|
| # of tweets | 3,090 | 441 | 884  |

Table 2: Training and Validation Data Statistics.

| Model                                      | F1-score |
|--------------------------------------------|----------|
| XLM-T (Barbieri et al., 2022)              | 99.83    |
| mBERT (Devlin et al., 2019)                | 80.96    |
| AfriBERTa (Ogueji et al., 2021)            | 78.07    |

Table 3: Benchmark results with weighted F1 scores.

We trained three different models on the HERDPhobia dataset by fine-tuning 3 pre-trained language models: mBERT, XLM-T and AfriBERTa to create a baseline. The models were trained using the same hyper-parameters as in Shode et al. (2022): a total of 20 epochs using a batch size of 32 and a maximum sentence length of 128. The weighted f1-score obtained for each model on the test set is shown in Table 3. The best performance was obtained from XLM-T with 99.83% weighted F1. This may be because HERDPhobia is dominated by English tweets, the same language that was used to pretrain XLM-T.

5 Conclusion and Future Work

While there are many forms of hate based on religious and ethnic stereotypes in Nigeria, the Fulani tribe suffers the most. In this paper, we present a new dataset for hate speech against Fulani. The dataset—HERDPhobia—consists of a total of 6,174 tweets that were manually annotated into three classes, hate, not-hate and indeterminate. Our baseline experiment with three pre-trained language models (XLM-T, mBert, AfriBerta) shows that XLM-T performs best with 99.83% weighted F1. In future work, we plan to extend our work to detecting hate speech to more ethical groups in Nigeria. We also plan to include offensive language in the classification category and label hate tweets according to hate types and intensity.

6 Ethical Consideration

We replaced all personally identifiable information from the dataset. Mentions are replaced with user.
References

Fatimah Alkomah and Xiaogang Ma. 2022. A literature review of textual hate speech detection methods and datasets. *Information*, 13(6):273.

Francesco Barbieri, Luis Espinosa Anke, and Jose Camacho-Collados. 2022. Xlm-t: Multilingual language models in twitter for sentiment analysis and beyond. In *Proceedings of the Language Resources and Evaluation Conference*, pages 258–266, Marseille, France. European Language Resources Association.

Fabio Celli, Mirko Lai, Armend Duzha, Cristina Bosco, and Viviana Patti. 2021. Policycorpus xl: An italian corpus for the detection of hate speech against politics. In *CLiC-it*.

Thomas Davidson, Dana Warmsley, Michael Macy, and Ingmar Weber. 2017. Automated hate speech detection and the problem of offensive language. In *Proceedings of the 11th International AAAI Conference on Web and Social Media*, ICWSM ’17, pages 512–515.

Flor Miriam Plaza del Arco, Arturo Montejo-Ráez, L Alfonso Urena Lopez, and María-Teresa Martín-Valdivia. 2021. Offendes: A new corpus in spanish for offensive language research. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2021)*, pages 1096–1108.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Frank N Enor, Stephen E Magor, and Charles E Ekpo. 2019. Contending perspectives and security implications of herdsmen activities in nigeria. *International Journal of Research-GRANTHAALAYAH*, 7(7):265–286.

Muhammad Okky Ibrohim and Indra Budi. 2018. A dataset and preliminaries study for abusive language detection in indonesian social media. *Procedia Computer Science*, 135:222–229.

Tian Xiang Moy, Mafas Raheem, and Rajasvaran Logeswaran. 2021. Hate speech detection in english and non-english languages: A review of techniques and challenges. *Technology*.

Shamsudddeen Hassan Muhammad, David Ifeoluwa Adelani, Sebastian Ruder, Ibrahim Sa’id Ahmad, Idris Abdulmumin, Bello Shehu Bello, Monojit Choudhury, Chris Chinenyte Emezue, Saheed Salahudeen Abdullahi, Anuoluwapo Aremu, Alipio Jorge, and Pavel Brazdil. 2022. *NaJiSaenti: A nigerian Twitter sentiment corpus for multilingual sentiment analysis*. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 590–602, Marseille, France. European Language Resources Association.

Kelechi Ogueji, Yuxin Zhu, and Jimmy Lin. 2021. Small data? no problem! exploring the viability of pretrained multilingual language models for low-resourced languages. In *Proceedings of the 1st Workshop on Multilingual Representation Learning*, pages 116–126, Punta Cana, Dominican Republic. Association for Computational Linguistics.

Nedjma Ousidhoum, Zizheng Lin, Hongming Zhang, Yangqiu Song, and Dit-Yan Yeung. 2019. Multilingual and multi-aspect hate speech analysis. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4675–4684, Hong Kong, China. Association for Computational Linguistics.

Fabio Poletto, Valerio Basile, Manuela Sanguinetti, Cristina Bosco, and Viviana Patti. 2021. Resources and benchmark corpora for hate speech detection: a systematic review. *Language Resources and Evaluation*, 55(2):477–523.

Fabio Poletto, Marco Straniscì, Manuela Sanguinetti, Viviana Patti, and Cristina Bosco. 2017. Hate speech annotation: Analysis of an italian twitter corpus. In *4th Italian Conference on Computational Linguistics, CLiC-it 2017*, volume 2006, pages 1–6. CEUR-WS.

Anna Schmidt and Michael Wiegand. 2017. A survey on hate speech detection using natural language processing. In *Proceedings of the fifth international workshop on natural language processing for social media*, pages 1–10.

Iyanuoluwa Shode, David Ifeoluwa Adelani, and Anna Feldman. 2022. YOSM: A new Yorùbá Sentiment Corpus for Movie Reviews. *AfricaNLP 2022 @ ICLR*.

Collins Udanor and Chinatu C Anyanwu. 2019. Combating the challenges of social media hate speech in a polarized society: A twitter ego lexalytics approach. *Data Technologies and Applications*.

William Warner and Julia Hirschberg. 2012. Detecting hate speech on the world wide web. In *Proceedings of the second workshop on language in social media*, pages 19–26.

Zeerak Waseem and Dirk Hovy. 2016. Hateful symbols or hateful people? predictive features for hate speech detection on twitter. In *Proceedings of the NAACL student research workshop*, pages 88–93.