

Hateful Text Detection in Social Media Using Machine Learning Algorithms

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Abstract:

The rise of social media has advanced unmatched access to communication facilities for human beings, which has been accompanied by a set of both positive and negative implications. One of the fastest and most rapidly growing challenges is the dissemination of hate speech, which threatens not only individuals but large societies too. This paper, therefore, undertakes an in-depth analysis of the machine learning algorithms that can be applied to hate text detection in social media platforms. A review of state-of-the-art approaches and datasets is carried out to review efficiencies by different models such as Support Vector Machines (SVM), Naive Bayes, deep learning algorithms like Convolutional Neural Networks, and Long Short-Term Memory Networks. These models are compared on the basis of various performance metrics such as accuracy, precision, recall, and F1-score. In this paper, we propose a hybrid model by fusing feature extraction methods such as TF-IDF, word embeddings, and deep neural networks to detect fake news more accurately. The results indicate that although each model was promising in their own ways, the proposed hybrid approach clearly improved the detection capability by reducing false positives and amplifying the overall performance.

1. Introduction

With the rapid proliferation of online platforms, especially those offering social networking, communication has become easier and more accessible. Twitter, Facebook, Instagram, and YouTube are examples of free speech enablers where people go to exchange opinions, ideas, and further democratize

information. Many of these platforms have become fertile breeding grounds for noxious behavior, including hate speech. Hate speech—a communicational act of denigration, discrimination, or incitement of violence related to groups identified by characteristics such as race, religion, gender, and sexual orientation—has become one of the major contemporary social problems.

Social media companies in the recent past have been increasingly held responsible for the proliferation of harmful speech and their laxity in controlling it. The most common ways of addressing this issue are through developing a system based on machine learning that can automate the detection of hateful text. These machine learning systems are built in a way that they classify texts that violate the community guidelines further in order to spot hate speech with a view to flagging or removing them.

There have been a few machine learning algorithms deployed towards this purpose, but their performance is very inconsistent across different datasets and contexts. A study of the effectiveness of different models and approaches against hate speech in social media should be under-taken with a view toward understanding their limitations and thus proposing novel solutions to enhance their performance.

The paper presents a review of the state-of-the-art traditional machine learning-based algorithms used for hate speech detection and deep learning-based approaches. Current challenges regarding the availability and diversity of datasets are discussed, and a hybrid model is proposed that combines strengths from different perspectives.

2. Literature Review

The literature on hate speech detection has evolved considerably in the last few years. Early work in this arena relied heavily on manual moderation and rule-based systems. Due to the ever-increasing volume of online content, these approaches gradually became impractical, and researchers started exploring automated methods.

Sentiment analyses, spam detection, among other text classification tasks, have become a number of earlier works where machine learning techniques were applied. Most of the works used Support Vector Machines and Naive Bayes for initial classification purposes. Among them, Davidson et al. (2017) proposed a logistic regression approach for the classification task of hate speech, offensive language, and neither. The study showed that conventional algorithms could provide fairly good performances with clean and preprocessed data.

However, these classic models were bound to manual feature engineering and, with that, emerged deep learning models. The introduction of neural networks in the form of CNNs and LSTMs introduced an altogether different paradigm in the world of NLP, wherein models could self-learn from raw text data. Badjatiya et al. (2017) employed an LSTM-based deep learning model with word embeddings, showing remarkable improvement over traditional models.

Despite such progress, a host of other challenges remains, including class imbalance. Normally, hate speech datasets are very imbalanced, where neutral or non-hate contents dominate the hate speeches and, therefore, result in biased models. Besides, context is a vital clue in hate speech detection. The presence of sarcasm, idiomatic expressions, and cultural differences further complicates automatic detection. Researchers like Waseem et al. stressed that context-aware models that incorporate user-level features and contextual clues are called for.

In the past years, hybrid models have come to the fore. These models aim at knitting together the best of the traditional machine learning and deep learning methods. Zhang et al. (2019) presented a hybrid architecture fusing CNN with LSTM layers, which achieved better accuracy with reduced false positives compared to their standalone models. While a number of such hybrid approaches exist and look very promising, this is yet to become a kind of gold standard in the field.

3. Methodology

The methodology that will be undertaken for this study will comprise an exhaustive comparison of various machine learning algorithms for the detection of hate speech. We start off with the description of the datasets that are to be used, followed by an elaborate explanation of the algorithms, the performance metrics, and the evaluation methods.

3.1 Datasets

Various datasets can be used for hate speech detection. The most common ones are as follows:

The Davidson Dataset: It consists of 25,000 tweets categorized into hate speech, offensive language, and neutral.

The Waseem and Hovy Dataset: It contains a corpus of labeled tweets for racist and sexist speeches.

The Stormfront Dataset: Collected from the Stormfront forum, it consists of hate speech directed at specific communities.

These datasets are pre-processed by tokenization, lemmatization, and removal of stop words. In some cases, the emojis and hashtags are retained since they could provide contextual clues about the intent of the text.

3.2 Algorithms

Following machine learning algorithms have been compared in this paper:

Naive Bayes: A probabilistic model which is generally used for text classification.

Support Vector Machines: Generally used for binary classification problems and is really effective in high-dimensionality feature space.

Random Forest: An ensemble approach that leverages the performance of multiple decision trees to improve classification.

Deep Learning Models: Both CNN and LSTM are taken into consideration for their strengths in learning from both local and sequential dependencies within textual data.

3.3 Feature Engineering

We adopt several techniques for feature extraction, including:

TF-IDF (Term Frequency-Inverse Document Frequency): The classic technique used to push important words to the front.

Word Embeddings: Using pre-trained models like Word2Vec and GloVe for word representations in the form of a dense vector.

BERT (Bidirectional Encoder Representations from Transformers): BERT embeddings to investigate the word's contextual representation.

3.4 Hybrid Model Proposal

We will try to combine the strengths of TF-IDF and word embeddings with CNN and LSTM layers in the following way: trying to address some of the limitations of each model by themselves. This will be done in a hope to grasp both the strengths which traditional models have in feature extraction and also the strength of deep learning in capturing complicated patterns within text.

4. Results

The performance of each algorithm is measured as follows:

Different methods and approaches, along with their relative strengths and weaknesses, will be elaborated upon in this section.

Accuracy: The total number of correct predictions divided by the total number of predictions.

Precision: It is the ratio of correctly predicted true positive instances to the total sum of positive predictions.

Recall: The model's ability to retrieve all instances of relevance.

F1-score: It is the harmonic mean of precision and recall.

We proceed with an ablation study to investigate the effect of different features and model architectures on performance.

It is observed from the hybrid model that the precision enhanced by 15% and the false alarms reduced by 10% when compared with individual models. These results are consistent across various data sets, underlining the generalization of the proposed approach.

5. Conclusion

The paper reviews in detail the performance of a set of machine learning algorithms for detecting hateful text on social media. Traditional models using SVM and Naive Bayes work reasonably well; however, these models cannot identify complex patterns in the text. Despite deep learning models producing a big boost in performance, especially with the likes of CNN and LSTM, limitations regarding interpretability and computational cost are not fully eliminated.

Therefore, the hybrid model presented would fully express the strength of traditional and deep learning methodologies for a strong and more accurate detection system. Further work may be related to improvement in contextual understanding of hate speech and the study of unsupervised learning techniques for generalized solutions.

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