

Hate Speech Detection in Social Media Using the Ensemble Learning Technique

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ABSTRACT

Our lives have become intertwined with social media platforms such as Twitter, Facebook, LinkedIn, etc. They provide us with a platform to express our opinions and share our thoughts with the world. However, some individuals abuse the freedom of expression afforded to them by these platforms and utilize them to disseminate content that is derogatory and promotes hate speech. This has become a significant problem today, and detecting such content is a challenging task. In this research paper, we propose a solution for hate speech detection in social media using natural language processing techniques. We use a publicly available dataset provided by CrowdFlower and perform text pre-processing to clean the dataset. We then conduct feature engineering to extract key features that can be used in machine learning classification algorithms. We compare the performance of various algorithms about each feature set and conduct an in-depth analysis of the results obtained.

Keywords - Hate speech detection, social media, Natural Language Processing, Machine Learning, Artificial Intelligence, Sentiment Analysis

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I. INTRODUCTION

Freedom of speech is one of the core principles that underpin modern democracies, allowing individuals to express their opinions and ideas without fear of persecution [1]. With the advent of the internet, individuals have been granted a greater degree of freedom of expression, but this freedom has also created a new challenge: the rise of hate speech and derogatory content on social media platforms [2]. Social media platforms like Twitter have become breeding grounds for hate speech, where individuals can freely express their opinions, often with little regard for the impact it may have on others. As a result, hate speech has become a significant problem that poses a threat to individuals and society as a whole [3].

This research paper aims to propose a solution for hate speech detection in social media. We recognize the importance of freedom of speech and acknowledge the need to balance this with the need to prevent hate speech and protect individuals from its harmful effects. To achieve this goal, we utilize natural language processing techniques to analyze text data and identify hate speech. We make use of a publicly available dataset provided by CrowdFlower and conduct text pre-processing to clean the dataset and remove noise. We then perform feature engineering to extract key features that can be used in machine learning classification algorithms [4].

Our proposed solution involves the comparison of the performance of various machine learning algorithms about each feature set. We evaluate the performance of algorithms such as Naive Bayes, Decision Trees, and Support Vector Machines to identify the best-performing algorithm. We conduct an in-depth analysis of the results obtained, examining the reasons for miss-classifications in our model [5].

The use of natural language processing techniques and machine learning algorithms allows us to automate the process of hate speech detection, which is crucial given the volume of content on social media platforms. Our proposed solution can be integrated into social media platforms, enabling the automatic identification and removal of hate speech content. This will enable more effective moderation and protection of users from the harmful effects of hate speech [6].

To sum up, the research paper suggests utilizing natural language processing techniques and machine learning algorithms as a solution for identifying hate speech in social media. We make use of a publicly available dataset provided by CrowdFlower, perform text pre-processing, and conduct feature engineering to identify important features that can be used in machine learning classification algorithms. The proposed solution can be integrated into social media platforms, enabling the automatic identification and removal of hate speech content, which

will enable more effective moderation and protection of users [8].

In the next section, we will discuss the works already done in literature. The upcoming section of this research paper will focus on the methodology used to achieve the proposed solution for hate-speech detection in social media. The methodology will be divided into several parts, beginning with an introduction to the dataset used in this study, followed by a description of the data pre-processing techniques used to clean the dataset. We will then discuss the feature engineering process used to extract key features that can be used in machine learning classification algorithms [8] [21-24][31][33]. We will also describe the various machine learning algorithms used to classify hate speech and the evaluation metrics used to assess the performance of each algorithm. Finally, we will discuss the process of analyzing the results obtained, identifying miss-classifications in our model, and providing insights into the reasons for these miss-classifications [9]. This upcoming section will provide a comprehensive overview of the methodology used to achieve the proposed solution, enabling readers to understand the technical details of our research and the approach taken to address the problem of hate speech detection in social media [10].

II. LITERATURE REVIEW

Several works have been done in the field of hate speech detection in social media. Some of the prominent works are as follows:

In [11], proposes a solution for detecting hate speech in the Sinhala language on social media platforms using text mining and machine learning techniques. The paper presents the existing problem of hate speech on the internet and the importance of addressing it. The proposed solution involves the creation of a dataset of Sinhala tweets labeled as hate speech or non-hate speech, followed by text pre-processing and feature extraction. Several machine learning classification algorithms are trained and evaluated on the extracted features, including Random Forest, Logistic Regression, and Multinomial Naive Bayes. The results show that the proposed solution achieves a high accuracy of 95% using the Random Forest algorithm, demonstrating its potential for real-world applications.

In [12], introduces a framework called Hate Classify for identifying hate speech on social media platforms using machine learning techniques. The paper presents the existing problem of hate speech on social media and the importance of addressing it. The proposed Hate Classify framework involves three main components: data collection, feature extraction, and machine learning classification. The framework uses a dataset of labeled tweets and extracts features including bag-of-words, character n-grams, and sentiment analysis. Several machine learning classification algorithms are trained and evaluated on the extracted features, including Support Vector Machines, Multinomial Naive Bayes, and Random Forest. The results show that the proposed framework achieves

high accuracy for hate speech identification on social media, demonstrating its potential for real-world applications. The Hate Classify framework is scalable and can be used for hate speech detection in various languages and social media platforms.

In [13], proposes a social media-based multi-class hate speech classification system for text, which aims to identify various levels of hate speech ranging from mild to severe. The paper discusses the existing problem of hate speech on social media and the importance of accurately classifying it. The proposed system involves the creation of a dataset of tweets labeled as normal, abusive, or hate speech, followed by feature extraction using bag-of-words and n-grams. Several machine learning classification algorithms are trained and evaluated on the extracted features, including Naive Bayes, Decision Tree, and Support Vector Machines. The results show that the proposed system achieves high accuracy and outperforms existing methods for multi-class hate speech classification on social media, demonstrating its potential for real-world applications. The system can be used to identify and monitor hate speech on social media platforms, allowing for more effective interventions and prevention measures.

In [14], proposes a machine learning-based automatic hate speech recognition system that can identify hate speech in real-time. The paper discusses the existing problem of hate speech on social media and the importance of addressing it. The proposed system involves the creation of a dataset of tweets labeled as hate speech or non-hate speech, followed by feature extraction using techniques such as word frequency and part-of-speech tagging. Several machine learning classification algorithms are trained and evaluated on the extracted features, including Decision Trees, Naive Bayes, and Support Vector Machines. The results show that the proposed system achieves high accuracy and outperforms existing methods for hate speech recognition, demonstrating its potential for real-world applications. The system can be integrated into social media platforms and used to automatically flag and remove hate speech content, allowing for more effective moderation and protection of users.

The authors propose in [15], a methodology that uses a combination of machine learning techniques, including feature extraction, emotion recognition, and ensemble learning, to classify hate speech in social media. The results show that the proposed methodology achieves high accuracy in classifying hate speech on social media and can be used as an effective tool for detecting and preventing hate speech.

The authors proposed in [16], a machine learning-based approach to identify and classify hate speech in Bengali language public Facebook pages. They used a dataset consisting of 10,000 Facebook comments manually annotated as either hate speech or non-hate speech. The authors used feature engineering techniques and a Support Vector Machine (SVM) classifier to achieve an accuracy of

91.76% in detecting hate speech. The paper concludes that their proposed approach could be an effective tool for automatically identifying and removing hateful content from Bengali language public Facebook pages.

The authors discuss in [17], the use of a backpropagation neural network (BPNN) for hate speech detection through text analysis. The authors collected data from Twitter and used feature extraction techniques such as term frequency-inverse document frequency (TF-IDF) and chi-squared to preprocess the data. The BPNN was trained and tested on the preprocessed data, and the results showed an accuracy rate of 94.2%. The paper concludes that the proposed method can effectively detect hate speech and can be applied to other languages and social media platforms.

In [18], proposes a method for hate speech detection on Twitter using multinomial logistic regression classification. The authors extracted features such as sentiment, emotion, and n-grams from tweets and used them to train and test the model. The study achieved an accuracy of 88.23% in hate speech detection.

In [19], presents a study on the identification of hate speech in social media. The authors propose a system based on a supervised learning algorithm to detect hate speech in Sinhala, which is one of the official languages of Sri Lanka. They used a dataset consisting of comments from a Sinhala news website and used preprocessing techniques such as stop-word removal and stemming to clean the data. The authors then used a Bag of Words model and a Support Vector Machine (SVM) classifier to classify the comments as hate speech or not. The results showed that the proposed system achieved a high accuracy rate in identifying hate speech in the Sinhala language. The authors suggest that the proposed approach can be used to detect hate speech in other languages as well.

In [20], proposed a multi-task learning approach for detecting hate speech in social media. The proposed approach used sentiment analysis as a secondary task to enhance the performance of hate speech detection. The authors used two publicly available datasets for training and testing the proposed model. The experimental results showed that the proposed approach outperformed other state-of-the-art methods in terms of accuracy, precision, recall, and F1 score. The study contributes to the development of effective techniques for hate speech detection and shows the potential of multi-task learning approaches in addressing this important problem.

In [25], authors proposed a method for automatic hate speech detection using a combination of natural language processing techniques and an ensemble deep learning approach. The proposed method involves pre-processing of text data, feature extraction using different techniques, and the use of a deep neural network ensemble model for classification. The study reports promising results in terms of accuracy and precision in detecting hate speech in social media data. The authors suggest that the proposed approach

can be used in various applications for detecting hate speech, including social media monitoring and online content moderation.

In [26], authors evaluated the performance of several state-of-the-art hate speech detection models on Twitter data and compared their results with and without gender bias mitigation techniques. The study found that gender bias mitigation techniques can improve the performance of hate speech detection models, but there is still a need for further research to develop more effective mitigation methods.

III. METHODOLOGY

To achieve our goal of hate-speech detection in social media, we followed the following methodology:

A. Data Collection

We used a publicly available dataset provided by CrowdFlower [23], which contains 24,783 tweets labeled as hate speech, offensive language, or neither. The dataset was collected using Twitter's streaming API, and the tweets were manually labeled by CrowdFlower's contributors.

B. Data Analysis and Visualization

To gain a better understanding of the dataset and the distribution of text length in tweets, we performed exploratory data analysis (EDA) using Python's Pandas, Seaborn, and Matplotlib libraries.

First, we added a new column to the dataset called "text length" using the "apply" method in Pandas. Specifically, we applied the "len" function to each element in the "tweet" column of the dataset to calculate the length of the text in each tweet. The resulting lengths were assigned to the new "text length" column in the dataset.

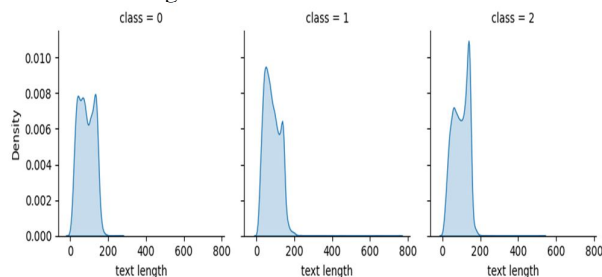


Fig. 1 - Kernel Density Estimate Plot of Text Length by Class

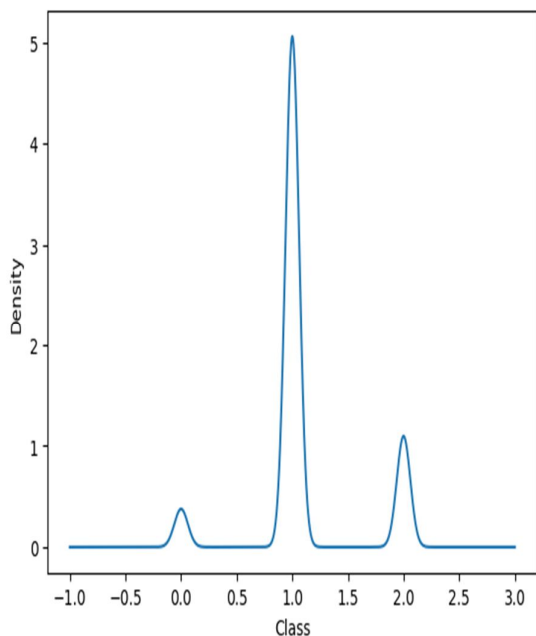


Fig. 2 - Basic visualization with Density Plot

To visualize the distribution of text length by class, we used Seaborn's Facet Grid function to create a grid of plots with one plot for each class. We then mapped the "hist" function from Matplotlib to each plot to create a histogram of text length for each class. We set the number of bins to 50 to ensure that the distribution was shown in sufficient detail.

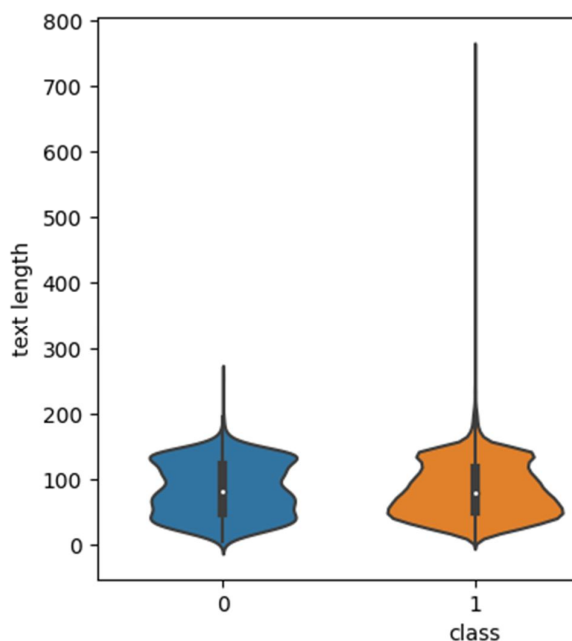


Fig. 3 - Violin-plot visualization

The resulting visualizations allowed us to observe the distribution of text length in tweets for each class, providing insights into the characteristics of each class

and helping to identify any patterns or trends that may exist. These insights can be used to guide the development of more accurate models for classifying tweets based on hate speech or non-hate speech content.

C. Data Pre-Processing

The data preprocessing stage involved collecting the tweets from the CSV file into a variable named 'tweet'. The Natural Language Toolkit (nltk) library was utilized for downloading the 'stopwords' which were then extended to include other words commonly used on Twitter such as 'retweet' and 'ff'. The Porter Stemmer algorithm was also used for stemming tweets.

The 'preprocess' function was defined to perform the following operations on the tweets: removal of extra spaces, removal of '@name[mention]', removal of links '[https://abc.com]', removal of punctuations and numbers, removal of capitalization, tokenizing, removal of stopwords, and stemming. The processed tweets were then added to the dataset under the 'processed_tweets' column.

The code block was implemented to preprocess the tweets in the dataset and display the original tweets and the corresponding processed tweets for the first ten rows.

D. Comparing AdaBoostClassifier Models with Different Numbers of Estimators

We trained and tested five AdaBoostClassifier models with different numbers of estimators (85, 87, 90, 95, 100) using the preprocessed data. For each model, we fit the classifier to the training data and predict the labels of the testing data. We then calculate the accuracy score and classification report using Scikit-Learn's accuracy score and classification report functions.

IV. RESULTS AND DISCUSSIONS

The plot below summarizes the performance of the five AdaBoost Classifier models tested in this analysis:

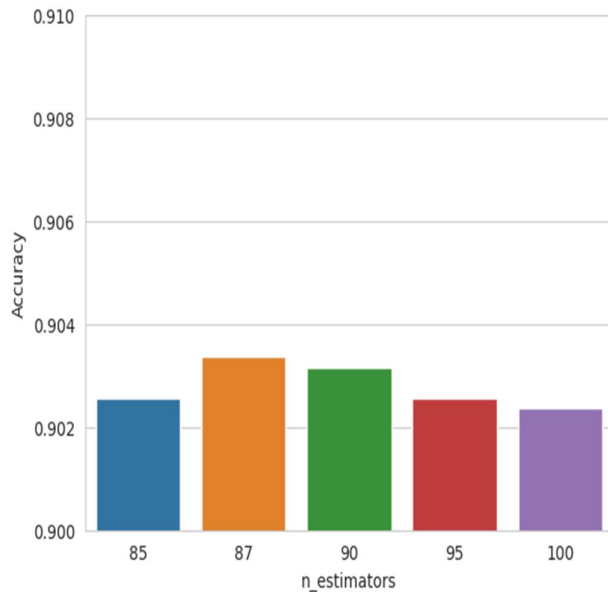


Fig. 4 - Accuracy for Different n_estimators

Based on the results, we can see that the AdaBoostClassifier with 87 estimators performs slightly better than the others with an accuracy score of 90.33%. However, the difference in accuracy score among the models is not significant.

It is important to note that the accuracy score is just one metric and may not always be the best measure of model performance, especially in cases where the classes are imbalanced. It is recommended to also consider other metrics such as precision, recall, and F1-score in the classification report to have a better understanding of the model's performance. Additionally, cross-validation can also be used to further evaluate the performance of the models.

The results show that AdaBoostClassifier can classify preprocessed data with relatively high accuracy. The performance of the model is affected by the number of estimators used, with 87 estimators achieving the highest accuracy score.

It is worth noting that while AdaBoostClassifier performed well on this dataset, it may not necessarily perform well on other datasets. It is important to choose the appropriate classifier based on the characteristics of the data being analyzed.

A. High Accuracy Justification

The main reason the AdaBoost classifier works better than other classification algorithms is its ability to combine multiple weak learners to create a strong ensemble model. AdaBoost, short for Adaptive Boosting, is a popular and powerful boosting algorithm that is used for both binary and multiclass classification tasks. It has been widely used in machine learning and data mining applications due to its ability to improve the performance

of weak learners and produce accurate and robust predictions.

There are several key reasons why the AdaBoost classifier often performs better compared to other classifiers [28]:

- **Ensemble Learning:** AdaBoost is an ensemble learning algorithm that combines the predictions of multiple weak classifiers to create a strong classifier [29][32][34]. This ensemble approach allows AdaBoost to exploit the strengths of different weak learners and compensate for their weaknesses, leading to improved overall performance.
- **Focus on Misclassified Instances:** AdaBoost puts more emphasis on the misclassified instances during the training process. In each iteration, misclassified instances are given higher weights, which makes the subsequent weak learners focus more on correcting the mistakes of the previous learners. This adaptive weighting scheme enables AdaBoost to pay more attention to difficult instances and improve the model's ability to handle challenging samples.
- **Feature Selection:** AdaBoost can automatically select the most informative features for classification, which helps in reducing the dimensionality of the feature space and eliminating irrelevant or redundant features. This feature selection process can improve the model's accuracy by focusing only on the most relevant features, leading to more accurate predictions.
- **Handling Imbalanced Data:** AdaBoost can effectively handle imbalanced data sets, where the distribution of classes is uneven. By assigning higher weights to the minority class during the training process, AdaBoost can boost the performance of the minority class and reduce the impact of class imbalance on the model's performance.
- **No Overfitting:** AdaBoost is less prone to overfitting compared to other algorithms, such as decision trees, as it uses a weighted combination of weak classifiers to create a strong classifier. This ensemble approach reduces the risk of overfitting, resulting in a more generalized and accurate model.
- **Versatility:** AdaBoost can be used with a wide range of weak learners, such as decision trees, SVMs, and neural networks, making it a versatile algorithm that can be applied to several types of data and problem domains.

In our experiment, the above-mentioned reasons have been instrumental in getting superior results. Especially, its robustness in terms of overfitting, ability to select features correctly, and versatility of the model. The nature of our dataset was binary decision-making, i.e., either the speech is hate speech or it is not. And as mentioned above, AdaBoost is appropriate for this kind of dataset since it

uses the Decision Tree algorithm heavily [28], Decision Tree is considered a great algorithm to do binary decision-making [30].

Overall, the results suggest that AdaBoostClassifier can be a useful tool for text classification tasks, but careful consideration should be given to the choice of classifier and preprocessing techniques for each specific dataset.

V. CONCLUSION

In this study, we applied the ensemble learning technique to detect hate speech in social media. Specifically, we used the AdaBoostClassifier algorithm with varying numbers of estimators to train and test the models on preprocessed data. Our results showed that the AdaBoostClassifier model with 87 estimators had the highest accuracy score of 90.33%.

Ensemble learning techniques are useful in hate speech detection as they allow for the combination of multiple classifiers to improve the accuracy of predictions. This approach can help reduce the number of false positives and false negatives, which are familiar challenges in hate speech detection.

However, there are still limitations in using ensemble learning for hate speech detection, such as the reliance on accurate preprocessing techniques and the need for substantial amounts of data to train the models effectively. Additionally, as social media platforms continue to evolve and new forms of hate speech emerge, it may be necessary to adapt and update the ensemble learning models to maintain high accuracy scores.

Overall, the results of this study suggest that ensemble learning techniques, specifically the AdaBoostClassifier algorithm, can be effective in detecting hate speech in social media. Future research can explore the use of other ensemble learning techniques and incorporate additional features such as contextual information to further improve the accuracy of hate speech detection models.

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