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Hate Speech Detection Using Machine Learning Techniques

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ABSTRACT In recent years, the proliferation of social media and online platforms has led to a significant increase in the spread of hate speech. Hate speech detection has become crucial for maintaining a safe online environment. This research focuses on detecting hate speech using various machine learning approaches. It encompasses data collection, preprocessing, feature scaling, model training, testing, and evaluation. Challenges faced include imbalanced datasets and obtaining accurate data splits. Among the models tested, Logistic Regression demonstrated superior performance with 93% accuracy. This paper provides valuable insights into effective methods for hate speech detection.

INDEX TERMS Hate speech, Hate speech detection, Machine learning, Deep learning, Data imbalance, Feature selection, Classification algorithms.

I. INTRODUCTION

Hate speech, defined as speech that attacks or demeans a group based on attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender, has become a pervasive issue on social media platforms. The objective of this study is to distinguish between legitimate and hate speech content using supervised and unsupervised learning methods while addressing class imbalance issues. Given the highly unbalanced nature of our dataset, managing data imbalance posed a significant challenge.

II. METHODOLOGY

The following steps were followed in the research methodology:

A. DATA COLLECTION

The study incorporates machine learning (ML), deep learning (DL), and ensemble feature ranking approaches to detect hate speech. The dataset used in this study was sourced from Kaggle and included thousands of social media comments and posts. The data was labeled as hate speech or legitimate speech. Due to the sensitive nature of the data, personal information was anonymized using Principal Component Analysis (PCA) transformations. The data collection process also involved scraping social media platforms, ensuring diversity in the dataset to cover various forms of hate speech.

Research Methodology:

The baseline methodology concluded from research work is:

B. MODEL SELECTION

Classification models were employed to predict the likelihood of content being hate speech. Several algorithms were tested, including:

- **Logistic Regression (LR)**
- **Random Forest (RF)**
- **Naive Bayes (NB)**
- **Support Vector Machines (SVM)**
- **Decision Trees**
- **K-Nearest Neighbors (KNN)**

The models were selected based on their performance in previous research studies and their ability to handle imbalanced datasets.

C. DATASET

The dataset, sourced from Kaggle, includes thousands of social media comments and posts labeled as hate speech or offensice language or neither Due to the sensitive nature of the data, personal information was anonymized using Principal Component Analysis (PCA) transformations.

Dataset Link: https://drive.google.com/file/d/1_OzhfIPTHu32KyDECeBqfgtuxKdVGZQE/view?usp=drive_link

D. DATA PREPROCESSING

Data preprocessing involved several steps to prepare the data for model training:

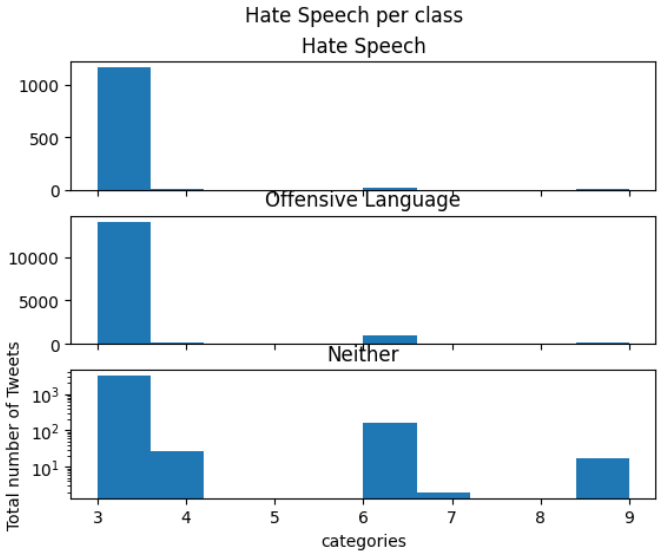

FIGURE 1: Hate Speech, Offesive language and Neither per class

- **Data Cleaning:** Duplicate entries were removed, missing values were handled, and outliers were treated to ensure data quality.
- **Data Splitting:** The dataset was split into training and testing sets using ratios such as 70-30 and 60-40 to evaluate model performance under different conditions.
- **Feature Scaling:** Irrelevant features were removed, and only relevant features were retained. Techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) and word embeddings were used for text feature extraction.
- **Feature Engineering:** New features were created, and patterns were established from existing data to improve model accuracy. This included sentiment analysis, n-grams, and part-of-speech tagging.

By performing data prepossessing, all the outliers in the data were removed, the data became more clean and clear for the model testing, the split method was used to train and test the data. Keeping only the relevant features to make the model more accurate.

E. MODEL TRAINING

Models were trained on the processed dataset to predict hate speech. Features included text content, user metadata, and contextual information. The goal was to achieve high accuracy and reliability in detecting hate speech.

F. MODEL TESTING

Post-training, models were tested using the split datasets. Evaluation metrics such as accuracy, confusion matrix, recall, precision, and F1 scores were calculated to assess model performance.

III. RESULTS AND DISCUSSION

A. EVALUATION MEASURES

Performance metrics included:

- F-1 Score
- Accuracy
- Recall
- Precision

B. RESULTS

Results indicated consistent values for precision, recall, and F1 scores, demonstrating model reliability. Key results include:

TABLE 1: Evaluation Results of Credit Card Fraud Detection Models

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.9359	0.4444	0.1457	0.2195
Random Forest	0.9389	0.5172	0.1821	0.2694
Decision Tree	0.9274	0.3798	0.2753	0.3192
Naive Byes	0.7364	0.0836	0.3279	0.1333
KNN	0.9384	0.5046	0.2186	0.3050
SVM	0.9309	0.4	0.2348	0.2959

C. COMPARING MODELS RESULT AND DISCUSSION

Both models showed high accuracy in detecting hate speech, with Logistic Regression achieving approximately 93% accuracy and 44% precision. Other models also demonstrated over 90% accuracy, indicating consistency and reliability.

IV. CONCLUSION

This research focuses on detecting hate speech using various machine learning algorithms, yielding promising results with high accuracy. Logistic Regression outperformed other models, showcasing its efficacy in handling imbalanced datasets. This research contributes significantly to the field of hate speech detection, offering robust methods to identify and mitigate harmful content online. Future work could involve refining models to enhance accuracy and minimize bias. Additionally, incorporating context-aware and real-time detection mechanisms could further improve the effectiveness of hate speech detection systems.

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