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Toxic Comment Classifier

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ABSTRACT: The rapid growth of online platforms has led to an increase in toxic comments, including hate speech, abusive language, and cyberbullying. These harmful interactions negatively affect user experience and online communities. This paper proposes a machine learning-based toxic comment classification system using Natural Language Processing (NLP) techniques. The system employs TF-IDF vectorization and classification models to detect toxic content efficiently. A Stream lit-based web application is developed for real-time analysis and visualization. Experimental results demonstrate that the system achieves high accuracy and effectively identifies toxic patterns. The proposed approach contributes to automated moderation systems for maintaining safer digital environments.

KEYWORDS— Toxic Comment Detection, Machine Learning, Natural Language Processing (NLP), TF-IDF Vectorization, Text Mining, Hate Speech Detection, Deep Learning Models, Sentiment Analysis, Real-Time Prediction, Content Moderation Systems

I. INTRODUCTION

1.1 Background of Toxic Comments

In recent years, the rapid expansion of online communication platforms such as social media, forums, and review systems has led to an unprecedented increase in user-generated content. While these platforms encourage open interaction and information sharing, they have also become a space where harmful and offensive language is frequently expressed. Toxic comments, which include hate speech, abusive language, personal attacks, and harassment, have become a serious concern for both platform providers and users. As the volume of online comments continues to grow, it becomes increasingly difficult for platforms to manually monitor and regulate such behavior effectively.

1.2 Limitations of Traditional Methods

Earlier approaches to toxic comment detection mainly relied on manual moderation or simple rule-based systems. Manual moderation involves human reviewers who analyze and filter inappropriate content. Although this method can be accurate in certain cases, it is not practical for large-scale platforms due to the time, cost, and effort involved. Moreover, human judgment may vary, leading to inconsistencies in moderation.

Rule-based systems, on the other hand, depend on predefined keywords or patterns to identify toxic content. While these systems are easy to implement, they often fail to capture the true meaning of a sentence. These limitations highlight the need for more intelligent and adaptable methods that can handle large volumes of data and understand the context of language.

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1.3 Role of Machine Learning in Toxic Comment Detection

Machine learning has emerged as a powerful tool for addressing problems related to text classification. Unlike traditional methods, machine learning models learn patterns from data rather than relying on fixed rules. By training on labelled datasets, these models can identify complex relationships between words and classify comments based on their level of toxicity.

Natural Language Processing (NLP) techniques play a crucial role in this process by converting textual data into a format that can be understood by machine learning algorithms. Techniques such as tokenization, stopword removal, and vectorization help in extracting meaningful features from text. Among these, TF-IDF (Term Frequency–Inverse Document Frequency) is widely used to represent the importance of words in a document.

1.4 Challenges in Toxic Comment Detection

Despite the advantages of machine learning, toxic comment detection remains a challenging task. One of the primary difficulties is understanding context, as the same word can convey different meanings depending on how it is used. Another challenge is the presence of sarcasm and irony, which are difficult for machines to interpret accurately. In addition, most datasets used for training are imbalanced, with non-toxic comments significantly outnumbering toxic ones. Language is also constantly evolving, with new slang terms and expressions emerging over time.

1.5 Proposed Framework

To address these challenges, this paper proposes a machine learning-based toxic comment classification system that integrates NLP techniques with real-time visualization.

The proposed framework includes:
Text preprocessing (cleaning, tokenization, normalization) Feature extraction using TF-IDF. Model training using machine learning and deep learning approaches. Toxicity prediction using probability thresholds. Identification of toxic words based on predefined categories. Visualization of results through charts and dashboards. Additionally, a user-friendly web interface is developed using Stream lit to allow real-time interaction with the system.

1.6 Objectives and Contributions

The primary objective of this work is to develop an efficient and reliable system for detecting toxic comments in online platforms. The study also aims to improve classification performance using machine learning techniques and to provide an interactive interface for real-time analysis. This work makes several contributions in the area of toxic comment detection. It presents a practical implementation of a classification system that combines machine learning and NLP techniques. The use of TF-IDF for feature extraction ensures efficient text representation, while the integration of visualization tools improves the interpretability of results. Furthermore, the system is designed to be lightweight and user-friendly, making it suitable for real-world applications in content moderation.

II. LITERATURE REVIEW

Toxic comment detection has become an important area of research due to the increasing use of online platforms and the rise of harmful user-generated content. Early approaches to detecting toxic comments mainly relied on rule-based filtering systems, where specific keywords or phrases were used to identify inappropriate content. Although these methods were simple to implement, they lacked flexibility and were not effective in understanding the context of language. As a result, they often failed to detect subtle forms of toxicity or produced incorrect classifications.

With the advancement of machine learning, researchers began to explore supervised learning techniques for text classification tasks. Algorithms such as Logistic Regression, Naïve Bayes, Support Vector Machines (SVM), and Decision Trees have been widely used for toxic comment detection. These models, when combined with feature extraction techniques like Bag of Words and TF-IDF, showed improved performance compared to traditional methods. For instance, studies have demonstrated that TF-IDF-based models can effectively capture the importance of words in a document, thereby improving classification accuracy.

In recent years, deep learning approaches have gained significant attention in this domain. Models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have been applied to capture sequential and contextual information in text. These models are capable of learning complex patterns and dependencies that traditional machine learning models may overlook. Research has shown that deep learning models achieve higher

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accuracy in detecting toxic comments, particularly when large datasets are available for training. However, these models often require high computational resources and longer training times.

More recently, transformer-based models such as BERT have further improved the performance of text classification systems. These models use contextual embeddings to better understand the meaning of words within a sentence. Studies indicate that transformer-based approaches outperform traditional machine learning and basic deep learning models in many natural language processing tasks, including toxic comment detection. Despite their effectiveness, these models are computationally expensive and may not be suitable for real-time applications with limited resources.

Another important area of research focuses on improving model performance through hybrid and ensemble techniques. By combining multiple models, researchers have been able to achieve better generalization and robustness. Ensemble methods such as Random Forest and boosting techniques have been successfully applied to toxic comment classification tasks. These approaches help reduce overfitting and improve prediction accuracy by leveraging the strengths of different models.

Despite the significant progress made in this field, several challenges still exist. These include handling sarcasm and implicit toxicity, dealing with imbalanced datasets, and ensuring model interpretability. While advanced models provide higher accuracy, they often act as "black boxes," making it difficult to understand the reasoning behind their predictions.

This study builds upon existing research by developing a toxic comment classification system that balances performance and practicality. Unlike purely deep learning-based approaches, the proposed system focuses on combining efficient feature extraction techniques with machine learning models to achieve reliable results. In addition, the integration of visualization tools enhances interpretability, making the system more suitable for real-world applications in content moderation.

III. METHODOLOGY

The proposed system for Toxic Comment Classification using Machine Learning and Natural Language Processing follows a structured pipeline consisting of multiple stages. Each stage is designed to process textual data efficiently, extract meaningful features, and accurately classify comments as toxic or non-toxic.

3.1 Data Collection

The first step involves collecting a dataset of user-generated comments from publicly available sources. The dataset contains labelled text data used for training and testing the classification model.

The dataset typically includes:

- User comments (text data)
- Toxicity labels (toxic / non-toxic)
- Categories of toxicity such as:
  - Profanity
  - Hate speech
  - Insults
  - Threats
  - Harassment

The dataset consists of two main classes:

1. Toxic comments (minority class)
2. Non-toxic comments (majority class)

In real-world scenarios, non-toxic comments are more frequent, leading to slight class imbalance.

3.2 Data Preprocessing

Text data is often unstructured and contains noise. Therefore, preprocessing is an essential step to improve data quality.

The preprocessing steps include:

Text Cleaning: Removal of special characters, punctuation, and numbers and conversion of text to lowercase

Tokenization: Splitting sentences into individual words or tokens

Stop word Removal: Removing common words such as "the", "is", "and" that do not add significant meaning.

Stemming: Reducing words to their root form.

These steps help in transforming raw text into a clean and structured format suitable for analysis.

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3.3 Feature extraction using TF-IDF

Machine learning models cannot directly process text data. Therefore, feature extraction is used to convert text into numerical form.

TF-IDF (Term Frequency–Inverse Document Frequency) is applied to:

1. Measure the importance of words in a document
2. Assign higher weights to meaningful words
3. Reduce the impact of commonly occurring words

Benefits of TF-IDF:

- Efficient text representation
- Improved model performance
- Reduced dimensionality compared to raw text

3.4 Toxic word Identification

In addition to classification, the system identifies toxic words present in the input text.

Predefined categories of toxic words are used:

- Profanity
- Hate speech
- Insults
- Threats
- Harassment

This step helps in:

- Providing explainability
- Highlighting specific harmful words
- Improving user understanding of predictions

3.5 Model Development

Multiple models are developed to perform classification and improve prediction accuracy.

Models used:

Logistic Regression:

- Simple and interpretable model
- Suitable for binary classification

Decision Tree:

- Captures decision rules and patterns
- Easy to visualize

Random Forest:

- Ensemble method combining multiple decision trees
- Provides higher accuracy and robustness

TensorFlow Neural Network (Deep Learning):

- Captures complex relationships in text
- Improves performance for large datasets

Why multiple models?

- To compare performance
- To select the most effective model
- To ensure robustness and reliability

3.6 Model Training and Testing

The processed dataset is divided into:

1. Training set (e.g., 70–80%)
2. Testing set (e.g., 20–30%)

Steps:

- Train models using training data
- Test models on unseen data
- Apply cross-validation to ensure consistency

This step ensures that the model generalizes well and avoids overfitting.

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3.7 Prediction Mechanism

The trained model predicts the toxicity level of input text.
Steps:

1. Input text is pre-processed
2. Text is converted into TF-IDF vectors
3. Model predicts probability score

3.8 Performance Evaluation

To evaluate the effectiveness of the model, several metrics are used:
Accuracy: Overall correctness of predictions
Precision: Correctly predicted toxic comments out of all predicted toxic
Recall: Ability to detect actual toxic comments
F1-Score: Balance between precision and recall
Importance: Recall is important to ensure toxic comments are not missed. F1-score provides balanced evaluation.

3.9 System Implementation

The final model is deployed into a real-time application for user interaction.
Implementation details:

- Developed using Python
- Stream lit used for web interface
- Integrated with machine learning model

User Interaction:

- User enters a comment
- System analyses the text
- Output is displayed as:

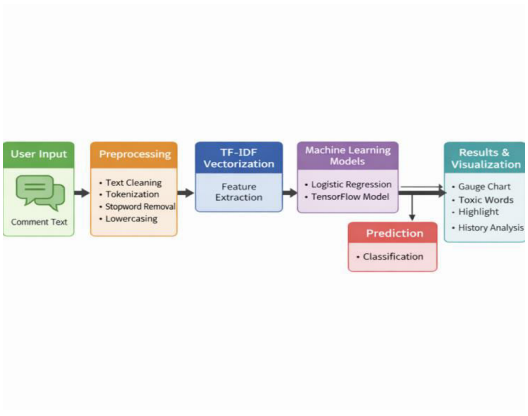
1. Toxicity probability score
2. Toxic / Non-toxic classification
3. Highlighted toxic words
4. Visualizations (charts/graphs)

3.10 Overall Workflow Summary

The complete workflow of the system is as follows:

- Collect toxic comment dataset
- Preprocess and clean text data
- Convert text into TF-IDF features
- Train multiple machine learning models
- Evaluate model performance
- Deploy the best model
- Provide real-time predictions with visualization

ARCHITECTURE DIAGRAM



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IV. MACHINE LEARNING AND DEEP LEARNING ALGORITHMS

In this study, several machine learning and deep learning algorithms are implemented to classify Comments as Toxic or Non- toxic. These algorithms are chosen based on their efficiency, accuracy, and ability to handle classification problems.

4.1 Logistic Regression

Logistic Regression is a statistical classification algorithm used for binary text classification tasks.

Key Points:
• Predicts whether a comment is Toxic or Non-toxic
• Works well with TF-IDF text features

Advantages:
• Simple and easy to implement
• Fast and efficient for large datasets
• Provides probability-based output

Limitations:
• Not suitable for complex non-linear relationships
• Performance depends on feature quality

4.2 Naïve Bayes

Naïve Bayes is a probabilistic classifier based on Bayes' Theorem, widely used for text classification.

Key Points:
• Assumes independence between words/features
• Works well with Bag of Words and TF-IDF
• Suitable for large-scale text data

Advantages:
• Very fast and computationally efficient
• Performs well for text classification problems
• Requires less training data

Limitations:
• Assumption of feature independence is not always realistic
• May reduce accuracy in complex datasets

4.3 Decision Tree

Decision Tree is a supervised learning algorithm that splits data based on feature values.

Key Points:
• Uses if-else conditions for classification
• Easy to visualize and interpret
• Captures non-linear relationships

Advantages:
• Simple to understand
• Handles both numerical and categorical data
• No need for feature scaling

Limitations:
• Prone to overfitting
• Sensitive to small changes in data

4.4 Random Forest

Random Forest is an ensemble learning method that combines multiple decision trees.

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Key Points:
- Builds multiple trees and combines their outputs
- Uses bagging (Bootstrap Aggregation)
- Reduces overfitting compared to a single decision tree

Advantages:
- High accuracy
- Handles large datasets efficiently
- Robust to noise and outliers

Limitations:
- Less interpretable compared to a single tree
- Requires more computational resources

4.5 Support Vector Machine (SVM)
Support Vector Machine is a powerful classification algorithm that finds the optimal boundary (hyperplane) between classes.

Key Points:
- Maximizes margin between classes Can handle linear and non-linear data using kernels
- Effective in high-dimensional spaces

Advantages:
- High accuracy in complex datasets
- Works well with clear margin of separation

Limitations:
- Computationally expensive
- Difficult to tune parameters

4.6 Deep Learning Model (Neural Networks)
Neural Networks are deep learning models used to capture complex patterns in text data.

Key Points:
1• Implemented using TensorFlow
1 • Learns patterns and relationships between words
1• Suitable for large datasets

Advantages:
• Captures complex and contextual patterns
• Provides better performance for large data

Limitations:
• Requires more training time
• Needs high computational power

4.7 Why These Algorithms Are Used
The selected algorithms provide a balance between:
- Interpretability (Logistic Regression, Naïve Bayes, Decision Tree)
- Accuracy and robustness (Random Forest, SVM, Neural Networks)

By comparing multiple models, the system selects the most suitable algorithm for toxic comment classification.

4.8 Role in Toxic Comment Classification
These models play an important role in detecting harmful content in text data:

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• Learn patterns from labelled comment datasets
• Identify abusive, offensive, or harmful language
• Classify comments into Toxic or Non-toxic categories
When combined with TF-IDF feature extraction, the models perform effectively by:
• Converting text into meaningful numerical features
• Improving classification accuracy

V. IMPLEMENTATION AND RESULTS

The proposed toxic comment classification system is implemented using a combination of machine learning techniques and web-based technologies to ensure efficient and real-time prediction. The frontend of the system is developed using Stream lit, which provides an interactive and user-friendly interface for entering text and viewing results. The backend is implemented in Python, where the machine learning models are integrated for prediction. Libraries such as Pandas and NumPy are used for data handling and preprocessing, while Scikit-learn and TensorFlow are utilized for model development and evaluation.

The system follows a structured workflow starting with data preprocessing. The input text data is cleaned by removing special characters, converting text to lowercase, and eliminating unnecessary words such as stop words. This step ensures that the data is consistent and suitable for further processing. Tokenization is applied to split the text into individual words, making it easier to analyze.

After preprocessing, feature extraction is performed using TF-IDF (Term Frequency–Inverse Document Frequency). This technique converts textual data into numerical vectors by assigning weights to words based on their importance in the document. This transformation enables machine learning models to process text effectively.

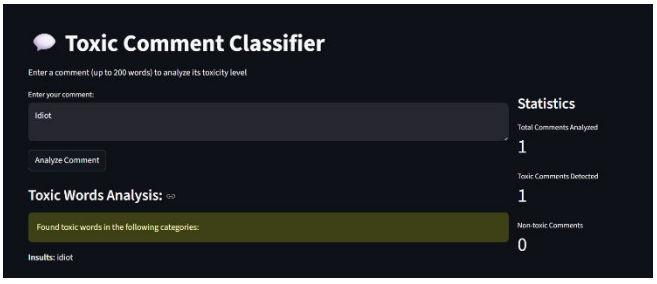
Once the data is transformed, multiple classification algorithms such as Logistic Regression, Naïve Bayes, Random Forest, and a TensorFlow-based neural network are applied. These models are trained on the processed dataset to learn patterns associated with toxic and non-toxic comments. The dataset is divided into training and testing sets to evaluate the performance of the models. The trained models are assessed using evaluation metrics such as accuracy, precision, recall, and F1-score to ensure reliable performance.

After evaluation, the best-performing model is selected and saved using serialization techniques. This model is then integrated into the Stream lit application to enable real-time predictions. The user can enter any comment into the interface, and the system instantly predicts whether the comment is toxic or non-toxic.

In addition to classification, the system also identifies toxic words present in the input text and categorizes them into groups such as profanity, insults, and threats. Visualization techniques such as gauge charts and bar graphs are used to display the toxicity score and highlight the contribution different categories.

The results show that the system is capable of accurately classifying comments based on their toxicity. Comments containing offensive or abusive language are correctly identified as toxic, while normal comments are classified as non-toxic. The use of TF-IDF along with machine learning models significantly improves classification performance. The integration of a real-time interface further enhances the usability of the system.

Overall, the implementation demonstrates that combining machine learning techniques with NLP and visualization tools results in an effective and practical solution for toxic comment detection in online platforms.



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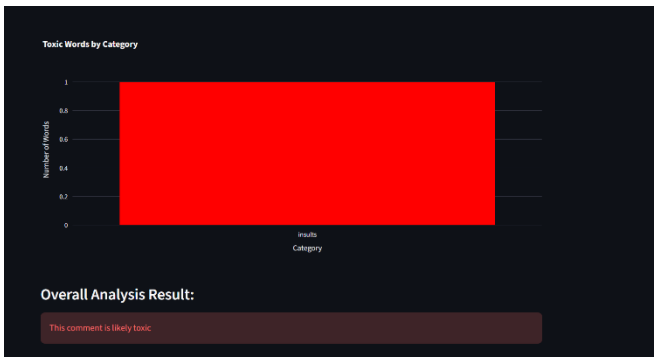

VI. CONCLUSION

This study presents an effective approach for detecting toxic comments using machine learning and natural language processing techniques. The system successfully addresses the challenge of identifying harmful content in large volumes of user-generated text by automating the classification process.

The experimental results indicate that machine learning models, particularly Logistic Regression and neural network-based approaches, provide reliable performance when combined with TF-IDF feature extraction. The system is able to accurately distinguish between toxic and non-toxic comments and also highlight specific harmful words present in the text.

Compared to traditional rule-based methods, the proposed system offers several advantages:
•Improved classification accuracy
•Ability to handle large-scale text data
•Better identification of complex language patterns
• Real-time prediction capability

The integration of a user-friendly interface further enhances the practicality of the system, making it suitable for deployment in real-world applications such as social media moderation and online content filtering.

Overall, this work contributes to the development of intelligent and scalable solutions for maintaining safe and respectful online environments.

VII. FUTURE WORK

To further improve the performance and capabilities of the proposed toxic comment classification system, several enhancements can be considered:

7.1 Advanced Deep Learning Models

Implement advanced NLP models such as BERT, Roberta, and GPT-based architectures to improve contextual understanding and classification accuracy.

7.2 Real-Time Content Moderation

Develop a real-time monitoring system that can analyze streaming data from social media platforms and detect toxic comments instantly.

7.3 Multilingual Toxic Comment Detection

Extend the system to support multiple languages and detect toxicity in multilingual and code-mixed text.

7.4 Improved Feature Engineering

Incorporate advanced text representation techniques such as word embeddings (Word2Vec, Glove) and contextual embeddings to enhance model performance.

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7.5 Multi-Class Classification

Extend the model to classify different types of toxicity such as hate speech, cyberbullying, threats, and harassment instead of binary classification.

7.6 Explainable AI Techniques

Integrate explainable AI methods to provide better insights into model predictions and improve transparency.

7.7 Performance Optimization

Optimize model parameters using techniques such as Grid Search and Hyperparameter Tuning to improve accuracy and efficiency.

7.8 Deployment and Integration

Deploy the system as a web API or integrate it with social media platforms for large-scale real-world usage.

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