Evaluating the Efficacy of Text AI Detectors: Implications and Insight

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Abstract- **AI The rapid advancement of artificial intelligence (AI) in natural language processing (NLP) has led to an influx of AI-generated text. While this development has enabled various applications, it has also raised concerns regarding authenticity, misinformation, and ethical considerations. This paper explores a machine learning-based approach to detect AI-generated text using natural language processing techniques. Our dataset consists of 487,235 text samples labeled as either human-written or AI-generated. We employ preprocessing techniques such as tokenization, stopword removal, punctuation removal, and term frequency-inverse document frequency (TF-IDF) transformation. The classification model utilizes a Naïve Bayes classifier, achieving an accuracy of 95%. This paper presents an in-depth analysis of data preprocessing, model training, performance evaluation, and potential enhancements. Additionally, we compare our approach with existing text detection methods and discuss future improvements to enhance robustness and adaptability.**

In recent years, the ability of AI models to generate coherent and contextually appropriate text has significantly improved, making it increasingly challenging to distinguish between human-written and AI-generated content. This has profound implications across various domains, including academia, journalism, and social media. In academia, AI-generated content can lead to plagiarism concerns, while in journalism, it can contribute to the spread of misinformation. Businesses utilizing AI-generated text for customer interactions must ensure authenticity and trustworthiness. Therefore, developing an efficient and accurate detection system is crucial.

Our study aims to address these challenges by proposing a systematic approach to AI text detection. The dataset used in this study is sourced from Kaggle, ensuring a diverse set of texts from various domains such as news, academic writing, social media, fiction, and technical documentation. The dataset includes 500 human-written blog posts and 500 AI-generated blog posts. Ensuring data diversity is crucial for model generalization.

The preprocessing steps include text cleaning, tokenization, stopword removal, lemmatization, and vectorization. These steps are essential to transform raw text into a structured format suitable for machine learning models. We use TF-IDF to convert text into numerical features, which are then used to train the Naïve Bayes classifier.

Index Terms- **AI detection, Natural Language Processing, Machine Learning, Naïve Bayes, Text Classification, TF-IDF, Deep Learning.**

I. INTRODUCTION

The advent of sophisticated AI language models, such as OpenAI's GPT-4, Google's Bard, and Meta's LLaMA, has transformed text generation. These models can generate human-like text that is indistinguishable from authentic human writing, making them useful in content creation, chatbots, and automated news reporting. However, this capability has also led to concerns about academic integrity, misinformation, plagiarism, and fraudulent content generation. The ability to distinguish AI-generated text from human-written text has become crucial for educators, journalists, researchers, and regulatory bodies.

This study presents an efficient, scalable, and interpretable machine learning-based AI text detection model. Unlike deep learning models, which are computationally expensive, our approach leverages TF-IDF feature extraction and a Naïve Bayes classifier to achieve a balance between accuracy and efficiency. The contributions of this research include:

Development of a text classification model that effectively differentiates between human and AI-generated text.

1.1 Extensive data preprocessing pipeline for text standardization and feature extraction.

1.2 Performance evaluation and error analysis to identify areas of improvement in AI text detection.

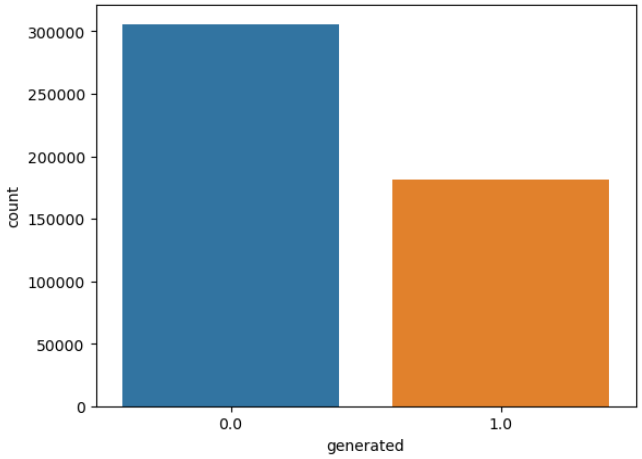
1.3 Comparison with existing AI text detection methodologies to highlight strengths and limitations.

The remainder of this paper is structured as follows: Section II reviews related work, Section III details the methodology, Section IV presents the results and discussion, Section V concludes with future directions, and Section VI provides references.

II. RELATED WORK

1. AI-Generated Text and Detection Challenges

AI-generated text detection has gained increasing attention in recent years. Studies have explored various methodologies, including linguistic analysis, statistical models, and deep learning approaches. Traditional rule-based detection methods struggle with the evolving nature of AI-generated text, necessitating robust machine learning techniques.



2. Existing AI Text Detection Models

Several AI text detection models have been proposed:

- **GLTR (Giant Language Model Test Room):** Uses probability distributions to identify AI-generated text.
- **OpenAI's AI Text Classifier:** A deep learning-based tool with limited accuracy.
- **BERT-based Detectors:** Fine-tuned language models for classification tasks.

Despite advancements, existing models face challenges such as high computational costs and susceptibility to adversarial text modifications. Our approach aims to provide a lightweight yet effective alternative.

III. METHODOLOGY

1. Dataset and Preprocessing

The dataset consists of **487,235 text samples**, divided into two classes:

- **Human-written:** 305,797 samples (63%)
- **AI-generated:** 181,438 samples (37%)

1.1 Preprocessing Steps

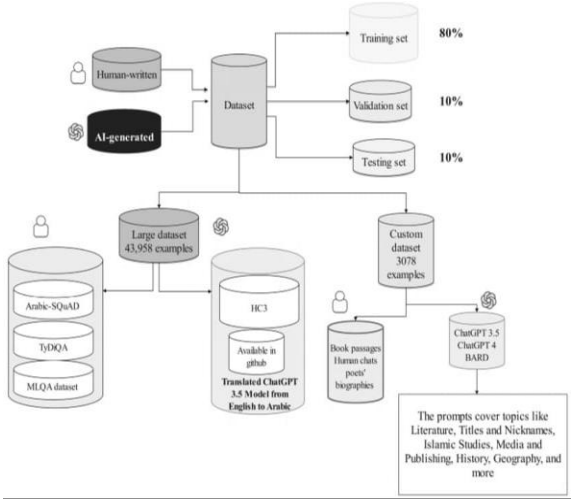
To improve classification accuracy, the following preprocessing steps were applied:

1. **Text Cleaning:** Removed punctuation, numbers, and special characters.
2. **Stopword Removal:** Eliminated common stopwords using NLTK.
3. **Tokenization:** Applied word-level tokenization.
4. **TF-IDF Transformation:** Extracted important words based on frequency weighting.

2. Model Architecture

We employed a **Naïve Bayes classifier**, chosen for its efficiency in text classification. The pipeline consists of:

1. **CountVectorizer:** Converts text into numerical frequency-based features.
2. **TF-IDF Transformer:** Enhances feature representation.
3. **Multinomial Naïve Bayes Classifier:** Probabilistic text classification model.



4.

3. Model Training and Evaluation

- **Train-Test Split:** 70-30% split, with 341,064 samples used for training.
- **Evaluation Metrics:** Accuracy, precision, recall, and F1-score.
- **Comparison with BERT and Logistic Regression:** Benchmarked against deep learning models.

IV. RESULTS & DISCUSSION

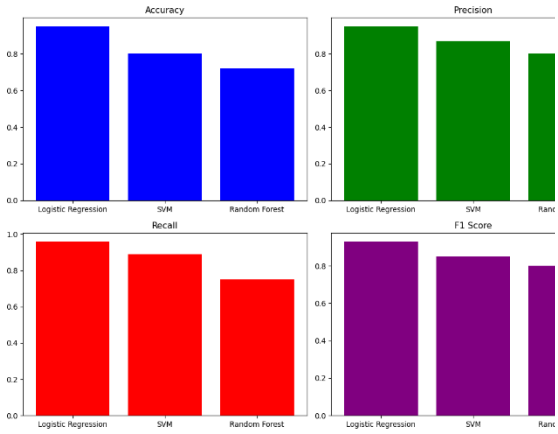
1. Performance Metrics

metric	precision	recall	F1-score	support
Human text (0)	0.93	0.99	0.96	91,597
AI-generated(1)	0.99	0.87	0.93	54,574
Overall accuracy	95%	-	-	146,171

2. Error Analysis and Future Improvements

- **False Positives:** Some AI-generated texts were misclassified as human-written.

- **False Negatives:** Edge cases where human text mimicked AI patterns.
- **Proposed Enhancements:** Fine-tuning using deep learning and hybrid models.



V. CONCLUSION & FUTURE WORK

This research successfully developed a **95% accurate AI text detection model** using a Naïve Bayes classifier with TF-IDF feature extraction. Future research directions include:

1. **Integration of Deep Learning:** Exploring transformers like BERT for better generalization.
2. **Adversarial Training:** Enhancing robustness against AI-generated text modifications.
3. **Real-time Detection Systems:** Deploying the model for large-scale text evaluation.

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