Unveiling Writing Styles: A Comparative Analysis of AI-Generated and Human Generated Content

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ABSTRACT

Artificial Intelligence (AI) has revolutionized the process of producing content, and this has raised many questions about the kind of difference the writing styles of material produced by AI and that of humans differ from each other in. This is essential in exploring this important topic by comparing or contrasting a wide range of writing style indicators. It attempts to identify observable trends and differences in writing styles by looking at the complexity of words, semantics, readability, sentiment analysis, vocabulary variety, and plagiarism rate. Using a strict methodology, the content generated by AI through language models is compared against the content produced by humans in this case, articles written by bloggers and professional authors. Some of these instruments and measurements are quite well-studied, such as readability formulae, sentiment analysis methods, plagiarism detection algorithms, and so forth, where there is a possibility of doing a detailed investigation on the variations in writing styles. This work adds to the ever-increasing corpus of study in computational linguistics and digital communication that is found in the literature on AI generated content and writing style analysis. The findings are not just illuminating what distinguishes AI generated content but also open the space for its impact on content development, quality evaluation, and ethical concerns. This project advanced knowledge about the rapidly changing environment of digital content generation and consumption by unveiling the intricacies of writing styles of material produced under the guise of human authorship and artificial intelligence.

Keywords: Writing styles, AI and Human generated content, Comparative analysis, Plagiarism rate, Cosine Similarity Algorithm

1. INTRODUCTION

Recently, there has been a tremendous boom in machine-generated content created without any human intervention. This boom is taking place as AI technologies advance, and it is becoming increasingly difficult to distinguish whether content is created by an AI or a human being. Understanding these differences can be the difference, as their applicability implications cut across various sectors like journalism, entertainment industries, and more. Being able to separate human writing from AI written text is essential. It is what ensures consumption of content without tampering with facts and compromising authenticity. Additionally, it is in the fight against erosion of human creativity in writing and artistry. Such distinctions help better adapt to changing practices in content creation and consumption in very fast-paced ways. Therefore, the main objective of this paper is to examine and compare the writing styles of AI generated content and human-written content. This effort helps in the identification of distinct features and characteristics that

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exist in each group. Knowing how AI works contributes to improving the technology's ability to mimic human writing or highlights its differences. These studies offer insightful findings into the creation of content by both humans and machines.

2. PROBLEM STATEMENT

Artificial Intelligence has become an integral part of modern life. With the advancement of technology, it has made tremendous progress, particularly in content creation. At present, it is also becoming very difficult to differentiate between computer generated and human written literary pieces. However, in the midst of these advancements, the identities, characteristics, and classifications of AI generated versus human authored content remain unclear. This debate is being taken up by many, including consumers, researchers, and content producers, due to several concerns, among which range ethical questions to questions of author legitimacy. There are too many things still left to discover about the minute characteristics of AI and human writing styles, tones, and other traits. Toward this end, content comparison between AI generated text and human-generated text aims to address challenges. The aim is to analyze the unique debates over content production using AI, its benefits, and difficulties in human communication. This study also yields valuable insight that can be used to improve AI writing software and algorithms. Understanding the development of AI and the factors distinguishing what it produces from what a human does would, therefore, require an in-depth investigation and systematic comparison of both forms of content. This study attempts to fill in that gap by providing insight into the capabilities and limitations of AI in content development.

3. LITERATURE REVIEW

The tremendous innovation in artificial intelligence has brought a great deal of analysis into the comparison of AI generated material with human written texts, considering authenticity, quality, and stylistic principles. Studies have highlighted the issues that arise in distinguishing AI generated fake news from information generated by humans, hence the employment of transfer learning algorithms in an attempt to solve this issue [1]. It also studied the data efficient approach to text generation and unveiled the special features of AI generated text and its outcomes in natural language processing. Further explorations of the enhancements on RNNs for text generation have sought to demystify the computational processes involved in AI text generation [2][3]. Concurrently, growth in green AI models has been acknowledged with renewed emphasis on how AI should embody ethical and environmentally conscious practice [4].

Another important domain is the study of the limitations and difficulties of plagiarism detection [5] and originality verification. Neural embedding methods have been studied for the purpose of making them address these issues. While both the possibilities and limitations of AI generated content highlight the issues at hand, two factors further add to the complexity of developing strong methodology in style analysis: the ambiguity of writing styles and the overlap between original and duplicated work. Such limitations can be addressed only by a multidisciplinary approach combining computer science and machine learning with that of digital humanities in devising comprehensive methods of writing style comparison across different textual formats.

4. METHODOLOGY

The proposed methodology section states an overview of a comprehensive comparison of AI with human generated texts by making use of varied analytical frameworks and technical implementations. There is a clear overview of the systematic process involved in collecting and processing data through multiple algorithms and tools that are used in analysis. The study includes a multi faceted analysis by integrated use of Python based technologies with some specific third-party libraries, namely NumPy, Pandas, and NLTK, showing due consideration to the areas of word complexity, semantic coherence, plagiarism detection, readability metrics, sentiment analysis, and vocabulary diversity. This approach makes use of the quantitative and qualitative measures with advanced algorithms, such as the Cosine Similarity, along with the Rainforest Algorithm alongside more established metrics, such as the Flesch Reading Ease Formula. This methodology will deepen the understanding of the distinction between AI generated content and that which is from the human pole through different lenses supported by solid data visualization techniques and statistical analyses. Thus, this methodological framework ensures a proper, systemic approach towards content difference evaluation with meaningful insights on the characteristic and qualities that can distinguish AI generated content from human authored materials.

4.1 Flow

First, it begins with the collection of subject specific and genre specific datasets, which would be used as the primary and secondary content sources for comparison between artificial and human generated content. The acquired data were cleaned by reducing the same word and phrases, and during that process, unnecessary material was removed. The data generated by artificial intelligence and natural authors was formatted into a comparative framework that maintained the characteristics of each group for comparison purposes. Advanced measures, such as complex word structure metrics, were used in place of some standard parameters. For example, for correlation comparisons, the following types of metrics were employed count, language diversity, plagiarism, and complexity of terminology. This involved semantic analysis using cosine similarity for the differentiation between both writing styles. For ease of interpretation and visualization, the findings of the comparison were used to highlight the difference between an AI produced and a human produced writing style and quality of content. Relevant graphs and charts were also provided, in order to illustrate some discrepancies that might characterize the results for better comparison and understanding. Figure 1 shows a graphical representation of the flow but starts with data collection, then dataset merging, analysis, and visualization in that order.

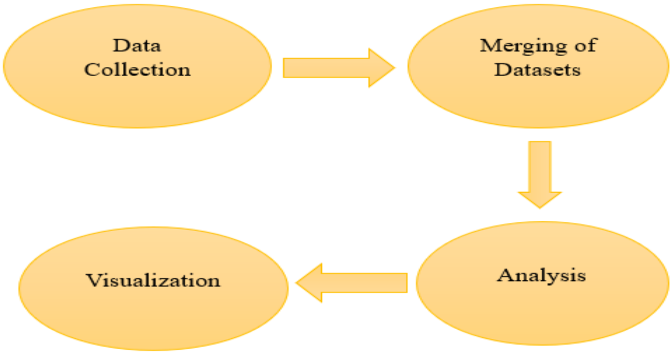

Figure 1: This figure depicts the sequential workflow followed throughout the project execution.

4.2 Technologies Used

The primary programming language used in the execution of studies was Python, which comprised data preparation, model development, and model analysis. This paper relies on several Python frameworks, such as NumPy, Pandas, and Scikit Learn, to improve feature engineering, data manipulation, and ML algorithm construction. Furthermore, Python makes it simple to incorporate a variety of tools and frameworks, expanding the scope of project execution. The comparative study focuses on machine learning, which is frequently utilized in both supervised and unsupervised approaches to model problems such as statistics, content, and plagiarism detection. Machine learning has the ability to detect patterns in data that may be used to back up a claim or argument. LLMs are also utilized when it is necessary to create AI based content or improve language abilities. This is conceivable because complicated models, such as GPT, have been implemented, in which LLM applications are tailored for creative writing assessment using the Python programming language, allowing such LLMs to become more consistent and relevant in the material they create hence improving the AI results in comparison analysis .

4.3 Modules in Use

To support the reliability and efficiency of data processing and analysis, certain modules have been chosen consciously for inclusion in the Python library. One of the most important is NumPy, a library that gives abundance of capabilities to work with arrays and carry out various numerical computations. These two operations are fundamental to any statistical analysis and features extraction. The fact that it can comfortably handle very large volumes of data made it easy to use it together with other Python libraries. This is further improved as Pandas provides interfaces for data analysis and data manipulation in the form of a Data Frame that easily supported data aggregation, transformation, and cleaning. In addition, it enabled this improvement along with other tools which are further strengthening their support to the other data formats and visualizations. Matplotlib is an integral part of this study in the sense that it helps in creating data visuals which helps in understanding what kind of trends and patterns are followed in the data. Using it, line graphs, scatter plots, histograms, and heatmaps, that most effectively presented the results. The last one added to the collection was the Natural Language Toolkit (NLTK), which is a very well Language

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Model known package for natural language processing (NLP) [6][7]. It allowed to do tokenization, sentiment analysis, and parsing among other things. These variety of libraries made analytical capabilities and data processing pipeline much more efficient. Text processing activities involve the use of imported libraries like NLTK (Natural Language Toolkit), that provides a vast array of functionalities for different kinds of tasks such as Tokenization, stop word removal and lemmatization, among others [8]. Except that, this paper also needs some libraries like seaborn and matplotlib, for some parts of visualization and plotting. Figure 2, Libraries used in the project, Python. It includes Pandas, NumPy, Matplotlib, Seaborn, NLTK, and spacy, along with the purposes of data manipulation, visualization, and natural language processing.

```
import pandas as pd
import numpy as np                     # For mathematical calculations
import seaborn as sns                  # For data visualization
import matplotlib.pyplot as plt
import seaborn as sn                   # For plotting graphs
%matplotlib inline
import warnings                        # To ignore any warnings
warnings.filterwarnings("ignore")
import nltk                            # For natural language processing tasks
import spacy                           # For advanced natural language processing tasks
```

Figure 2: This figure highlights Python libraries used to streamline and support the investigation

4.4 Creating a Data Set and plotting Visuals

This dataset was obtained from GitHub and was then cleaned and refined according to specifications. Prior to processing data to analyze it, it was examined and adapted based on the results. The main features of the collection are Content, Type, Source, Originator. In this regards, each feature contributes to the achievement of a goal mainly through their contextualization and classification of the matter being analyzed. This paper hopes to get important insights that will allow for sound judgments about study aims using this rigorously picked dataset, Sno, source, and so on. Using only some of the basic visualization methods, such as generating histograms, will help in evaluating the quality of AI and human generated material. Histograms were also utilized to compare the patterns of distribution, frequency, and so on between these two material groups. The qualitative evaluation offers an overview of the content distribution and, thus enables better understanding of the dataset. The overview presented here through Table 1 gives an idea about the overall structure of the dataset consisting of various examples of content types, in this case, Python code that falls within the category of Code, sourced from ChatGPT, and is labeled as AI generated. Figure 3 presents the distribution of AI generated content in the categories: essays as the most prevalent, followed by poetry and code. Figure 4 shows the distribution of human generated content with essay being significantly dominant to the rest that includes code and poetry.

Table 1: *The data set shown was chosen for the study, it includes the content, kind of material, source of information, and origin.*

Sno	Content	Type	Source	Origin
1	Python code to find the factorial of a number	Code	ChatGPT	AI
2	There are several ways to accomplish this	Code	ChatGPT	AI
3	Import math	Code	ChatGPT	AI

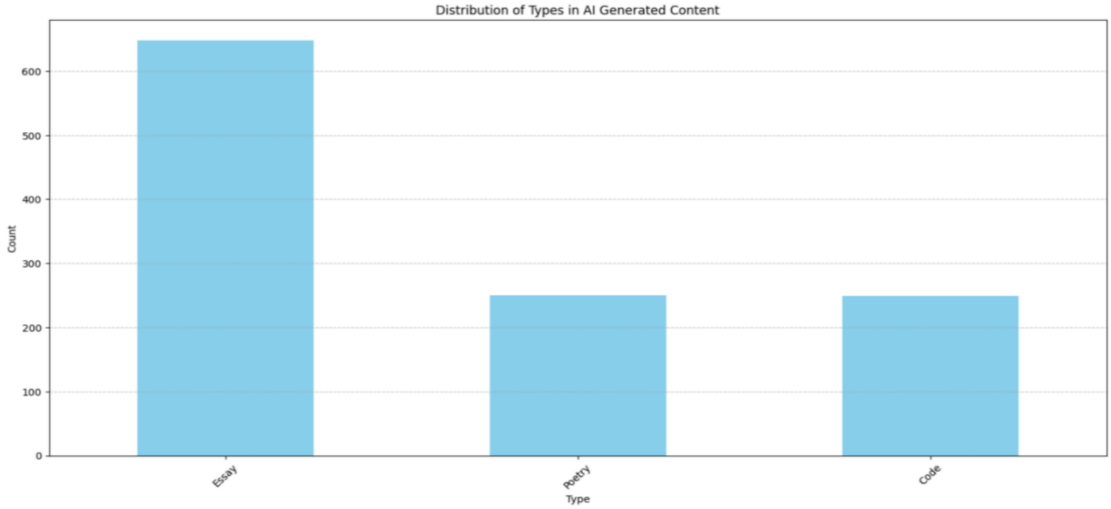

Figure 3: This histogram shows the distribution of AI generated content across various categories.

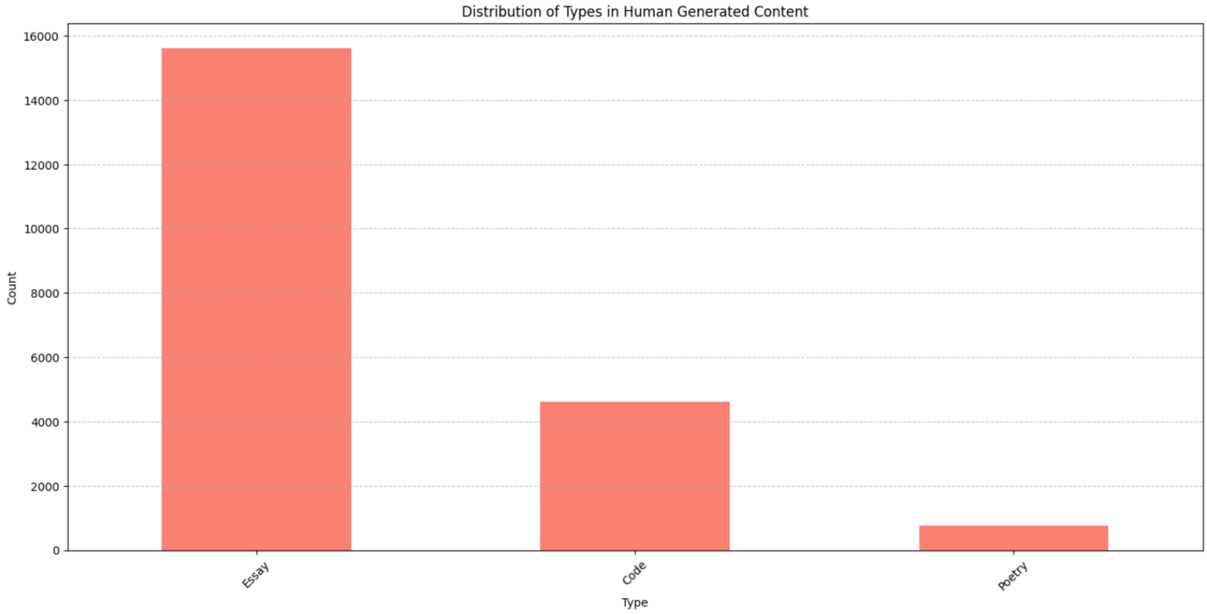

Figure 4: This histogram illustrates the distribution of content created by human contributors.

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4.5 Algorithms Used

Algorithms are critical tools in today's effort at studying and computing. Algorithms are essentially a systematic set of instructions needed to process, analyze, and interpret massive amounts of information. Such orderly instructions are composed to perform certain operations correctly and efficiently and solve specific problems.These are the very processes which govern computing, ranging from data processing to information searching. They enable the implementation of activities such as optimization, pattern recognition, and making decisions in many fields. This versatility and functionality are the reasons for the improvement of science and technology in addressing societal needs.

4.5.1. Cosine Similarity Algorithm: Cosine Similarity Algorithm is one of the most distinctive algorithms used in text mining and data retrieval. It works by determining the cosine angle from the vector representation of data in a high domain space. This algorithm is most suitable for measuring contents of similarity in two or more documents and has numerous applications in text classification, miracle systems, and even in clustering of documents. It is a cheap and efficient tool for text analysis in big volumes as it helps many defenders, researchers, and other users to get important insights and detect relevant tendencies from text corpuses.

$$cos\ cos\ (\theta)\ = \frac{A \cdot B}{|A||B|} \tag{1}$$

4.5.2. Rainforest Algorithm: The Rainforest Algorithm combines notions of swarm intelligence and evolutionary computation, in the spirit of the cooperative behavior exhibited by natural ecosystems. It explores solution spaces quickly and adapts itself to changing environments by optimizing solutions iteratively, based on the relationships among different species inside a rainforest ecosystem. It can easily be used to optimize an immense number of allocation tasks, including resource distribution, data clustering, combinatorial optimization, and many others. The Rainforest Algorithm provides a novel type of approach to solving complicated computational problems with its flexibility and dynamic nature, thus opening ways for creative solutions in many fields. Figure 5 illustrates the confusion matrix generated by the Rainforest Algorithm. It provides a visual representation of the algorithm's classification performance across different categories, showing the number of correct and incorrect predictions for each class. The diagonal elements represent correctly classified instances, while off-diagonal elements indicate misclassifications. This matrix highlights the algorithm's accuracy and areas where improvements may be needed.

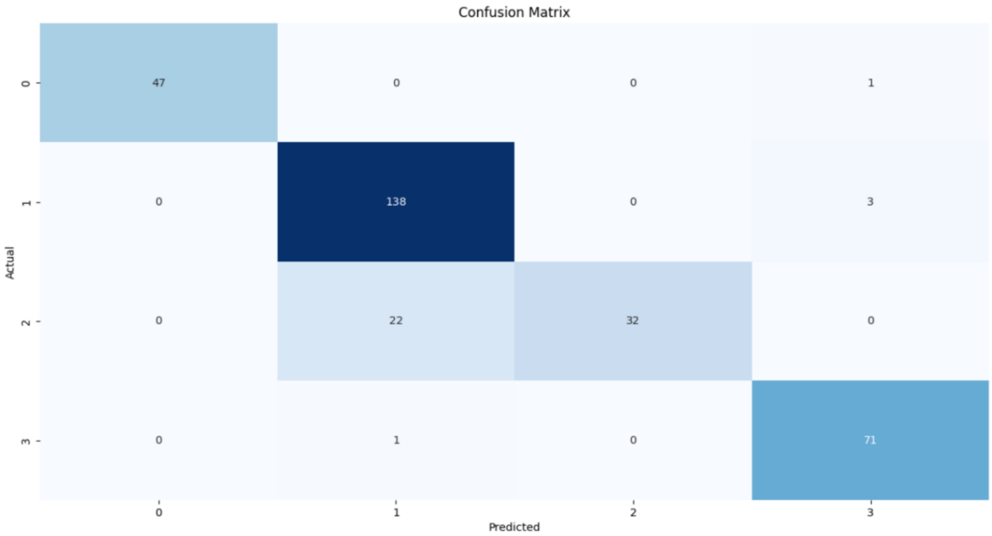

Figure 5: Confusion matrix generated by Rainforest Algorithm

4.5.3. The Flesch Reading Ease Formula: Rudolf Flesch created the formula that defines the readability score of a text based on its metrics in terms of average length of sentences, average number of syllables per word, among others. It assigns a numerical value for the complexities associated with written materials thereby aiding in evaluating how easy or hard any text is to read. The extensive use of the formula within publishing houses, schools, and websites creating content shows its relevance in making communication clearer to diverse readers.

$$206.835 - 1.015\left(\frac{total\ words}{total\ sentences}\right) - 84.6\left(\frac{total\ syllables}{total\ words}\right) \tag{2}$$

4.5.4. Using SpaCy: SpaCy is an established natural language processing toolkit with very rich and beneficial resources for linguistic and textual analysis. It improves the efficiency of operations including dependency parsing, named entity recognition, and part of speech tagging, all because of the advanced models and algorithms. To researchers and developers working on any text processing solution, from machine translation to sentiment analysis, it is considered the most accurate and efficient tool, well known for its easy integration.

4.5.5. Counting lexicon and treating syllables: Discourse Functions are among the centerpieces of text analysis because they account for understanding the nature of written materials. The Lexicon Count function also helps in developing lexicon richness and complexity without stress on the counting technique, by providing a tally for the number of words in a given document. In contrast, the Syllable Count function items a single word by the number of its syllables, which serves the process of evaluating the clarity and pronunciation. These features often found in larger text evaluation systems contribute towards understanding the structure of the language and allow a variety of linguistic analyses ranging from phonetic studies to tests of readability.

4.6 Word Count Analysis

Word count analysis is the method of word counting in a given text. The following study discusses the number of words in a material authored by both AI and humans, placing a special focus on the count of words in a piece of text generated by AI [9]. The technique highlighted verbosity as well as stylistic preferences of each form of writing. It imported the data set as a CSV file, filtered out specific features, and ensured only the desired ones, like Code, Essay, and Poetry, along with content source types AI and Human, were kept. Then, it labeled and divided the data into several generations. The counts of words by all groups were summed up, with the average word count for a group being computed by each category. For the purpose of better illustration, a bar chart was developed showing the average number of words for different forms of text created by AI and by humans. Figure 6 represents a comparison of word count for various types of text that were created using AI and humans, emphasizing differences in language level and stylistic preferences [10]. It was found to be true that AI would be much more productive than humans when it came to word count as far as coding jobs are concerned, although human generated content is way more productive than AI based content when one compares average word count in essays and poetry.

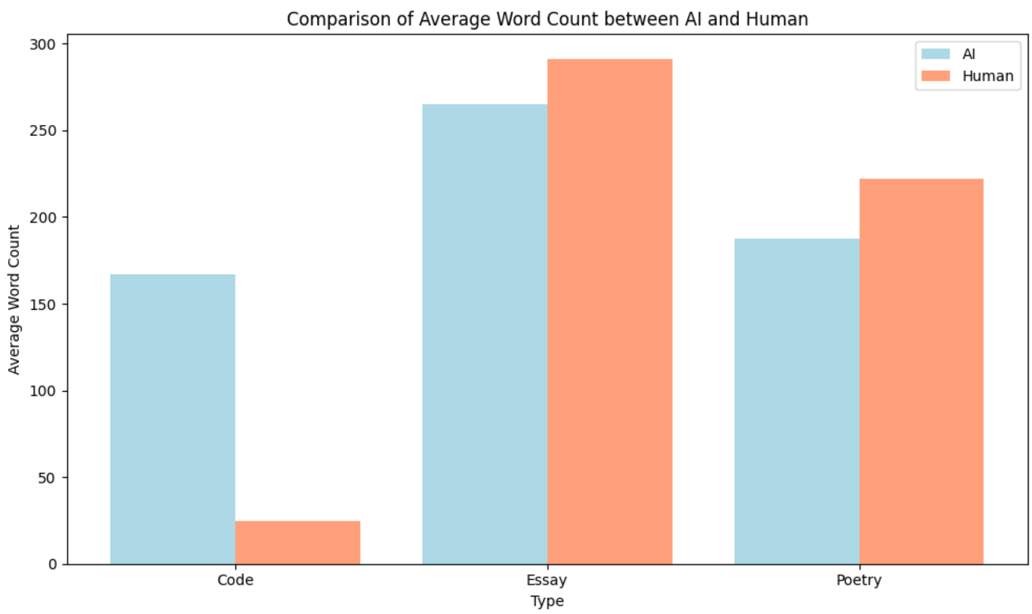

Figure 6: Word Count Comparison for various types of text generated by AI and Humans

4.7 Plagiarism Checking

Checking for plagiarism ensures that the material is original and reliable. This study used methods to compare works written by humans and artificial intelligence to existing literature in order to detect instances of plagiarism [11]. By measuring plagiarism incidences in both kinds of publications, this study examined the level of content overlap and the ability of AI systems to generate novel content. Cosine similarity, a mathematical concept, was applied to the given problem to determine the level of similarity between two publication content. With the help of TF IDF improvement graphs, this technique has analyzed the level of replication between artificial and human created texts. A kernel density estimation graph has been utilized to present the similarity in the distribution of cosine similarity metrics for artificial as well as human created text. A score of 0.8 means the existence of plagiarism. Figure 7 Plagiarism detection based on the kernel density estimate of cosine similarity scores.

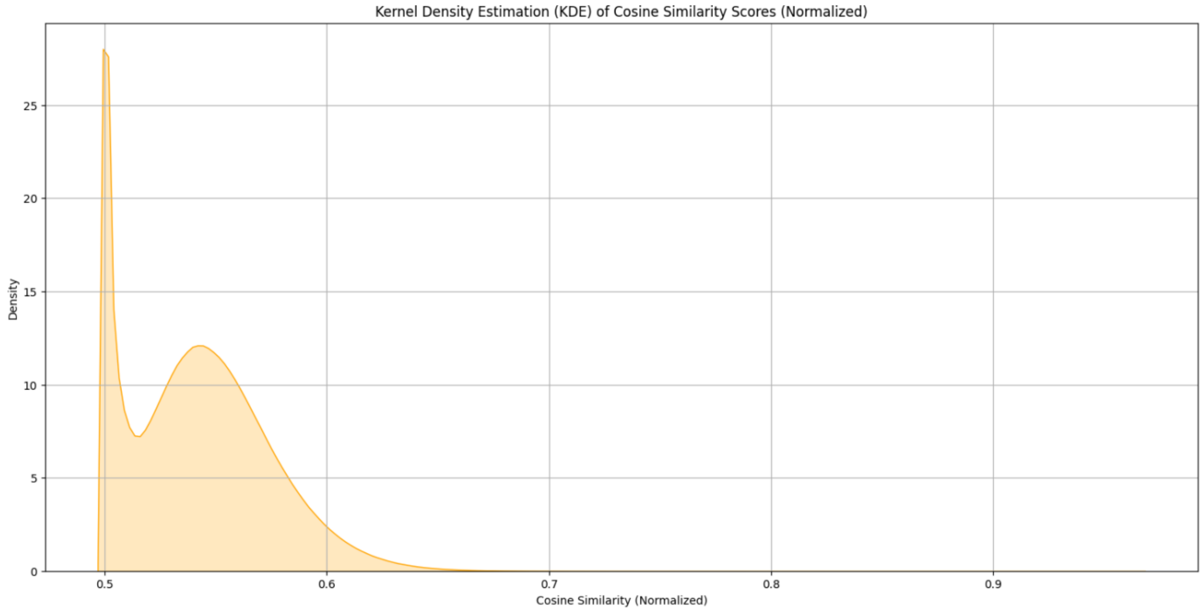

Figure 7: Kernel Density Estimation of Cosine Similarity Scores for checking plagiarism

4.8 Word Complexity

Word complexity refers to how difficult the vocabulary of a particular text is. The level can sometimes be ascertained through the use of indices, such as the Flesch Kincaid Grade Level or the Coleman Liau Index. Of course, comparing the word complexity of different texts can be a useful way of assessing the former's level of elaboration and readability [12]. It seems that multiple tones or dialects increase the complexity of word. The findings suggest that the content written by humans showed richer word usage than the AI generated content, meaning that humans tend to use more elaborate and diverse language [13]. This finding is further depicted in Figure 8, showing the distribution of the word complexity for AI and human generated content using the Flesch Reading Ease Score. The figure shows huge words difference, and indeed, it shows how the human created text often scored low on the Flesch Reading Ease Scale, indicating increased complexity relative to AI generated material.

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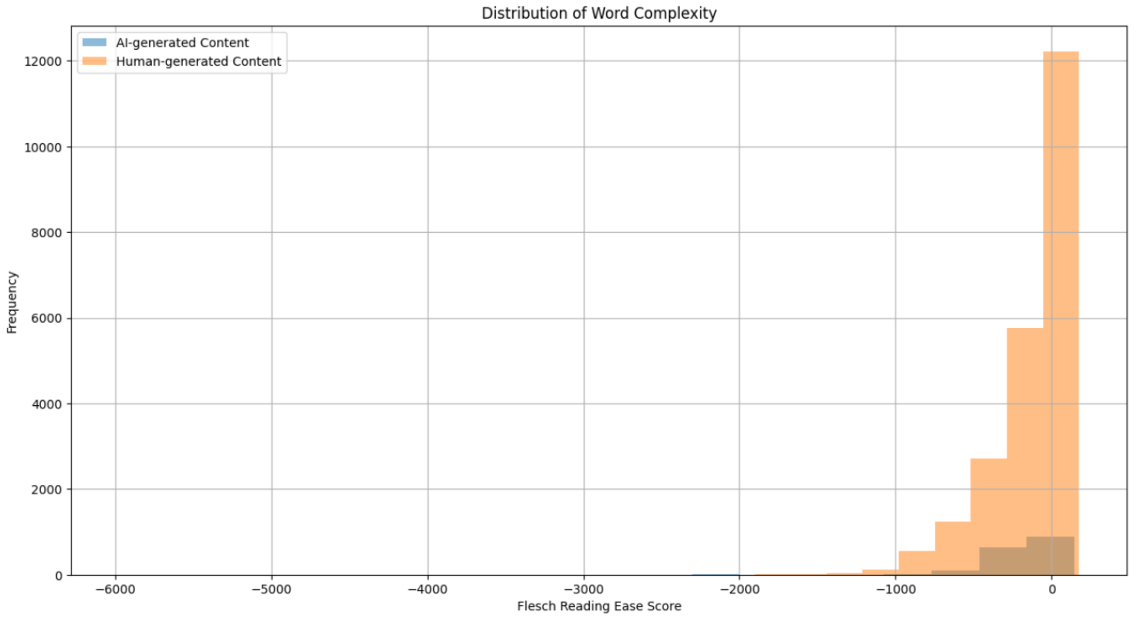

Figure 8: Distribution of Word Complexity for AI and Human Generated Content using Flesh Reading Ease Score

4.9 Semantic Analysis

Semantic analysis deals with the comparison of the output content developed by artificial intelligence and humans [14]. That is, the purpose of this kind of study is to find semantic errors and check the coherence and readability of the text. In this work, an approach was used to check semantic consistency in AI generated content by analyzing the semantic structure of it. Figure 9 , the results show a heatmap that indicates differences in semantic accuracy and coherence of content created by AI as against that created by humans. Therefore, the heatmap presents significant differences and points out areas where the semantic understanding of AI systems falters compared to human created content. These findings point toward the importance of determining the inability of an AI system to come up with precise and cohesive output and pushing for better performance in this area [15][16].

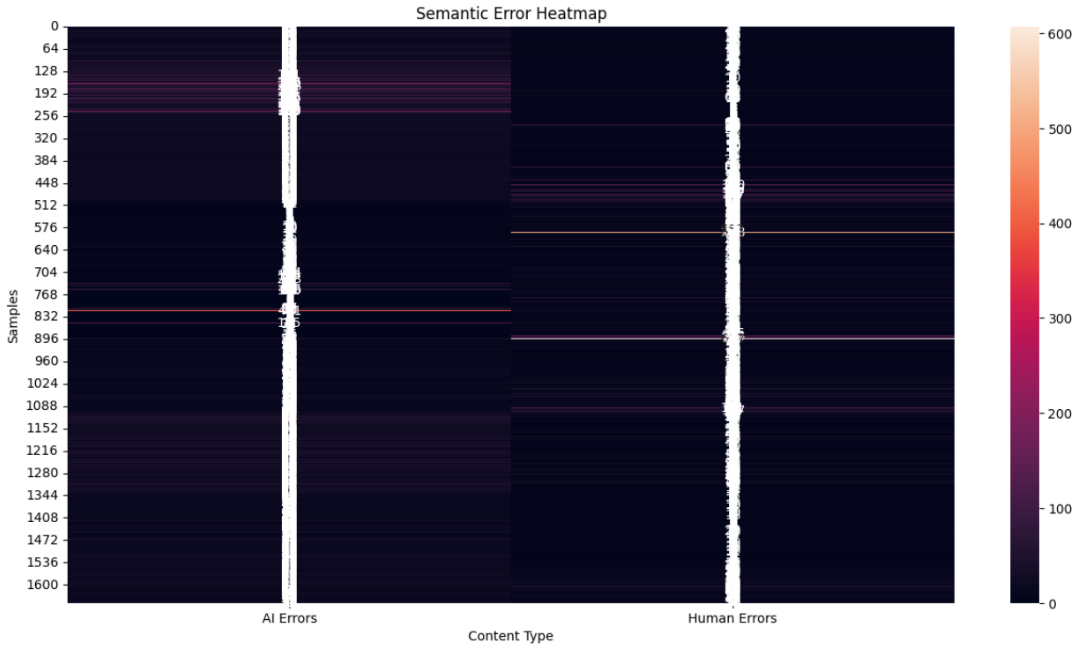

Figure 9: Heatmap for Semantic Analysis to find out presence of errors in AI and Human Generated Content

4.10 Readability

Readability is the ease with which a piece of text can be read. Some tools measure the readability using Flesch Reading Ease scores. For the purpose of this study, readability was estimated and calculated to compare between AI generated texts and human written texts and to see if there were differences in terms of how easy and readable the texts seemed to be from either source [17]. Several visualization techniques, such as box plots, histograms, and scatter plots, were employed to depict the distribution and relationship of readability scores. Figure 10 presents a side by side comparison of readability scores, while Figure 11 depicts their distribution for both AI and human generated texts. The results suggest a general trend, AI generated texts have higher readability scores meaning that they are easier to read. This is further proven in Figure 12, which has used a scatter plot to portray readability distribution. It clearly shows that more frequent higher readability scores occurred in AI generated content, thus making the content easily readable and coherent [18]. The findings show that the texts generated through AI tend to be much more reader friendly compared to their human counterparts, thus revealing various strengths of AI systems while comparing it with human based writing, especially about coherent text composition.

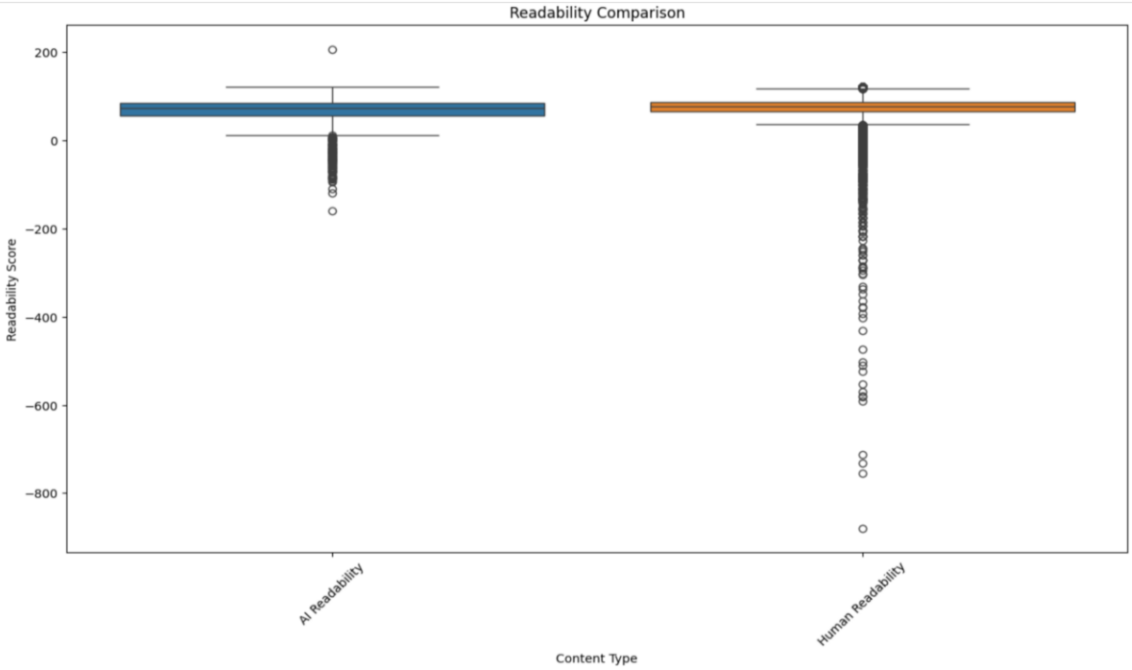

Figure 10: Readability Comparison between AI and Human Generated Content based on the readability Scores

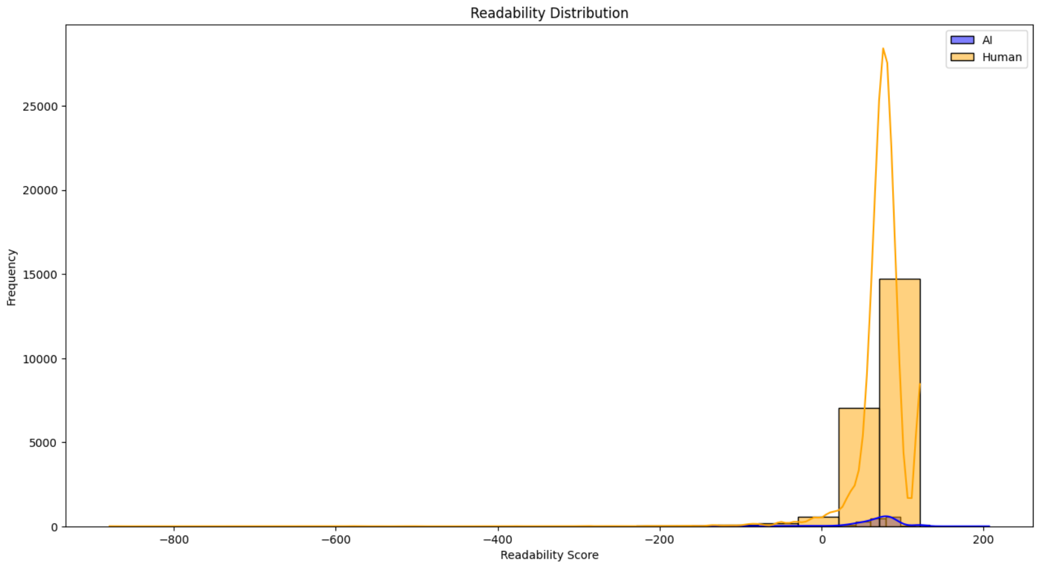

Figure 11: Readability Distribution of AI and Human Generated Content

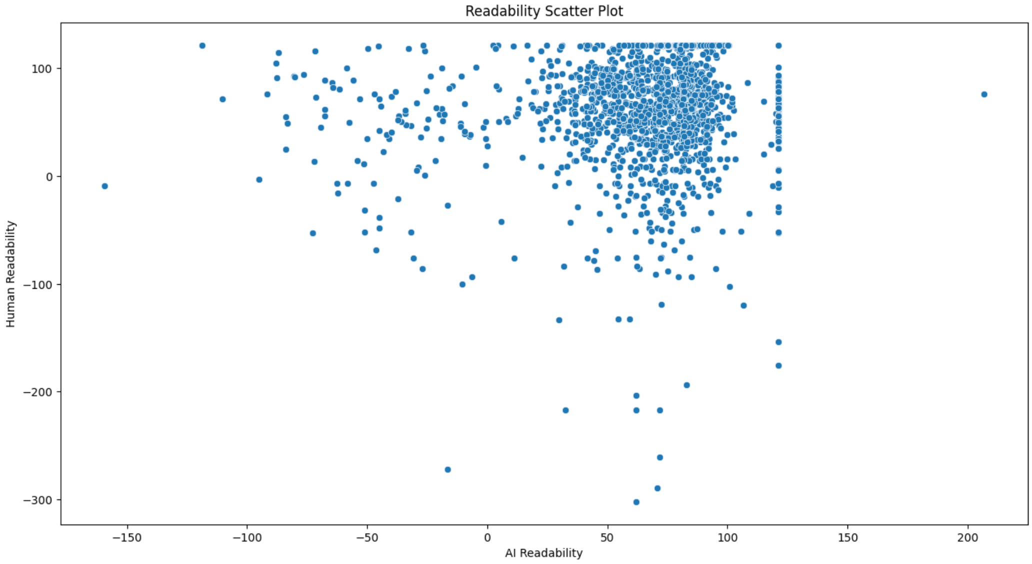

Figure 12: Scatter Plot for Readability Distribution of AI and Human Generated Content

4.11 Sentiment Analysis

Sentiment analysis provides a marvelous opportunity to delve deeper and classify the emotional elements in written works. In this study, it is applied to identify the emotional differences between human written texts and AI generated texts by comparing the scores they showed on their sentiment level. This made the study indicate the vibrant contrast in how emotions are portrayed among the two types of writing sources [19].

Figure 13 illustrates these differences, with an apparent gap in tone of emotions between AI generated and human written texts. Unpacking this, Figure 14 demonstrates how the distribution varies between the two. The human created texts move with more depth and resolution, indicating a more nuanced comprehension of their feelings. In contrast, AI generated content typically shows more spread sentiment scores, indicating inconsistencies and periods of potential emotional incoherence. Figure 15 takes it further, to actually make a scatter plot capturing the patterns and connections in emotional expression between the two types of texts. The results suggest that human writing does indeed manifest a strength in its ability to clearly identify and present emotions. In the meantime, AI generated text, fascinating as it is in its unpredictability, often fails to achieve consistency and coherence in emotional content. These results go to the very heart of what makes human writing so powerfully expression and emotionally meaningful.

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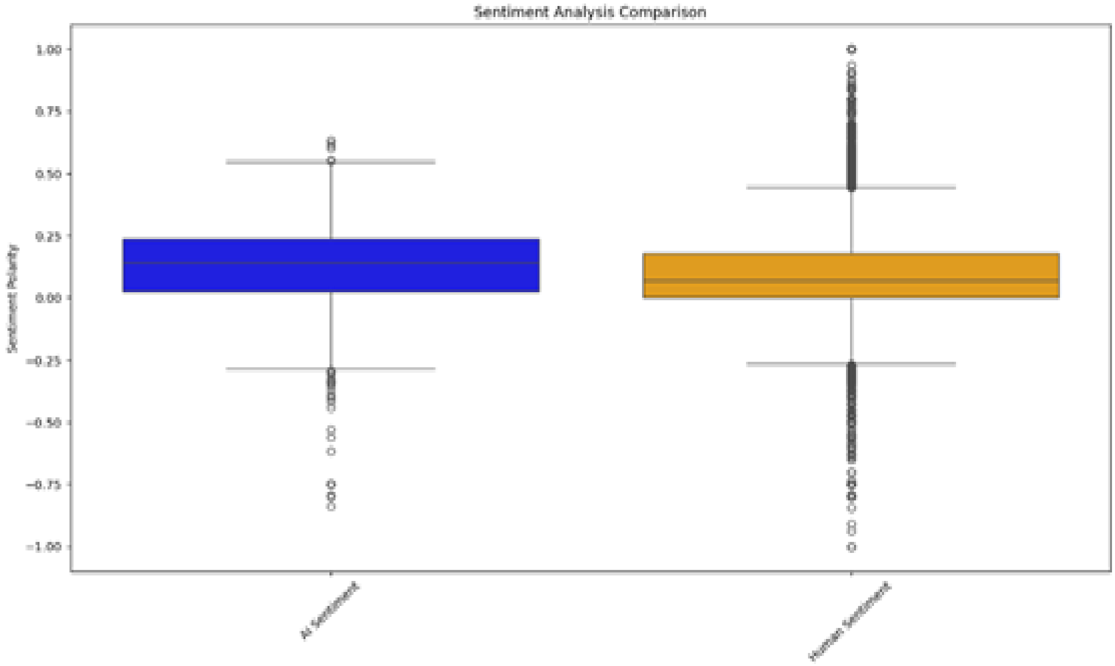

Figure 13: Sentiment Analysis Comparison for AI and Human Generated Content

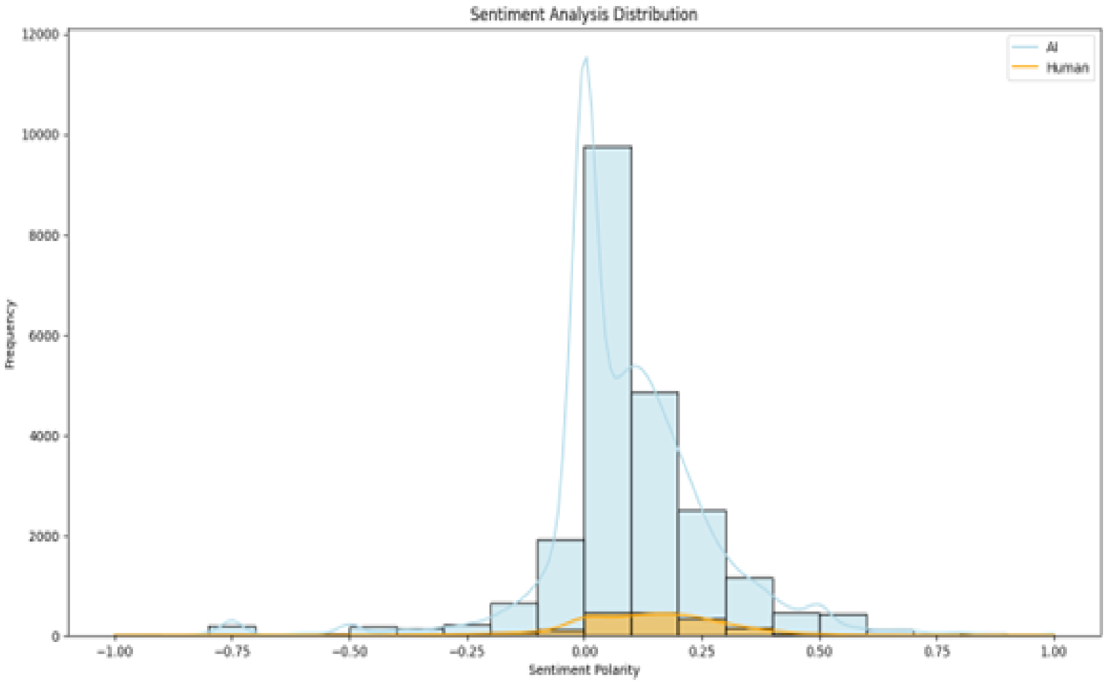

Figure 14: Sentiment Analysis Distribution of AI and Human Generated Content

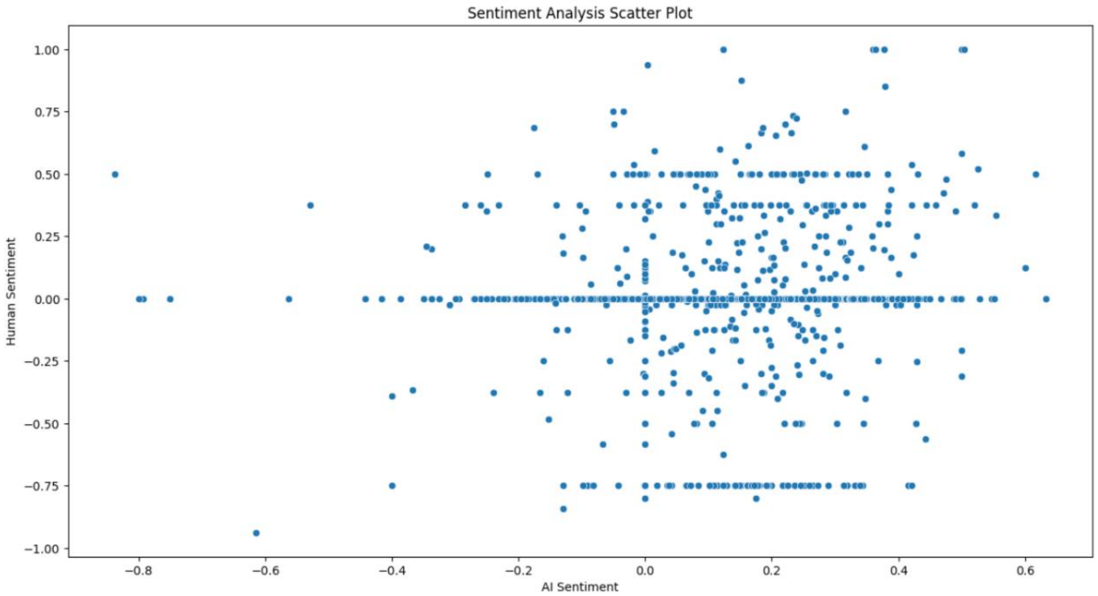

Figure 15: Scatter Plot for Sentiment Analysis between AI and Human Generated

4.12 Vocabulary Diversity

In terms of vocabulary diversity, it encompasses the richness and depth of language used in a text through which one could gain some insights into linguistic variation. This paper examined and contrasted the AI generated texts with human written ones based on the type token ratio and the lexical diversity index [20]. These measures show the variety and richness of vocabulary in a document, which is useful in marking differences in the way language is expressed between AI written and human written content.

The analysis reveals distinct patterns in the use of language by both sources. Figure 16 Vocabulary diversity comparison was done to illustrate the clear differences between AI and human vocabulary usage. A closer look is taken in the vocabulary diversity distribution through vocabulary count and vocabulary density in Figure 17. The generated texts by AI show a wider lexical range in most cases, as these metrics highlight. Figure 18 presents another scatter plot that displays how the vocabulary diversity is distributed, offering a fine grained account of linguistic variation for the two genres [21].

The results indicate that, although human written material tends to have a lower vocabulary diversity in general, AI generated texts are often very likely to have an extensive and diverse vocabulary. This is because large language models used in AI based writing are able to tap into huge datasets and complex algorithms in order to draw and produce vocabularies. Underlying results represent contrasting approaches to language richness in human and AI generated writing.

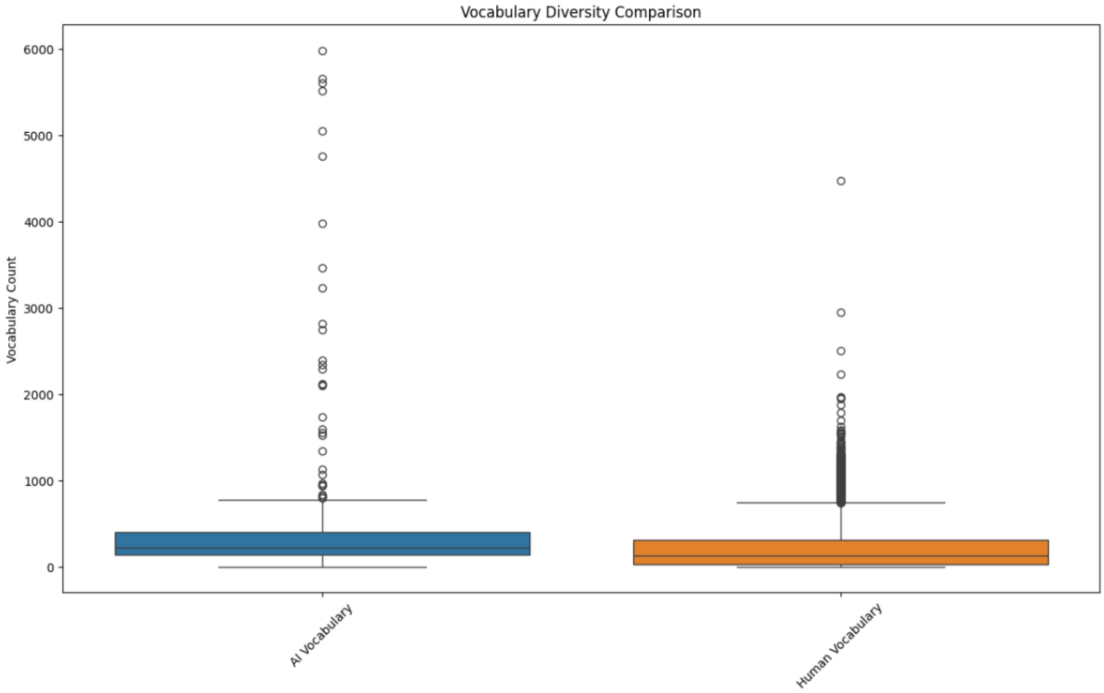

Figure 16: Vocabulary Diversity Comparison for AI and Human Content based on Vocabulary Count

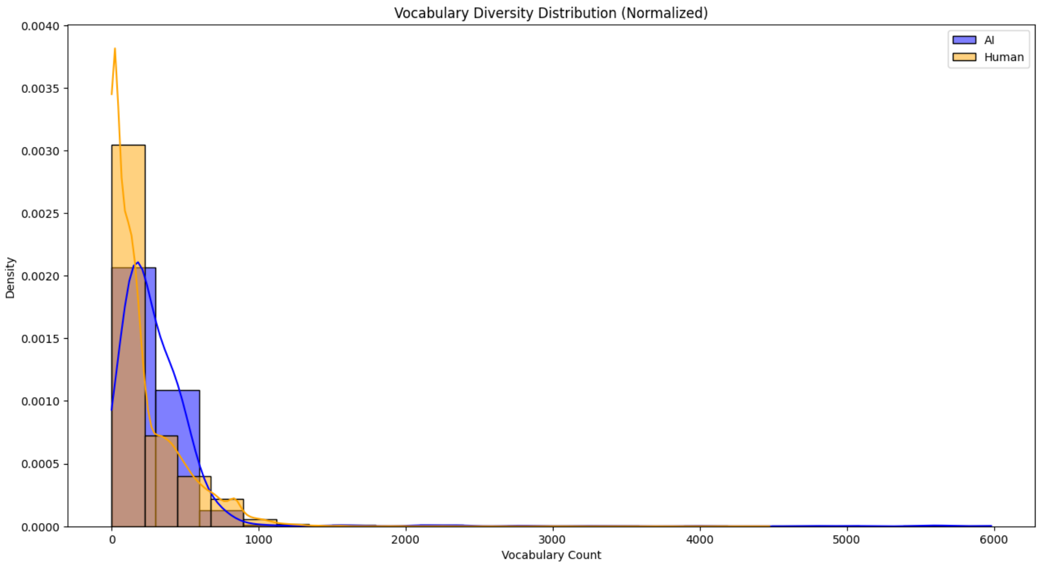

Figure 17: Vocabulary Diversity Distribution based on Vocabulary count and Density for AI and Human Content

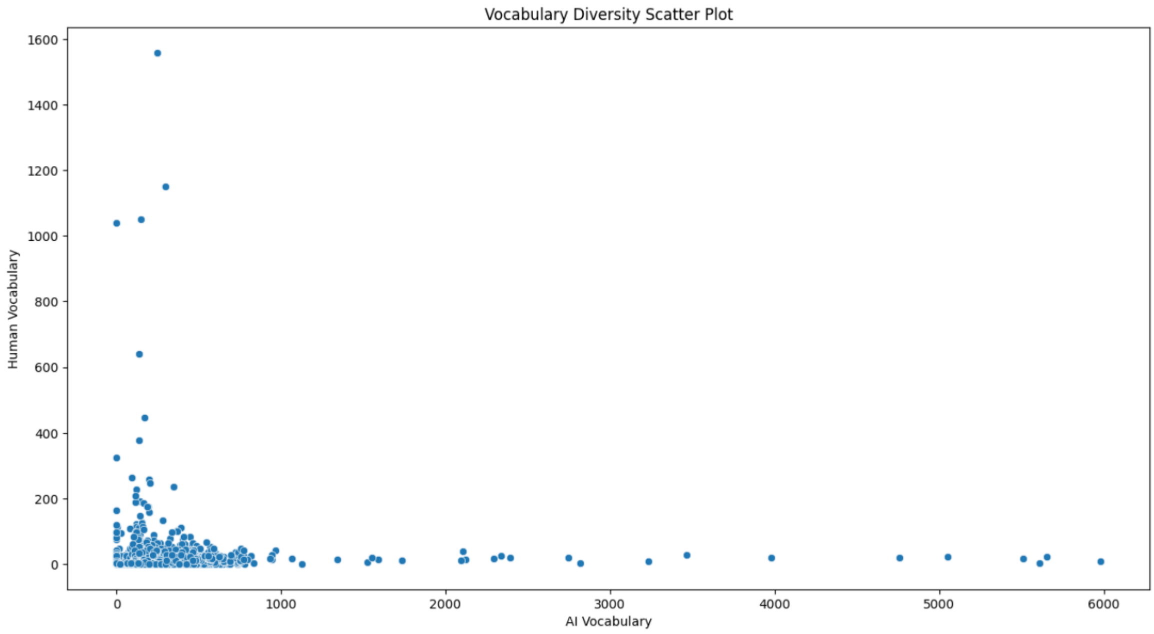

Figure 18: Scatter Plot for Vocabulary Distribution of AI Generated and Human Generated Content

5. CONCLUSION

The paper compares the basic writing design for AI generated and human written content with the rapid advancement in digital communication motivated by AI technologies. With the difference between both content types becoming important with increasing AI technologies, a systematized approach is adopted to compare various indicators such as word difficulty, text complexity, emotional analysis, unique vocabulary proportion, and content borrowing. It also analyzes text samples of amateur bloggers and professionals in quest of finding common patterns. In most cases, the clarity and coherence of AI scripts differ from the texts of humans, who mainly include impassioned and imaginative elements in their writings. Texts from the interdisciplinary genre would also have diverse structures that reflect culture and creativity. These differences become ethical issues, questioning authorship and copyright rights and at the same time distinguishing between human and machine writings. This study also explores how these differences impact content generation, quality assessment, and the evolution of AI. It contributes to the existing literature on computational linguistics and digital communication as it analyzes complex writing patterns. The study has laid the groundwork for future work into human computer content creation partnerships and addresses concerns in these fields. Actually, by advancing through this study, future work may include a better analyzing method due to the development of advanced NLP techniques that might better separate writings written by humans and AI. It could further look at the nature of cultural and linguistic differences in writing styles through different languages to understand how AI content is developed in different contexts. Longitudinal study may show over time how AI writing styles change, giving greater insight. Therefore, another area of importance is ethical concerns in AI writing systems and their consequences toward the establishment of trust for responsible use and better quality of transparent AI generated content.

Declarations

Competing Interests

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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