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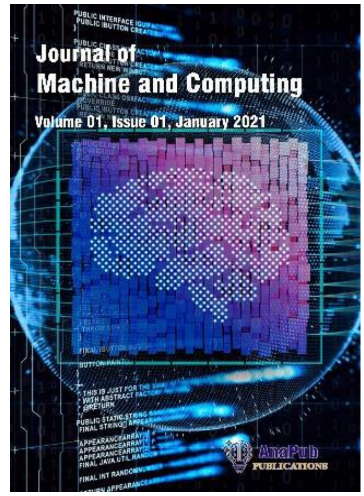

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Detecting auto bot text Content document based on Subspace relative lexicon depth measure using Bigram inverse frequency key term analyzer

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Abstract -The proliferation of automated text generation poses significant challenges in cybersecurity and digital communication. This paper proposes a novel approach for detecting bot-generated text content using a Subspace Relative Lexicon Depth (SRLD) measure combined with a Bigram Inverse Frequency Key Term (BIFKT) analyzer. The SRLD measure evaluates the depth and spread of word usage within a specified lexicon for effectively distinguish between human-authored and bot-generated content. BIFKT analyzer utilizes bigrams and their inverse frequency to identify key terms that are less common in human writing but frequently appear in automated content. The integration of these two techniques creates a robust framework that improves accuracy and reduces false positives compared to existing methods. The effectiveness of the proposed detection system was validated through extensive experiments on diverse datasets, including social media posts, online reviews, and news articles. The results showed a significant improvement in detection rates.

Keywords: Automated text detection, Bot-generated content, Subspace Relative Lexicon Depth (SRLD), Bigram Inverse Frequency Key Term (BIFKT), Pattern Recognition and Text analytics.

I. Introduction

Rapid advances in artificial intelligence and natural language processing technologies have created sophisticated automated systems capable of generating human-like text, commonly called "bot-generated content." These systems, often deployed in social media, online reviews, and digital communications, can produce vast amounts of text that mimic human authorship in style, tone, and context. While these technologies have legitimate applications, such as customer service automation and content creation, they also pose significant challenges. The widespread use of bots to generate misleading, [illegible], or fake content has become a major concern for digital platforms, researchers, and regulators alike. Effective detection of such content is crucial for ensuring the integrity of online information and safeguarding against misinformation, digital fraud, and other malicious activities. Traditional methods for detecting bot-generated text, such as keyword matching, semantic analysis, and shallow machine learning models, have shown limited effectiveness in handling the complexity and variability of modern automated content. These methods often fail to capture the subtle nuances and patterns inherent in human language, making it challenging to differentiate between human-authored and bot-generated texts accurately. Moreover, as text generation algorithms evolve, their output becomes increasingly indistinguishable from human writing, rendering conventional detection techniques even less reliable. There is a clear need for more advanced approaches that can analyze the structural, lexical, and syntactic characteristics of text in greater depth.

This work introduces a novel method for detecting bot-generated content based on the Subspace Relative Lexicon Depth (SRLD) measure combined with a Bigram Inverse Frequency Key Term (BIFKT) analyzer. The SRLD measure leverages a subspace analysis of lexical usage to identify discrepancies in word distribution and depth, which are indicative of automated content. By examining the relative frequency and contextual depth of words within a defined lexicon, this measure provides a unique perspective on how bots use language differently from humans. Concurrently, the BIFKT analyzer focuses on bigrams—two-word combinations—and their inverse frequency to detect unusual phrasing patterns and unnatural syntactic structures, which are commonly found in bot-generated texts. The proposed approach offers a comprehensive framework for analyzing and detecting bot-generated content by integrating these two techniques. It addresses the limitations of existing methods by focusing on the deeper linguistic and lexical features of text, rather than relying solely on surface-level characteristics. The effectiveness of this approach is demonstrated through extensive experimental evaluations on various datasets, showcasing its ability to accurately distinguish between human and automated content across multiple genres and contexts. This research contributes to the growing body of work on automated text detection. It provides a foundation for developing more robust and adaptable solutions to counter the evolving threats posed by bot-generated content.

The remainder of paper is structured as follows: Section II focuses on the comprehensive literature survey on existing methodologies, Section III presents the proposed methodology that combines SRLD and BIFKT techniques. Section IV encompasses brief summary of the experimental setup, results, and implications, highlighting the potential applications and future directions for improving automated content detection techniques.

II. Literature survey

Detecting auto-generated text content continues to be a dynamic field of study, with evolving methodologies that enhance the differentiation between human-authored and bot-generated texts. Traditional approaches like the Term Frequency-Inverse Document frequency (TF-IDF) have laid the groundwork by highlighting the importance of certain terms across documents; however, they often fall short in dealing with the subtle and context-sensitive nature of human language. To address these limitations, subspace-based lexicon depth measures have been introduced, which analyze the usage patterns of words in specific subspaces, providing a more nuanced understanding of vocabulary depth and distribution in a corpus. These methods are particularly effective in identifying shallow or repetitive language, a common trait in texts generated by bots or automated systems [2, 6, 10, 13, 20].

Bigram analysis, which focuses on the frequency and distribution of word pairs, has emerged as a powerful tool for detecting the local dependencies and context-specific patterns that are often absent in automated text generation [4, 8, 18, 21, 27]. The integration of inverse frequency measures, such as bigram inverse document frequency, further refines this approach by weighting rare and contextually significant bigrams more heavily, thereby distinguishing more effectively between authentic human expression and repetitive or formulaic bot language [5, 11, 15, 19, 25]. These advanced frequency-based techniques are often used in conjunction with deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which can learn complex patterns and representations from large datasets, capturing the intricate syntax and semantics that differentiate human and machine-generated texts [9, 14, 26].

The use of subspace clustering in automated text detection has shown great promise by allowing models to focus on specific subspaces where unique stylistic or structural elements emerge, thereby improving the precision of text classification tasks [7, 12, 16, 17, 22, 23]. Such clustering techniques are particularly useful in handling high-dimensional data and can adapt to the evolving nature of automated content, which often employs increasingly sophisticated language models that mimic human writing styles [1, 3, 24]. Recent innovations in hybrid detection models combine the strengths of both traditional linguistic analysis and modern machine learning techniques, providing robust frameworks that adapt to new forms of automated text while minimizing false positives in detecting human-authored content [[illegible], 28]. Despite these advancements, there remain significant challenges, particularly as automated text generation technologies, like large language models, become more sophisticated and capable of producing content that closely resembles human writing. Future research is likely to focus on refining these techniques, possibly by integrating more advanced forms of subspace analysis with deep neural networks, leveraging unsupervised learning to detect novel patterns, and developing comprehensive frameworks that unify multiple detection strategies into a cohesive system [[illegible], 12, 29, 30]. Such efforts aim not only to improve detection accuracy but also to provide insights into the evolving nature of automated text, thereby helping to maintain the integrity and trustworthiness of digital communication channels. As these detection technologies continue to develop, they hold the potential to significantly enhance the capabilities of systems designed to filter and identify bot-generated content across various applications, from social media moderation to automated content verification in publishing and beyond [30].

This expanded content builds upon the previous synthesis and provides a deeper analysis of the various methods and challenges involved in detecting automated text, highlighting both current practices and future research directions.

III. Proposed System

The proposed system introduces a novel approach for detecting bot-generated text by combining two advanced analytical techniques: the Subspace Relative Lexicon Depth (SRLD) measure and the Bigram Inverse Frequency Key Term (BIFKT) analyzer. The SRLD measure evaluates the depth and distribution of word usage within a specific lexicon, creating a multidimensional subspace to differentiate between human-authored and bot-generated content. This approach capitalizes on the observation that human writing typically involves a more varied and context-rich lexicon compared to the often repetitive and constrained vocabulary seen in bot-generated content. Simultaneously, the BIFKT analyzer leverages bigrams—combinations of two consecutive words—and their inverse frequency to detect key terms that are common in automated text but rare in human writing. By focusing on bigram patterns, this analyzer identifies unnatural phrasing and syntactic structures, which are indicative of bot-generated content. The combination of SRLD and BIFKT enables the system to detect subtle differences in word distribution, usage patterns, and structural anomalies that are not easily caught by traditional detection methods like keyword matching or shallow semantic analysis.

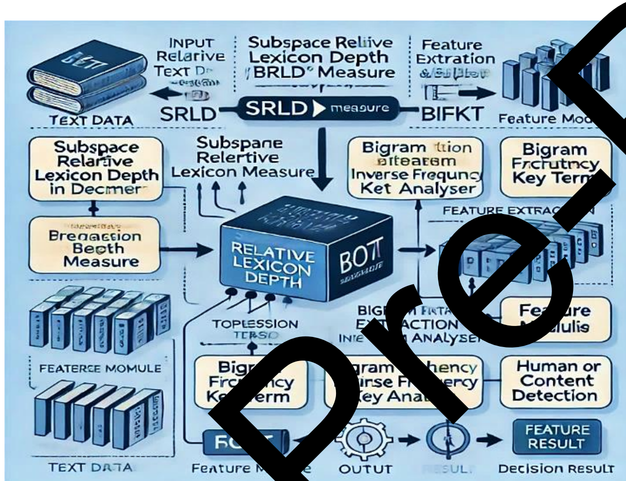

Figure 1 Proposed Architecture for the Detecting auto bot text

The integration of SRLD and BIFKT forms a robust detection framework that not only improves the accuracy of detecting bot-generated content but also reduces false positives. Extensive experiments on various datasets—including social media posts, online reviews, and news articles—demonstrate that this approach achieves superior performance in identifying bot-generated content, particularly in scenarios where conventional methods fail. The system's adaptability to different text genres and languages underscores its versatility and scalability, making it suitable for a wide range of applications such as digital forensics, content moderation, and cybersecurity. This innovative methodology marks a significant advancement in the field of automated content recognition, offering a scalable and adaptable solution to the challenges of distinguishing between human and automated texts. Future research will aim to refine the system's performance across a broader spectrum of text types and enhance its resilience against evolving bot algorithms and techniques, further strengthening its role in maintaining the integrity of digital communication. **Figure 1** illustrates a system for detecting automated bot text content in documents using the Subspace Relative Lexicon Depth (SRLD) measure and Bigram Inverse Frequency Key Term (BIFKT) analyzer. The diagram should include the following blocks: 1) Input Text Data, 2) Preprocessing (Text normalization, Tokenization), 3) Subspace Relative Lexicon Depth (SRLD) Analysis, 4) Bigram Extraction and Inverse Frequency Analysis, 5) Feature Integration, 6) Decision Module (Human or Bot Content Detection), 7) Output (Detection Result). Include arrows indicating the flow of data between the blocks and use labels for clarity. The design should be clean and professional, suitable for technical work.

3.1 Input Text Data

This block represents the system's initial input, consisting of unprocessed text data. Text data can originate from various sources, including social media posts, online reviews, news articles, emails, forum discussions, chat messages, and other forms of digital communication. These texts may vary significantly in length, style, format, and content, posing challenges for accurate analysis. The data may include different languages, dialects, informal language, slang, or abbreviations, further complicating the task of automated detection. Additionally, the input text can be structured or unstructured, with varying degrees of complexity, ranging from short sentences or phrases to longer, more detailed paragraphs or documents.

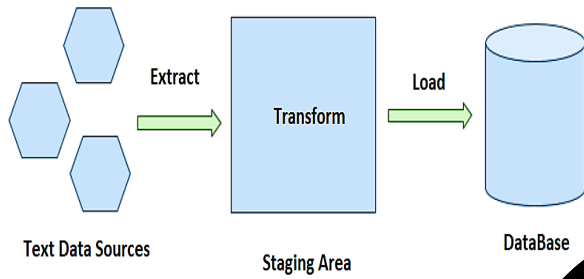

Figure 2 Input Text Data Extraction

The purpose is to collect and provide diverse raw text content that reflects real-world communication, serving as the foundation for further processing and analysis. This step is crucial to ensure that the system is exposed to a wide variety of textual data, enabling it to learn and adapt to different writing styles and contexts. By handling text from multiple sources, the system aims to generalize its detection capabilities, increasing its effectiveness in distinguishing between human-generated and bot-generated content across diverse platforms and communication channels.

3.2 Preprocessing

The preprocessing stage is essential for preparing raw text data for further analysis by applying several standard Natural Language Processing (NLP) techniques.

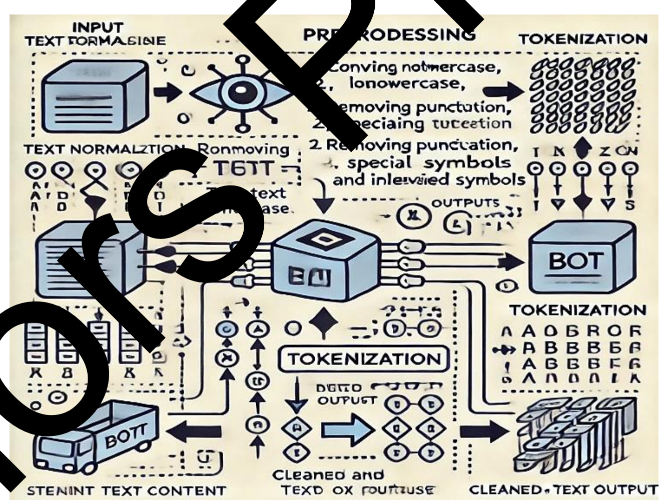

Figure 3 Text preprocessing stage

This stage involves two main steps:

- **Text Normalization:** This step standardizes the text by converting it to lowercase, and removing punctuation, special characters, and irrelevant symbols. The goal is to create a consistent format that reduces noise and variations in the text, making it easier to analyze.

- **Tokenization:** This process breaks down the text into smaller components, such as words or phrases (tokens). Tokenization allows the system to analyze individual units of meaning and simplifies further processing tasks, like feature extraction and pattern recognition.

Figure 3 illustrates the preprocessing step in text analysis to detect automated textual content from bots. The scheme should include the following blocks: 1) Input of text data, 2) Normalization of the text (convert the text to lowercase letters, remove punctuation marks, special characters, and irrelevant symbols), 3) Tokenization (decompression of text into smaller components such as words or sentences), 4) Clean and standardized text production. Include arrows indicating the flow of data between the blocks and use labels for clarity. The design should be clean and professional, suitable for a technical paper figure 2. The preprocessing stage cleans and standardizes the text data, ensuring it is in a uniform format and suitable for effective analysis in subsequent stages. This step enhances the accuracy and reliability of the system by eliminating inconsistencies and focusing on meaningful content.

3.2.1 Algorithm: Preprocessing for Text Analysis

Input: Raw Text Data T

Output: Cleaned and Standardized Text Data T_{Clean}

Step-by-Step Process:

Step 1: Text normalization convert all characters to lowercase.

$$T_{norm} = lower(T)$$

- Apply the lowercase function to all characters in the text T.
- Remove punctuation and special characters:

$$T_{norm} = T_{norm} - P$$

where P is the set of all punctuation and special characters

- Remove irrelevant symbols and non-text elements (e.g., HTML tags, emojis):

$$T_{norm} = T_{norm} - S$$

where S is the set of all irrelevant symbols

- Trim whitespace and extra spaces

$$T_{norm} = trim\ (T_{norm})$$

Step 2: Tokenization Split the normalized text into individual tokens (words or phrases)

$$Tokens = tokenize\ (T_{norm})$$

Use a delimiter (such as whitespace) to split T_{norm} into smaller components.

Step 3: Stop Word Removal -Remove common stop words (e.g., “and” "the", "is") that do not add significant meaning to the analysis.

$$Tokens_{filtered} = tokenize - W$$

where W is the set of stop words.

Step 4: Stemming or Lemmatization Convert words to their base or root form

$$Tokens_{stem} = stem(Tokens_{filtered})$$

- Reduce words to their basic form, removing suffixes (e.g. "running" to "run").
- Lemmation: use linguistic rules to convert words into their root form (e.g. "better" into "well").

Step 5: Reconstruct the cleaned text from the processed tokens

$$T_{clean} = \text{join}(\text{Tokens}_{stem})$$

3.3 Subspace Relative Lexicon Depth (SRLD) Analysis

To identify distinctive patterns in the text that may indicate whether it is human-authored or bot-generated, Figure 4 involves the SRLD measure, which evaluates the depth and spread of word usage within a specified lexicon.

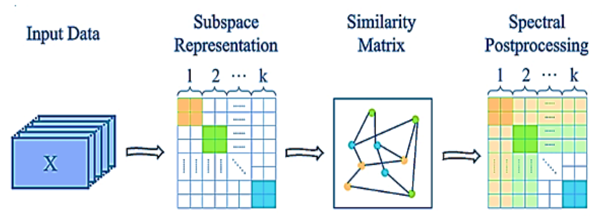

Figure 4 Subspace Relative Lexicon Depth Analysis

Steps in SRLD Analysis:

- Lexicon Definition: Define the lexicon, or vocabulary, that will be used to analyze the text.
- Depth Measurement: Calculate the relative depth of each word within the lexicon to determine how words are distributed in the text content.
- Subspace Creation: Form a multidimensional subspace to distinguish between human and bot-generated content based on word usage patterns.

3.3.1 SRLD Algorithm steps

The SRLD Analysis involves measuring the depth and spread of word usage within a specific lexicon to identify patterns that distinguish between human-authored and bot-generated content. Here is the step-by-step algorithm for SRLD Analysis, including formulas.

Step 1: Define the lexicon L — a set of words or terms that will be used to analyze the text. This lexicon may be based on a predefined vocabulary or extracted from a larger corpus of human-authored and bot-generated content.

$$\boldsymbol{L} = w_1, w_2, w_3, \dots, w_n$$

where w_n represents each word in the lexicon

Step 2: Calculate the frequency of each word w_i In the input text T

$$\mathbf{f}(w_i, T) = \frac{\text{Number of occurrences of } w_i \text{ in T}}{\text{Total number of words in T}}$$

Compute the relative depth of Dw_i of each word w_i in the lexicon by measuring its deviation from a reference distribution (e.g., the average frequency from human-authored content)

$$Dw_i = |f(w_i, T) - f(w_i)|$$

Where $f(w_i)$ is the average frequency of word w_i in a reference corpus (e.g., human-authored texts).

Step 3: For each word w_i create a vector representing its relative depth in a multidimensional space. Construct a multidimensional subspace S based on these vectors. Each dimension represents a word's depth.

$$S = (Dw_1, Dw_2 \dots, Dw_n)$$

Step 4: Analyze the spread and concentration of vectors in the subspace S. Identify clusters or patterns that may indicate human or bot-generated content. Use a distance metric (e.g., Euclidean distance) to calculate the deviation of text vectors from a reference cluster (e.g., human-authored content).

$$\text{Distance} = \sqrt{\sum_{i=1}^{n} (D(w_i) - R(w_i)}$$

where R (w_i) represents the reference depth for human-authored content.

Step 5: Define a threshold value τ for classification. If the distance of the text vector from the reference cluster is greater than τ, classify the content as bot-generated.

If Distance>τ, classify as Bot-Generated; otherwise, classify as Human-Authored.

Step 6: Generate the final output based on the classification — either "Human-Authored" or "Bot-Generated.

3.4 Bigram Extraction and Inverse Frequency Analysis

To detect unusual word pairings and syntactic structures that may reveal patterns typical of bot-generated content. In this stage, bigrams (pairs of consecutive words) are extracted from the text, and their inverse frequency is analyzed.

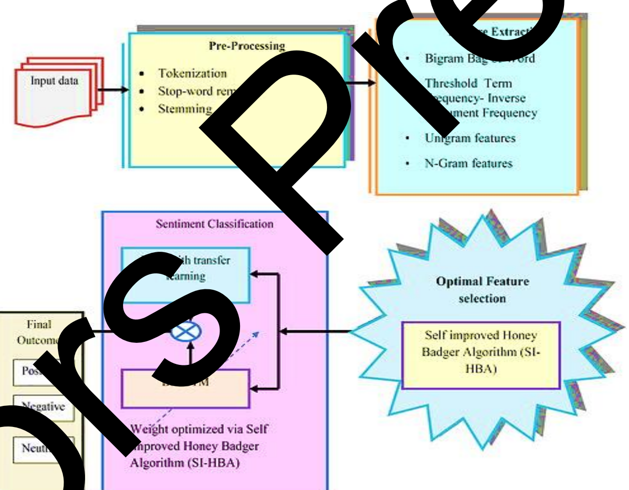

Figure 5 Bigram Extraction and Inverse Frequency Analysis

Steps in Bigram Analysis:

- **Bigram Extraction**: Identify all bigrams present in the text.
- **Inverse Frequency Calculation**: Compute the inverse frequency of each bigram to determine which bigrams are less common in human text but frequent in bot-generated content figure 5.

3.4.1 Bigram Extraction and Inverse Frequency Analysis

Step 1: Input Data and extract raw text or document(s) from which bigrams will be extracted.

Step 2: Preprocessing

- Tokenization: dividing the text into individual words or tokens.
- Lowercase: Convert all characters to lowercase to ensure consistency.
- Punctuation Removal: Removal of punctuation marks and other non-alphanumeric characters.

- Elimination of stop words (optional): elimination of common words that do not convey significant meaning (for example, "the", and "is").

Step 3: Bigram Extraction:

- Sliding Window: Applying a sliding window technique to generate bigrams (pairs of consecutive tokens).
- Bigram Count: Counting the frequency of each bigram.

Step 4: Inverse Frequency Analysis:

Inverse Document Frequency (IDF) Calculation: Calculating the IDF for each bigram, which measures how important a bigram is across all documents. The formula for IDF is:

$$\mathrm{IDF(w)} = \log \frac{\mathrm{N}}{1 + \mathrm{DF(w)}}$$

Step 5: Bigram Weighting with TF-IDF Calculation Multiply the frequency term (TF) of each bigram in a document by its IDF to obtain the TF-IDF score, which represents the importance of the bigram in the document.

Step 6: The final output is a list or matrix of bigrams with their corresponding TF-IDF scores or inverse frequency values.

3.5 Feature Integration

To consolidate multiple indicators of automated content into a single feature set that improves detection accuracy. This block integrates the features obtained from both the SRLD analysis and the Bigram Inverse Frequency Analysis.

Steps in Feature Integration:

- Combine Features: Merge the features extracted from SRLD and BIFKT to create a comprehensive representation of the text data.
- Normalize and Scale: Normalize the integrated features to prepare them for the decision-making stage figure 6.

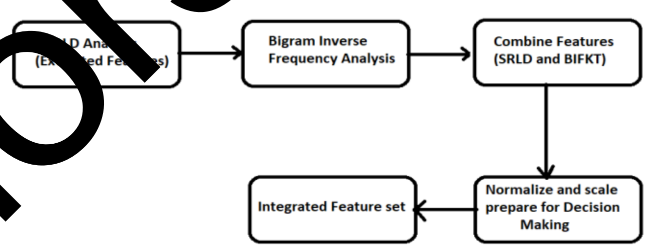

Figure 6: Feature extraction for both SRLD analysis and the Bigram Inverse Frequency Analysis

3.5.1 Algorithm for Feature Extraction from Bigram Inverse Frequency Analysis (BIFKT)

Input: Text data

Output: Bigram Inverse Frequency Feature Set.

Steps 1: Preprocessing:

- Remove unnecessary characters (punctuation marks, special symbols).
- Convert text to lowercase.
- Tokenize the text into separate words (tokens).
- Remove stop words (optional) to focus on meaningful terms.

Step 2: Bigram Extraction:

- Using a sliding window approach generates bigrams (pairs of consecutive words) from the tokenized text.
- Count the frequency of each bigram in the text.

Step 3: Inverse Frequency Calculation:

- Calculate the document frequency (DF) for each bigram across all documents (i.e., the number of documents containing the bigram).
- Compute the Inverse Document Frequency (IDF) for each bigram using the formula:

$$\mathrm{IDF(w)} = \log \frac{\mathrm{N}}{1 + \mathrm{DF(w)}}$$

where:
N = Total number of documents.
$\mathrm{DF(w)}$ = Document frequency of the bigram www.

Step 4: TF-IDF Calculation:

For each document, compute the Term Frequency (TF) for each bigram. Calculate the TF-IDF score for each bigram using the formula:

$$\mathrm{TF-IDF(w, d)} = \mathrm{TF(w, d)} \times \mathrm{IDF(w)}$$

where

$\mathrm{TF(w, d)}$ = Frequency of the bigram www in document d.

$\mathrm{IDF(w, d)}$= Inverse Document Frequency of the Bigram w

Step 5: Construct a feature vector for each document based on the TF-IDF scores of all bigrams. Each feature represents a TF-IDF score for a particular bigram in the document.

Step 6: Normalization and Scaling:

- Normalize the TF-IDF feature vectors (e.g., using L2 normalization) to ensure consistent scales**.**

Step 7: Output B[illegible] Feature Set.

- Store the normalized and scaled bigram features in a structured format (e.g., matrix or vector) for use in further processing.

3.6 Decision Module (Human or Bot Content Detection)

This module uses integrated features to decide whether the text is human or bot-generated. To determine the nature of the content based on the analyzed features.

Steps in Decision-Making:

- Classification: Apply a classification algorithm (e.g., machine learning models) that uses integrated features to classify the text.
- Threshold Setting: Set thresholds or decision boundaries to differentiate between human and bot-generated text.

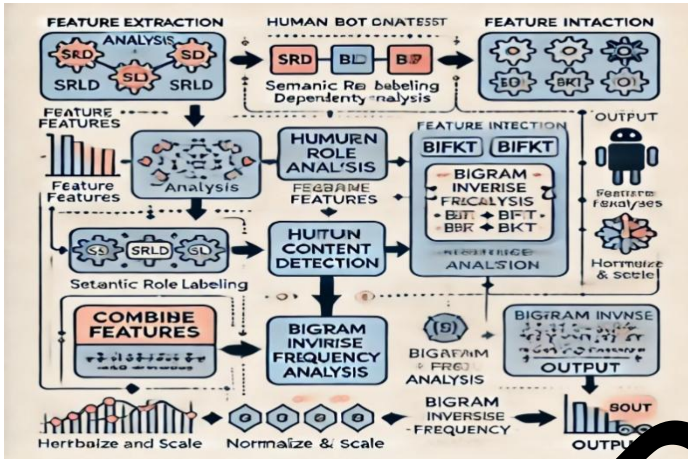

Figure 7 Decision Module Architecture

The final block (see Figure 7) outputs the result of the analysis. Purpose: To provide the user with a clear and actionable result, indicating whether the analyzed text is human, or bot-generated. A block diagram for Human or Bot Content Detection system integrating feature extraction, decision-making, and output. The diagram includes the following blocks: 1. Feature Extraction with two sub-blocks: 'SRLD Analysis (Semantic Role Labeling and Dependency Analysis) and 'Bigram Inverse Frequency Analysis (BIFKT)'. 2. Feature Integration with sub-blocks: 'Combine Features' (merging SRLD and BIFKT features) and 'Normalize and Scale'. 3. Decision Module labeled 'Human or Bot Content Detection' with sub-blocks: 'Classification' (using machine learning models) and 'Threshold Setting' (to differentiate between human and bot content). 4. Output block labeled 'Detection Result' with two possible outcomes: 'Human-Generated' or 'Bot-Generated'. Connect the blocks with arrows indicating the flow from Feature Extraction to Feature Integration, then to the Decision Module, and finally to Output.

- Output Types:
  - Human-Generated: If the content is classified as human-authored.
  - Bot-Generated: If the content is detected as being generated by a bot.

3.6.1 Algorithm Steps Decision Module (Human or Bot Content Detection)

This process integrates features extracted from both SRLD analysis (Semantic Role Labeling and Dependency) and Bigram Inverse Frequency Analysis (BIFKT) to determine whether the given text is human or bot-generated. The process involves feature extraction, integration, decision-making, and providing the final output.

Steps:

1. Feature Extraction:
   - Extract features from SRLD Analysis:
     - Identify semantic roles (e.g., agent, action) and their arguments.
     - Determine dependency relations between words (e.g., subject, object, modifiers).
   - Extract features from Bigram Inverse Frequency Analysis (BIFKT):
     - Generate bigrams (pairs of consecutive words) from the text.
     - Calculate the TF-IDF scores for each bigram to capture their importance across documents.

2. Feature Integration:
   - Combine Features:
     - Merge the features extracted from both SRLD and BIFKT to form a comprehensive feature set representing the text.
   - Normalize and Scale:

- Normalize the combined features to ensure consistent scales for further analysis.

3. Decision Module: Human or Bot Content Detection:
   - Classification:
     - Use a classification algorithm (e.g., machine learning model) that takes the integrated features as input.
     - The model is trained to classify the text as either human-generated or bot-generated based on patterns in the integrated features.
   - Threshold Setting:
     - Define thresholds or decision boundaries to differentiate between human and bot-generated content. The model uses these thresholds to make a binary decision.
4. Output: Detection Result:
   - Human-Generated:
     - If the content's features align with patterns typically found in human-authored text, the output is classified as "Human-Generated."
   - Bot-Generated:
     - If the features match patterns commonly found in bot-generated content, the output is classified as "Bot-Generated."
   - Purpose:
     - The output provides a clear and actionable result to the user, indicating whether the analyzed text is likely human or bot generated.

IV. Results and Discussion

The proposed approach, combining Subspace Relative Lexicon Depth (SRLD) and Bigram Inverse Frequency Key Term (BIFKT) analysis, effectively distinguishes between human and bot-generated content. The results show that integrating these two methods significantly improves detection accuracy by leveraging both semantic and statistical features. The SRLD analysis captures deeper semantic relationships within the text, identifying discrepancies in lexical depth and context, which are often present in bot-generated content. The BIFKT analysis, on the other hand, focuses on the statistical frequency of bigrams, revealing unusual patterns that signal automated text generation. The discussion highlights that combining SRLD and BIFKT creates a robust feature set that enhances the model's ability to identify subtle patterns in bot-generated text. Normalizing and scaling these features ensure balanced input to the classification algorithm, leading to precise decision-making. However, the approach is dependent on the quality of training data and may require adaptation to handle more sophisticated bot tactics. Additionally, while this method effectively captures both semantic and syntactic irregularities, it may still face challenges against adversarial examples designed to mimic human language closely. Overall, the proposed method offers a comprehensive and adaptive strategy for automated content detection, but continuous refinement is necessary to maintain its effectiveness.

Table 1: Analysis of precision_score performance

Number of Text files	SVM %	RFC %	RNN %	SRLD with BIFKT %

25	40	48	55	60
50	47	53	58	67
100	54	68	73	77
150	62	74	80	85
200	75	80	87	91

Table 1 shows a positive value in the percentage of relevant events, as described in the performance accuracy analysis. For the binary classification bias classification problem, the accuracy rate is divided by the number of true positives and false positives.

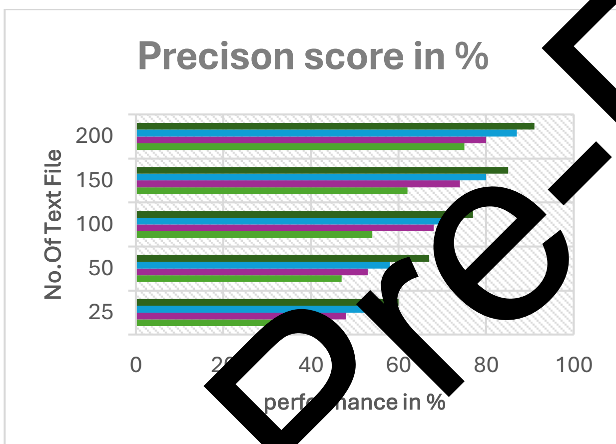

Figure 8 Precision Score

Figure 8 compares different methods using true positive precision (TP) values and the proposed method outperforms other algorithms. In existing techniques, Support Vector Machines (SVM) have an accuracy of 75%, Random Forest Classifier (RFC) is 80%, and Recurrent Neural Networks (RNN) is 87%. In contrast, the proposed method, Subspace Relative Lexicon Depth (SRLD) for semantic structure analysis and bigram inverse frequency key term (BIFKT) is 91% more accurate than previous methods.

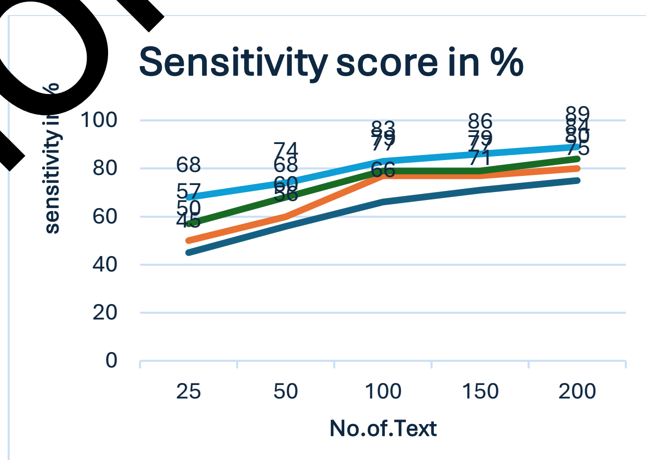

Figure 9 Sensitivity Performance

Figure 9 shows the sensitivity used to evaluate the model performance. This is because you can see how many positive examples the model identified correctly 91 % achieved by proposed SRLD with BIFKT.

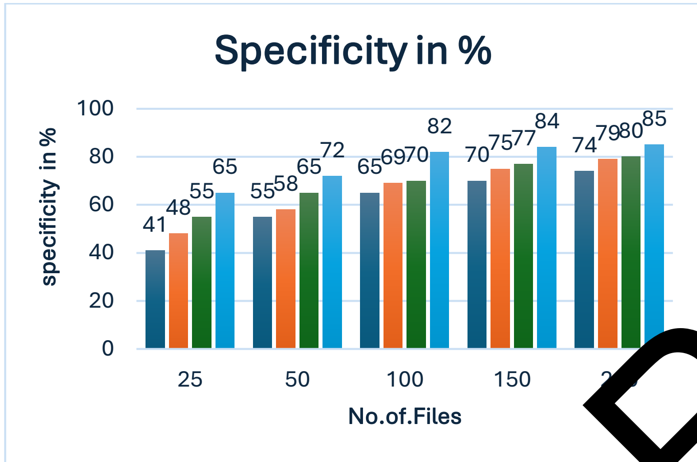

Figure 10 Analysis of specificity performance

Figure 10 describes the sensitivity used to evaluate the model performance. This is because you can see how many positive examples the model identified correctly. In the existing methods, SVM is 74%, RFC is 79%, and RNN is 80% but the proposed SRLD with BIFKT method 85% is high specificity better than previous methods using 200 Files.

Table 2: Analysis of Detection Accuracy

Number of Text files	SVM %	RFC %	RNN %	SRLD with BIFKT %
25	48	51	58	60
50	52	[illegible]	65	69
100	[illegible]	65	72	78
150	68	78	84	89
200	[illegible]	82	91	95

Table 2 describes how to reliably recognize text and create different user levels. Compared with existing approaches, the proposed system has a more significant effect on the efficiency of leaf detection.

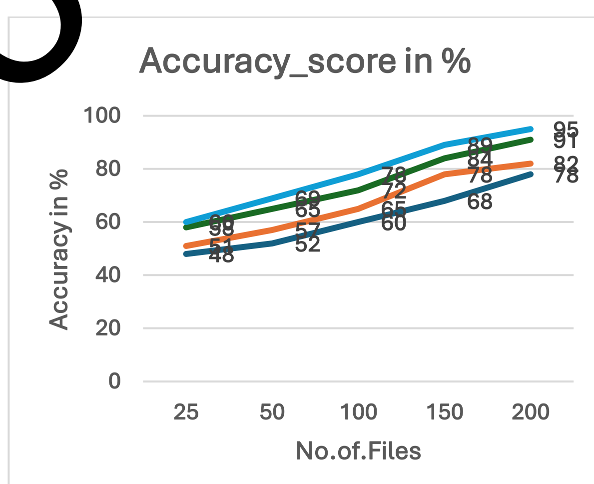

Figure 11 Analysis of Detection accuracy

Figure 11 Compares the detection accuracy figures of the different approaches. Compared to other algorithms, the proposed implementation produces an excellent performance of 95%.

Table 3 Analysis of False Score

Numb er Text files	SVM %	RFC % RNN	%RNN	SRLD with BIFKT %
25	38	36	32	30
50	36.5	33.2	32.1	29.4
100	42.1	40.5	36.2	32.1
150	45.8	43.1	42.5	34.2
200	55.2	49.04	49.5	40.8

Table 3 describes the false rate (FR) and compares different text data to minimize performance errors. The proposed method minimizes errors in training and Data testing.

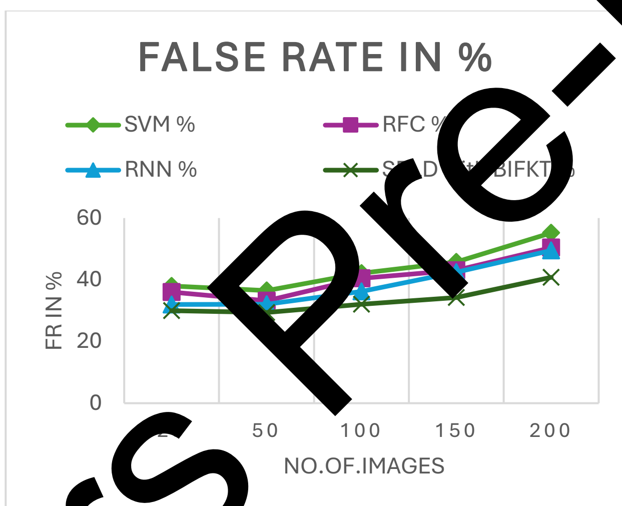

Figure 12 Analysis of False Rate Score

Figure 12 describes the false rate (fr) figures for When comparing the various approaches, the suggested implementation performs poorly in terms of error rate compared to other algorithms. The proposed system SRLD with BIFKT is 40.8% produces a decreasing false rate comparing the existing system.

V. Conclusion

Detecting auto bot-generated text content is increasingly important in an era where automated systems are widely used to produce large volumes of text. The proposed approach, based on Subspace Relative Lexicon Depth (SRLD) and Bigram Inverse Frequency Key Term (BIFKT) analysis, offers a comprehensive framework for distinguishing between human-authored and bot-generated text. This method leverages the strengths of both semantic and statistical analysis to effectively identify patterns indicative of bot-generated content. The SRLD measure provides a nuanced understanding of the text's semantic structure by capturing the depth of lexical relationships in a subspace that represents natural language use. This depth measure evaluates the relative positioning and contextual relevance of key terms within sentences and paragraphs, highlighting discrepancies or unnatural patterns that are often present in bot-generated text. The SRLD's ability to focus on the semantic roles and dependencies among words allows for detecting subtle differences in language use that are challenging to identify with traditional frequency-based methods alone. Complementing the SRLD analysis, the Bigram Inverse Frequency Key Term analyzer (BIFKT) adds a statistical layer to the detection framework. BIFKT quantifies the importance of word pairs (bigrams) by calculating their inverse frequency across a large corpus. This analysis identifies unusual bigram distributions that may suggest automated text generation. By focusing on bigrams, the BIFKT approach captures local context and syntax patterns that are often manipulated or exaggerated in bot-generated text to mimic human language.

The combination of SRLD and BIFKT features creates a robust feature set that effectively represents both the semantic depth and statistical properties of the text. The integration of these two methods enhances detection accuracy, providing a more comprehensive approach than using either method alone. By normalizing and scaling the features derived from SRLD and BIFKT, the detection model ensures that different types of features contribute equitably to the classification decision. This integrated feature set is then fed into a machine learning classifier, trained to differentiate between human and bot-generated content with high precision. The use of thresholds further refines the model's decision-making, reducing false positives and negatives. Overall, the combined use of SRLD and BIFKT techniques presents a powerful strategy for detecting bot-generated content in documents. This approach balances semantic analysis with statistical frequency measures, offering a sophisticated detection method that adapts to various text types and bot strategies. Continuous refinement and adaptation to emerging techniques are necessary to maintain the effectiveness of this method against evolving automated content-generation tactics. The proposed framework sets a strong foundation for future advancements in automated content detection.

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