Rabin-Karp Algorithm Enhanced With Hierarchical Clustering For Plagiarism Detection

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***Abstract*—One of the most important tasks in academia and content-driven fields is the ability to detect plagiarism from vast databases of documents. Traditional string-matching algorithms, such as Rabin-Karp, can be used for this, but these algorithms incur a high computational cost when dealing with large data sets. This paper describes an integrated approach, combining Rabin-Karp with hierarchical clustering, which reduces comparisons to similar groups of documents and optimizes the process of search. The procedure in hierarchical clustering reduces the overhead of pairwise document comparison by clustering similar documents, and then the Rabin-Karp algorithm does precise string matching within each cluster. Hence, this hybrid method greatly improves both time efficiency and accuracy; it offers a scalable solution for large-scale plagiarism detection. The experimental results show a dramatic improvement over the traditional Rabin-Karp and because of that, it also shows both time- and cost-computational benefits.**

Keywords—*Plagiarism Detection, Rabin-Karp Algorithm, Hierarchical Clustering, Text Similarity, Exact Matching, Scalability, Computational Efficiency, Clustering Techniques, Semantic Analysis, Document Comparison, Data Preprocessing, Academic Integrity, Machine Learning, N-grams, Content Analysis, Text Mining, Approximate Matching, Performance Metrics, Precision and Recall, Large Datasets*

I. INTRODUCTION

This has led to the gross problem of plagiarism in this current world of digitalization, especially in academic, publishing, and content creation [1]. The emergence of more online textual content production creates difficulties in checking large datasets for plagiarism [2], [3]. Traditional detection can be string-matching-based, although it is relatively effective for smaller datasets and not scalable for larger datasets [4], [5].

The string-matching techniques include the Rabin-Karp algorithm, which utilizes a highly efficient hashing technique, making it ideal for plagiarism detection when exact or near-exact word matching is required [6], [7]. However, with an increase in the size of the data, the efficiency of Rabin-Karp decreases because it must compare repeated pattern strings across numerous documents [8], [9].

There are other types of clustering algorithms; hierarchical clustering, for example, can group similar documents to reduce the number of required comparisons [10], [11]. Using the Rabin-Karp algorithm within clusters lowers the search space, making detection faster and more accurate, as it requires fewer comparisons [12], [13]. This paper introduces a novel approach that integrates hierarchical clustering into a framework based on the Rabin-Karp algorithm, effectively addressing issues of scalability and computational cost [14], [15].

II. LITERATURE REVIEW

The job of plagiarism detection has changed enormously over the last few decades, evolving from purely text comparison techniques to more sophisticated processes enabled by increasingly powerful computational abilities and advanced algorithms [1], [2]. Approaches based on brute-force string matching were initially employed, often utilizing algorithms such as Rabin-Karp, which provided a straightforward framework for exact matching in small datasets [6], [16]. Although the Rabin-Karp algorithm is effective for single document comparison due to its time complexity of $O(m + n)$, where m is the pattern length and n is the length of the text, scaling this method to larger datasets proves inefficient due to high computational costs [7], [9].

When plagiarism detection was in more demand, especially in academic and publishing environments, scientists started researching better techniques for this purpose [3]. Indexing and approximate string matching techniques were developed to make the comparison faster along with easing processing of a massive textual information [4], [6]. N-gram techniques demonstrated high success since they transformed the detection process into a feature extraction problem—an approach in which contiguous sequences of characters were promising for analyzing document structure [8]. That rendered huge increases in performance for large datasets [9], [10]. These developments marked the beginning of a paradigm shift in the design of plagiarism detection systems. The focus was on scalability and efficiency, just like it is today [12].

Clustering has emerged as one of the promising areas for the advancement of plagiarism detection systems. Clustering brings together a collection of similar documents with respect to a similarity metric to yield an almost drastic reduction in the comparisons involved during the detection process [5]. Hierarchical clustering also has been popular in the way that it clusters all the documents under a tree representation to allow efficient retrieval of similar documents without exhaustive pairwise comparisons [6]. The result of combining clustering with exact-matching algorithms, such as the Rabin-Karp algorithm, shows promising outcomes with high

detection accuracy and reduced computational complexity, especially when the Rabin-Karp algorithm can be selectively applied within identified clusters instead of the whole dataset [7], [8]

The latest research focused on merging advanced clustering techniques with machine learning algorithms to further calibrate detection abilities of plagiarism. The researchers discovered that the integration of k-means clustering with deep learning methodologies enhances detection speeds and accuracy while capturing subtle patterns and associations in textual data [9], [10]. These methods are not only efficient in the detection process but also address the paraphrased content challenges that mostly go undetected by other traditional approaches [12], [13]. Continuous evolution of algorithms and use of machine learning mark a significant shift toward much more intelligent plagiarism detection systems [15].

This has led to attention being given to plagiarism detection based on semantic analysis. Meaning understanding beyond just similar terms: this type of research aims at enhancing system performance in identifying paraphrased content. Methods such as LSA and Word2Vec embeddings are effective in the capture of semantic relationships and can also identify content which is semantically similar but expressed differently [11], [12]. The integration of these techniques is a giant step forward from the very conventional methods of plagiarism detection, which often fail to trace the subtle essence in paraphrased material [16].

In conclusion, though there has been tremendous progress in the plagiarism detection system, newness is still being researched in terms of working out innovative techniques and methodologies. The very promising answer to the problems of scalability and efficiency lies in a combination of hierarchical clustering with conventional algorithms such as Rabin-Karp [7], [8]. Other clustering methodologies should be emphasized in future studies, along with inclusion of advanced semantic analysis techniques in order to hold a wide, holistic, and effective plagiarism detection, especially in the growingly digital and well-connected academic world [11], [12].

III. OVERVIEW OF THE RABIN-KARP ALGORITHM

Probably the most popular choice for string matching is the Rabin-Karp algorithm, and indeed the motivation was that hashing was used for fast comparison of substring patterns [1], [2]. The algorithm works by calculating hash values both for the pattern and substrings of text so that actual matches can be detected within a timeframe. The time complexity of this algorithm, when the algorithm is applied to a single document, will be O(m + n), where m is the length of the query string and n is the length of the document [7]. However, if one applies this to large sets, then the time complexity will be O(D * (m + n)), where D is the number of documents [7]

Although the Rabin-Karp algorithm is very efficient in finding all exact matches [1], [2], it's not very useful for plagiarism detection on large scales because the number of documents increases, and every document must be compared, which has huge computation overhead [3], [4].

IV. HIERARCHICAL CLUSTERING

Another algorithm popularly used is Hierarchical clustering, which merges similar objects in space with a measure of distance or similarity [5], [6]. It can be classified into two classes:

1) Agglomerative Clustering: This is a bottom-up method where each document is considered a cluster, and step by step, the closest pair of clusters is merged together until all the documents become part of a single cluster or a pre-set number of clusters [5], [6].

2) Divisive clustering: This is the technique of a top-down approach that begins by keeping all the documents in one single cluster and then recursively splits a cluster based on dissimilarity [5], [6].

In the case of plagiarism detection, agglomerative clustering is helpful since it will group the documents that have similar content, which means one can target the string-matching process much more efficiently. The system reduces the number of document pairs that need to be compared by limiting comparisons to documents within a cluster [5], [6]

V. INTEGRATION OF HIERARCHICAL CLUSTERING WITH RABIN-KARP

To address the scalability issues that arise in using Rabin-Karp alone, hierarchical clustering is incorporated into plagiarism detection. Here, all the text documents are clustered initially based on content similarity, and then the Rabin-Karp algorithm is implemented within each cluster as described below [7], [8]:

1) Clustering Phase: Hierarchical clustering is applied to group the documents into clusters based upon the content similarity. Each cluster holds all the documents that are likely to have similar content [5], [6].

2) Pattern Matching Phase: After allotting the query document to a specific cluster, the Rabin-Karp algorithm is applied only to the documents available within that cluster, thereby reducing the number of comparisons required for plagiarism detection [7], [8].

The combined system improved time efficiency, as well as scalability, by limiting comparisons to only those made within the appropriate cluster [9], [10]. Thus, this could be applied to larger datasets than the original system without a significant increase in computational complexity.

VI. MATHEMATICAL COMPARISON OF TIME COMPLEXITY

A. Original Rabin-Karp for Plagiarism Detection:

1) Time Complexity:

a) For one document, the time complexity is O(m + n), where m is the length of the query document, and n is the length of the document in the database.

b) For D documents, the total time complexity is O(D * (m + n)).

2) Example:

Number of documents (D): 1,000

Length of the query document (m): 1,000 characters

Average document length (n): 100,000 characters

Time complexity for each document:

O(m + n) = O(101,000)

Total time complexity for all documents:

O(D * (m + n)) = O(101,000,000) operations.

B. Rabin-Karp with Hierarchical Clustering:

1) Time Complexity:

a) Hierarchical clustering takes $O(D^2)$ time to cluster the documents.

b) After clustering, Rabin-Karp is applied only to the documents in the relevant cluster. If the average cluster size is k, the time complexity for pattern matching is O(k * (m + n)).

2) Example:

D = 1,000, m = 1,000, n = 100,000, k = 100

Cluster in time complexity: $O(1{,}000^2)$ = O(1,000,000)

Pattern match time complexity: O(100 * 101,000) = O(10,100,000)

Total time complexity: O(1,000,000) + O(10,100,000) = O(11,100,000) operations.

TABLE I. MATHEMATICAL COMPARISON

Parameter	*Traditional Rabin-Karp*	*Integrated Rabin-Karp with Clustering*
Total Documents (D)	1,000	1,000
Query Document Length (m)	1,000	1,000
Average Document Length (n)	100,000	100,000
Average Cluster Size (k)	N/A(no clustering)	100 (10% of total documents)
Clustering Complexity	N/A	O(1,000,000)
Pattern Matching Complexity	O(1,000*101,000) = O(101,000,000)	O(100*101,000) = O(10,100,000)
Total Complexity	O(101,000,000)	O(1,000,000) + O(10,100,000) = O(11,100,000)

VII. RELATED WORK

This is an area of plagiarism detection as well-resourced since the subject is very crucial in both academic and publishing fields as well as the law. Over time, various approaches have emerged to manage the task of detecting duplicate or plagiarized content efficiently and effectively [11], [12]. Because the number of digital contents has greatly increased, the methods hitherto applied can no longer be sufficiently scalable and less accurate, thus the development of more complex techniques through indexing, approximate matching, and clustering is needed [13], [14].

A. Traditional Approaches: Brute-Force Comparison:

Simple traditional approaches use simple brute-force comparison. It compares all documents against all other documents in the dataset by exploring each character of a document against all characters of another document. This is

efficient only for a small dataset, and the time complexity makes it unacceptable for large datasets. Suppose you have a set of D documents, and each of them has n characters. Then, clearly, the time taken by the brute-force approach is $O(D^2 * n)$. This will then lead to its inability to be applied in the real world if someone has datasets with thousands of millions of documents [15], [16]

B. String Matching Algorithms: Rabin-Karp and Others:

Brute-force comparison is now known to be inefficient. Based on this, Knuth-Morris-Pratt (KMP), Boyer-Moore, and Rabin-Karp are developed as string matching algorithms [17][18]..

1) Rabin-Karp Algorithm: This algorithm is especially known for its efficiency in exact-match searching in a text. The Rabin-Karp algorithm uses a rolling hash function to compute hash values for substrings of the text and compares them with the hash values of the query document. In the case of hash values matching, further character-by-character comparison authenticates the match. The time complexity is given by O(m + n) for one document in the Rabin-Karp algorithm, mainly due to the usage of hashing, which reduces character-by-character comparisons most of the time [19][20].

a) Challenges: Although the Rabin-Karp algorithm is better than brute-force algorithms, it still struggles when dealing with huge datasets. In applying the algorithm to a set of D documents, the time complexity becomes O(D * (m + n)), and this will grow linearly with the size of the dataset. This growth poses a significant bottleneck for large-scale plagiarism detection systems [21][22].

C. Indexing-Based Approaches:

As soon as plagiarism detection was applied to large datasets, indexing techniques were introduced to speed up the process of detecting. These techniques create an index of documents, facilitating fast lookups for comparison purposes when comparing a query document with the dataset [1][4].

1) Suffix Trees : A suffix tree is a data structure that holds all possible suffixes of a text. By building a suffix tree of a document, one can obtain the matching substrings of the query document and the documents stored [5][12]. After constructing a suffix tree, pattern searching in the dataset is faster than using traditional string matching algorithms [3][8].

a) Advantages: After constructing a suffix tree, pattern searching in the dataset is faster than using traditional string matching algorithms.

b) Challenges: The significant disadvantage of suffix trees is that they have a high space complexity, and thus for really large datasets, it can be inhibitive. Additionally, it takes up considerable time to construct the tree, and therefore this method cannot be utilized when a detection facility needs to be real-time or scaled up.

2) Inverted Indexing: Another technique used to handle large-scale plagiarism detection tasks is inverted indexing. This method preprocesses the documents to retrieve a set of unique words or substrings and their occurrences within the data. When a query is presented, only relevant documents from the index need to be compared, which greatly minimizes comparison counts [2][7].

a) Advantages: In this method, the document count which must be checked is lessened; thus, it increases efficiency.

b) Challenges: However, inverted indexing focuses more on word-level match detection and may not work easily with more paraphrasing or semantic similarity types of plagiarism.

D. Approximate String Matching:

Another innovation in plagiarism detection is approximate string matching, which involves the aim of finding substrings for a given query to approximate rather than match exactly. This method is very helpful to identify cases of paraphrased plagiarism where the style of text is changed but the semantics of the expression are still intact [6][11].

1) Edit Distance (Levenshtein Distance): This measures the number of minimum edits, including insertion, deletion, or substitution required to change one string into another. The Levenshtein Distance aids in plagiarism detection by identifying minor modifications made to the content [19][21].

a) Advantages: This technique has a potential to identify lesser, or less obvious forms of plagiarism-possibly involving paraphrasing or shuffling text.

b) Challenges: The running time complexity of edit distance algorithms is O(m * n), which makes it quite expensive to compute edit distance if the documents or datasets are large. This approach could also continue to be inefficient when large portions of the text have been plagiarized directly, thus making it more than a killer for an exact match [18][20]

E. Clustering-Based Approaches:

Clustering techniques have become popular today in enhancing the efficiency of plagiarism detection systems, especially when dealing with large datasets. This is because such a system clusters similar documents together, thereby requiring fewer comparisons during plagiarism detection, thus lowering time complexity and reducing computational resource usage [14][16].

1) K-means Clustering: Divide the dataset into kkk clusters based on the similarity of their document vectors—for example, using TF-IDF vectorization. Once the appropriate clusters are obtained, compare the query document only with those in the relevant cluster, thus streamlining the plagiarism detection process [12][13].

a) Advantages: The k-means algorithm thus offers an efficient way to reduce comparisons, leading on to improved efficiency.

b) Challenges: One of the main disadvantages of k-means is that kkk has to be predetermined. In addition, the clusters generated by k-means are sensitive to initial centroids, which could influence plagiarism detection efficiency [15][17]

2) Spectral Clustering: Spectral clustering is a technique where the eigenvalues of a similarity matrix are used to lower the dimensionality of the information so as to form a cluster of similar relationships.

a) Advantages: Spectral clustering performs very well on non-linear data and may capture the most complex relations between documents.

b) Challenges: It might be computationally expensive for large datasets and usually requires quite an adjustment of many hyperparameters to achieve the best clustering results.

F. Integration of Clustering with String Matching:

While many clustering techniques have been applied for plagiarism detection enhancement, relatively less literature has specifically addressed the combination of hierarchical clustering with traditional string-matching algorithms, mainly the Rabin-Karp algorithm. Hierarchical clustering has the following advantages over other clustering methods [12][22]:

1) Hierarchical Clustering: This is a clustering algorithm that generates a dendrogram, which describes the nested sets of documents at different levels. Because no predefined definition of the number of clusters is needed, it may be considered more flexible than k-means [12][14].

a) Advantages: The benefits of hierarchical clustering include the fact that it captures multi-level similarities for documents, which may be significant in many plagiarism cases, especially as the dataset becomes quite large and diverse. In short, using hierarchical clustering to group similar documents can drastically decrease the number of comparisons needed during plagiarism detection [14][16]

b) Challenges: Time complexity of Hierarchical Clustering is $O(D^2)$ which can get pretty costly when working with a large number of data. However, with Rabin-Karp, the overall time complexity is dropped since the query document is compared only to documents present in a relevant cluster[12][20].

G. Integration of Clustering with String Matching:

Although hierarchical clustering has lots of advantages, its integration with the Rabin-Karp algorithm for plagiarism detection had not been presented in detail. The Rabin-Karp algorithm performs exceptionally well on detecting exact matches but performs woefully bad if applied to large data sizes as it needs comparisons to be exhaustive. In this scenario, the number of comparisons to be carried out in the Rabin-Karp phase can be significantly minimized by adopting hierarchical clustering. This integration works in this way [9][12][14][21]:

1) Clustering Phase: Apply hierarchical clustering on the data set so as to group similar documents based on the content similarity.

2) Pattern Matching Phase: Place the query document in a cluster and apply the Rabin-Karp algorithm only on the documents in that particular cluster, thus reducing the computational complexity.

This integration is promising because it combines the strengths of two algorithms: the ability of hierarchical clustering to reduce the number of comparisons and the Rabin-Karp algorithm's efficiency for exact pattern matching. In this regard, this can improve the scalability of plagiarism detection systems without demoting the accuracy of detection [9][14][20][21].

VIII. METHODOLOGY

The plagiarism detection system was developed in two phases that increase the performance and efficacy of plagiarism detection. Both phases are crucial for the performance of the system, which depends on both hierarchical clustering and Rabin-Karp algorithm for scalability and accuracy with large data sets [12], [14], [20], [21].

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A. Phase 1: Document Clustering with Hierarchical Clustering: The first phase of the system utilizes a hierarchical clustering approach that groups documents that resemble each other in terms of their attributes such as title, creator, and publisher [10]. In this stage, clustering together all the documents with similar content is the idea; this reduces unnecessary comparisons while doing plagiarism detection [12]. This optimizes the system considerably, particularly for huge datasets [13], [20].

1) Cosine Similarity for Document Similarity Measurement: The core of hierarchical clustering measurement for the estimation of cosine similarity determines the similarity of pairs of documents [9]. Cosine

similarity is defined as the cosine of the angle between two non-zero vectors and ranges from 0 to 1 [10], [11].

- 0 precisely means there is no similarity between the documents-they are completely dissimilar.
- 1 means the documents are exactly identical-perfectly similar.

To apply cosine similarity, a set of documents must first be converted to a vectorized format of the importance of terms in a document [12]. TF-IDF is a common transformation method for that purpose [13]..

a) TF-IDF Vectorization: Each document would be represented as a vector where the n-th dimension has the number of occurrences of each unique word or term in the document collection [14]. The value in each dimension is the TF-IDF score of the word in the document, which reflects how important that word is in the document, in the context of the entire dataset [15]. This ensures that common words like "the," "and," or "is" have lesser importance and that more appropriate words hold more importance [16].

Once the documents are represented as vectors, the cosine similarity measure is conducted for all pairs of the documents to find the degree of similarity between the documents [17]. The more enormous cosine similarity between any two documents is, the more probable they belong to a plagiarized version or heavy overlap content [18].

2) Methodology for Hierarchical Clustering: After calculating the cosine similarity, hierarchical clustering is applied to group the documents [12]. A dendrogram or tree-like structure is constructed that depicts the hierarchy of nested clusters of documents [13]. In an agglomerative clustering or bottom-up approach, the single documents are considered as a cluster [14]. In each iteration, the two most similar clusters are merged [15]. Thus, the structure of such clusters is gradually developed in this bottom-up approach [16].

a) Linkage Criteria: The system uses complete linkage [17]. The distance between two clusters is based on the maximum distance between any two points in the clusters [18]. Thus, all documents within this cluster are very similar to each other [19].

b) Clustering: In this approach, highly similar documents accumulate in a group [20]. Then the clusters of documents are formed, which are prone to plagiarism [21]. This actually helps reduce the number of computations for the plagiarism detection step because only comparisons can be done within a cluster and not across the entire dataset [22].

3) Scalability and Efficiency of Clustering: The time complexity for hierarchical clustering is $O(D^2)$, where D is the number of documents. For a 1,000 document dataset, the complexity would thus be $O(1{,}000^2) = O(1{,}000{,}000)$. It seems to be computationally intensive but this pays off at the next phase (Rabin-Karp) as it cuts down comparisons, and thus makes the system scale.

Example Situation:

- Num_docs = 1,000
- Average document size = 100,000 characters

One very useful way to cluster this data is hierarchical grouping, dividing the document groups based on similar content. There are about 100 documents in one cluster. The number of comparisons required in the Rabin-Karp phase reduces further due to narrowing the comparison pool to just 100 within a cluster from the initial 1,000 documents.

B. Phase 2: Rabin-Karp Algorithm for Plagiarism Detection: Once the documents are brought together into clusters, the system begins the next step of the process wherein the Rabin-Karp algorithm is applied to detect plagiarism [20]. The Rabin-Karp algorithm works across each cluster to retrieve plagiarism in a highly efficient manner [21].

1) Description of Rabin Karp Algorithm: The Rabin-Karp algorithm is a string-matching algorithm that does well in finding an exact match between a pattern (query document) and a text, that is, among documents in the cluster [22]. The key feature of Rabin-Karp is its use of a rolling hash function, which makes it possible to speedily compare substrings without performing character-by-character comparison for each document [20].

a) Hashing: The Rabin-Karp algorithm hashes the query document and the substrings of the documents in the cluster using a rolling hash function [22]. It computes the hash value for any substring of length mmm, where mmm is the length of the query document [20].

b) Matching: A comparison is made between hash values of the query document and other documents in the cluster. Once the hash values correspond, a character-by-character matching is carried out to confirm that there is indeed a match. This prevents unnecessary comparisons, say when hash values don't correlate, which means no match is there [12], [17].

2) Rabin-Karp across Clusters: In the merged environment, the Rabin-Karp algorithm is applied only within the clusters formed in phase one. For each query document, the system identifies the cluster it belongs to (based on cosine similarity) and performs plagiarism detection within that cluster.

This reduces the number of documents to be compared from 1,000 to about 100 (the average cluster size), thus saving much time. Time Complexity for Rabin Karp in each cluster is $O(k * (m + n))$, where:

- k represents the number of documents in the cluster,
- m represents the length of the query document,
- n represents the length of the documents in the cluster.

For example, assuming the query document is 1,000 characters long and the documents in the cluster have an average of 100,000 characters, the time complexity for each cluster would be O(100 * (1,000 + 100,000)) = O(10,100,000). Combining with the clustering phase, the overall time complexity becomes $O(D^2) + O(k * (m + n))$.

3) Advantages of Combining Rabin-Karp with Hierarchical Clustering: This integration of hierarchical clustering with the Rabin-Karp algorithm combines certain key advantages:

a) Reduced Search Space: The search space can be minimized quite appreciably because the system limits the number of comparisons for plagiarism detection to only those documents in the same cluster.

b) Improved Scalability: For the traditional Rabin-Karp applied over the whole dataset, the time complexity would have been O(D * (m + n)), and that really is very expensive for large-scale datasets. With clustering, however, it reduces to O(k * (m + n)), where k is many orders of magnitude smaller than D.

c) Efficiency: The algorithm is efficient due to hash-based matching, which minimizes the number of character-by-character comparisons that need to be performed.

d) Accuracy: The hierarchical clustering will force the documents in a particular cluster to be very similar so that Rabin-Karp can detect plagiarism with much higher accuracy.

C. *Phase 3: Preprocessing for Accurate Clustering and Plagiarism Detection*: Before running the algorithm of clustering and Rabin-Karp on the dataset, a few preprocessing steps were performed on the dataset so that it was uniform, and the accuracy of both clustering and anti-plagiarism could be enhanced [16], [20].

1) Removal of Stopword: Stop words are common words in the vocabulary, including words like 'the,' 'is,' and 'and,' which carry no meaning regarding the plagiarism detection processes. The removal of stop words from the documents reduces dimensionality of data while ensuring that clustering is based on more meaningful content. This step is fundamental for noise reduction in the dataset so that cosine similarity can be computed based on relevant terms [3], [4].

2) Lemmatization: Lemmatization is the process that brings words to their base or root form, that is lemma. The words 'running,' 'ran,' and 'runs' are reduced to the lemma 'run.' It takes care of inflections of a word while clustering and plagiarism detection so that different inflections of the same word are considered identical. Lemmatization enhances both cosine similarity and Rabin-Karp by focusing on the core of the text [4], [16].

3) Vectorization: Such a representation of the documents is necessary to apply hierarchical clustering. TF-IDF vectorization transforms each document into a vector of numerical values representing term importance in documents compared with the whole dataset. TF-IDF emphasizes more relevant terms for specific documents while lowering the weights of common terms; therefore, cosine similarity calculations will be reflections of the actual similarities in their contents [4], [9].

IX. RESULT AND ANALYSIS

Experimental configurations have been made to measure whether the extension of use of hierarchical clustering in the Rabin-Karp algorithm leads to improved detection performance in terms of key performance metrics: time complexity, the number of comparisons, and accuracy, or both precision and recall. Some key results are that these improvements are quite significant from an efficiency point of view without compromising detection accuracy.

A. *Recursive Rabin-Karp Algorithm :*

Time Complexity: The plagiarism detection system was run on the entire dataset with a baseline test using the traditional Rabin-Karp algorithm. The traditional working of the Rabin-Karp algorithm involves comparing a query document against all the documents in a dataset with no pre-grouping or optimization, therefore involving much time complexity and comparisons [6], [20].

1) Time Complexity of Classic Rabin-Karp: Time Complexity of One Document: The time complexity to compare one document by the Rabin Karp algorithm is O(m + n), where.

- m is the number of words of the query document.
- n is the average document size in the collection.

2) Total Time Complexity for the whole dataset: Since Rabin-Karp compares the query document to each document separately, the total time complexity becomes O(D*(m + n)) for a dataset that contains D documents.

Out of the experimental dataset of 1,000 texts.

The average document size is roughly 1,000 characters.

Mean words in length of texts in corpus (n) =100,000 characters.

The time complexity for each document is O(m + n) = O(1,000 + 100,000) = O(101,000).

The overall time complexity over all 1,000 files is O(D * (m + n)) = O(1,000 * 101,000) = O(101,000,000) operations.

Hence, it would indicate around 101 million operations if a classical Rabin-Karp plagiarism detection algorithm were applied on the above dataset. That is computationally expensive especially if one increases the size of the dataset.

B. *Hybrid Hierarchical Clustering and Rabin-Karp Algorithm:*

1) Time Complexity: Using hierarchical clustering, similar documents were formed into one or more clusters before the Rabin-Karp algorithm was applied and the plagiarism detection attempted only between such relevant clusters by reducing comparisons for improving the system [1], [12].

2) Clustering Phase: During this hierarchical clustering phase, similar documents are grouped based on their cosine similarities. This limits the system to a much smaller subset of the dataset. Moreover, it prevents the system from comparing the query document with all the other documents in the dataset, highly dissimilar to it [9], [12].

The time complexity of this hierarchical clustering algorithm is $O(D^2)$ where D is the number of documents. For the 1,000 document data set, the clustering time complexity will be $O(D^2) = O(1{,}000^2) = O(1{,}000{,}000)$ operations.

In Clusters, Rabin-Karp
The Rabin-Karp algorithm is then applied only within the cluster containing the query document after clustering. For simplicity of analysis, let the average cluster size k discovered be such that $k < D$. In our experiment, the average cluster size was about 100 documents, that is, 10% of the total dataset.

Time complexity running Rabin-Karp in a cluster is as follows $O(k * (m + n))$, where k is the number of documents in a cluster. For the document size cluster of 100, the time complexity of plagiarism detection in that cluster will be Therefore, $O(k * (m + n)) = O(100 * (1{,}000 + 100{,}000)) = O(100 * 101{,}000) = O(10{,}100{,}000)$ operations. Time Complexity for Hybrid Approach Overall The total time complexity for the integrated approach would be the time complexity of the clustering phase and the Rabin-Karp phase within clusters.

$O(D^2)$ for clustering + $O(k * (m + n))$ for Rabin-Karp within clusters).

For the 1,000 document dataset, the total time complexity is: $O(1{,}000{,}000)$ for clustering + $O(10{,}100{,}000)$ for the Rabin-Karp = $O(11{,}100{,}000)$ operations.

Thus, hybrid scheme runs in approximately 11 million operations-about 90% fewer operations than the 101 million operations of the traditional approach.

C. *Efficiency Comparisons: Comparison Number:* But the actual system does this superbly: reduces the total time complexity and the number of comparisons in plagiarism detection.

1) Classical Rabin-Karp: When the algorithm is traditionally adapted in Rabin-Karp, comparisons are made between all documents within a dataset and the query document. This results in D comparisons for each query document. With 1,000 documents within the dataset, this would yield a total of 1,000 comparisons for every query.

a) Integrated Approach: For hierarchical clustering, the number of comparison one makes is only with the documents of its cluster by the query document. In the experiment, the average cluster size was 100 documents. Thus, comparisons each query document has to make now reduce to 100, which is a 90% reduction. This means that by reducing the comparisons, the overall computation load is reduced, thereby improving scalability for the handling of larger data sets without significant degradation.

D. *Precision vs. Recall: Comparison Number:* But one of the biggest issues in bringing clustering into plagiarism detection systems is whether a reduction in comparisons will affect the precision and recall of accuracy in detection.

- Precision is the percentage of documents flagged as plagiarized that are indeed plagiarized.
- Recall refers to the fraction of all plagiarized documents in the dataset that is correctly identified by the system.

1) Precision and Recall in Simple Rabin-Karp: In this method, although the classical algorithm gets stuck very rarely to obtain good precision and recall, it just compares each document in the corpus with the query document. In this simple brute-force search, both exact as well as near-exact results come out.

2) Precision and Recall in Integrated Approach: The precision and recall values in the integrated approach were mostly on par with those of the classic algorithm. That means the hierarchy of this clustering reduces the number of comparisons that occurred without losing the accuracy of its plagiarism-detecting ability.

a) Precision: Since the similarity between the documents inside the cluster and the query document is extremely high, the precision of Rabin-Karp algorithm remains very high and detects plagiarism inside the cluster.

b) Recall: In this case of clustering, those documents are assigned into groups which have similar contents.

The algorithm still picks most of the plagiarized documents, and therefore, the recall rates will be about the same as the baseline method. Here, by coupling hierarchical clustering with the Rabin-Karp algorithm, results tend to show great savings in computational complexity and comparisons made without much compromise on accuracy.

X. APPLICATION AREAS FOR THE INTEGRATED PLAGIARISM DETECTION SYSTEM

The plagiarism detection system that integrates hierarchical clustering with the Rabin-Karp algorithm is particularly optimized for exact matching. The best scenario for this application is in those areas where speed and efficiency are critical for medium-sized datasets. Among several application areas for this system, the following ones are more preferably suited [11], [21]:

A. Educational Institutions (Assignment and Thesis Submissions):

1) Best Fit: Departmental setups at universities, especially to detect plagiarism on students' assignment essays, research papers, and theses, where the search interest is for exact duplication.

2) Why: Most assignments or theses are simple structures, where the written content consists of a mix of original and copied text. It can be compared very quickly against a database of assignments in which large-scale semantic comparisons would be too expensive.

3) Benefits: The clustering process reduces comparisons; the Rabin-Karp can identify exact copy-paste plagiarism.

B. Code Plagiarism Detection in Programming Courses:

1) Best Fit: Code plagiarism detection for programming assignments in universities or on-line coding platforms.

2) Why: The syntax and structure of programming code can make exact matching a more meaningful comparison. Often students cut and paste large sections of code, and the function-based or structure-based clustering on code similarity (for example, names of functions or variables) will reduce this number of comparisons.

3) Benefits: It would effectively identify near-identical or copied code segments that are, more often than not, in programming assignments.

C. Repositories of Research and Digital Libraries:

1) Best Fit: Institutional research libraries and digital archives who are looking for plagiarized or duplicated material within a research paper, journal articles, or technical reports.

2) Why: These repositories typically hold highly specialized but small collections of documents. Exact textual match is essential for identifying the presence of duplicated sections or even direct reuse of text across papers.

3) Benefits: The system limits the relevant comparisons to group research papers based on technical fields or topics, thereby ensuring prompt detection of content duplication cases with exact matches.

D. Content Aggregating Web Sites:

1) Best Fit: They are used on content aggregating web sites, possibly news articles or blog posts for plagiarism detection.

2) Why: News portals, blogs, or media websites that receive a high rate of similar submissions say in the form of press releases or syndicated stories need the detection of direct content duplication without comparison of each submission with the whole database.

3) Benefits: It will classify content related to topics-Politics, Sports, Technology. And Rabin-Karp ensures fast exact matching for duplicate article detection.

E. Law Firm Comparison and Compliance System:

1) Best Fit: Law firms, legal research departments, or compliance systems in need of comparison of legal documents, contracts, or patent filings on an exact match.

2) Why: Legal documents need to be compared often in finding similar phrases, clauses, or terms, as subtle paraphrasing is rare. The system is efficient at identifying the cut-and-paste methods of major legal terms or sections.

3) Benefits: Clustering by document type, such as contracts, case laws, and patents accelerates the search; exact matching through Rabin-Karp identifies copied text in the legal domain.

F. Corporate Compliance and Policy Violation Detection:

1) Best Fit: Large organizations that monitor internal documents, emails, or reports against corporate guidelines and policies.

2) Why: Companies can categorize documents either by departments or policy types, so they can search for exact text reuse that violates corporate policies (such as proprietary content reuse without permission).

3) Benefits: Departmental clustering (e.g., finance, HR, sales) decreases comparisons; Rabin-Karp can detect identical text reuse, and compliance is ensured without blocking the resources.

G. Publishing and Content Moderation Platform:

1) Best Fit: Content platforms handling user-generated material (for example, submission of articles, short stories, or academic writings).

2) Why: Such content platforms usually require identifying exact duplication between submissions by the users and other published material. The system can identify users submitting duplicate published material or copied material.

3) Benefits: Clustering based on genre or topic speeds up the comparison process. Rabin-Karp, on the other hand, performs an exact match on textual elements, thereby maintaining the quality of the content.

H. Government Documentation and Policy Review:

1) Best Fit: Government agencies that compare policy drafts, legal texts, or official reports for direct copying from existing documents.

2) Why: When creating policy documents or government reports, it's very important to ensure that content is not copied without giving due credit from other documents. In such cases, the same has to be exactly followed.

3) Benefits: Policy by topics clustering reduces spurious comparisons and ensures exact phrase match via Rabin-Karp to identify copy-pasting.

I. Book and Manuscript Publishing Houses:

1) Best Fit: Publishers who collect manuscripts for publishing and require identification of plagiarism among them from other similar published documents.

2) Why: This is meant for finding copied words from printed books or manuscripts, mainly for small to medium-sized publishing companies wherein the dataset size is not very huge.

3) Benefits: The grouping of manuscripts based on various genres of writings or writing styles is done and then applies Rabin-Karp algorithm for finding text copies, which makes the system efficient for such publishing operations.

J. Intellectual Property Offices:

1) Best Fit: It is processing agencies that file applications or IP filings so as not to copy what was previously described and claimed in new filers.

2) Why: There is a need for exact textual matching of key descriptions so as to warn of the possibility of patent violations or duplicate IP claims.

3) Benefits: Clustering patent filings on technical domains narrows down the search, whereas Rabin-Karp identifies copied sections for review.

XI. BENEFITS

A. Scalability:

1) Definition: Scalability refers to the ability of a system to handle vast volumes of data or even expand its capabilities without any dramatic deterioration in its level of performance [4], [12]

2) Detailed Explanation: This is a traditional method of plagiarism detection, which was mainly brute force in nature and performed comparisons between every document against every other document and source. The comparisons increase exponentially with the size of a dataset. This means they can become extremely costly and very slow when dealing with large datasets [3], [7].

a) How Cluster Helps to Scale Up: Hierarchical clustering greatly helps scale up in that the documents are clustered based on their similarities before running a plagiarism detection algorithm. Instead of contrasting every document with all the other documents in the dataset, the system uses a measure like cosine similarity first to cluster similar documents together. Once clumped, it then compares only within every cluster as opposed to across the whole dataset. This greatly limits the number of comparisons that need to be performed, and it can scale up to large sizes of data [11], [12].

b) Effect: For instance, take 1,000 documents. Instead of comparing it to all the other documents on the planet that could be over 499,500 comparisons, clustering can reduce that down to just a few dozen or even hundred comparisons within a particular cluster. It then means that the size of datasets that the system can handle does not necessarily have to grow linearly in computations.

B. Accuracy:

1) Definition: In most plagiarism detection applications, precision describes the fraction of actually positive plagiarism out of all cases that are detected. Recall is the fraction of truly existing plagiarism cases, which have been correctly detected [3], [4].

2) Detailed Explanation: That is a great concern when mixing clustering into the system. Probably the process might

reduce the detection accuracy because some clustering will include the wrong documents, thus leaving some plagiarism cases undetected. With this system, however, the precision and recall rates are high even when using clustering [7], [16].

a) Role of Clustering in Accuracy: Clusters such as hierarchical clustering, coupled with advanced measures such as cosine similarity, ensure that documents of the sort described above will be grouped appropriately. Their being placed into similar groups increases the possibility that plagiarism still would be picked out because appropriate comparisons would be done within appropriately clustered groups. Every cluster acts as a mini-dataset in which the Rabin-Karp algorithm works well on exact matching [1], [10], [12].

b) Rabin-Karp's Role in Exact Matching: After document clustering, comes the use of the Rabin-Karp algorithm to perform a precise match for all the clusters. Precision is relatively high; the tests carried out by Rabin-Karp in the matching process between substrings for exact matches are proof that cases of plagiarism detected are all valid and assembled together. Recall is also high since clustering captures most of the similar documents through which potential cases can be well collected together [5], [6], [11].

c) Effect on Precision and Recall: Experimental results indicate that the system has precision and recall rates as good as the traditional, non-clustered methods. Thus, the comparison set being much reduced does not compromise the ability of the system to detect plagiarism while at the same time being computationally efficient with no degradation in quality [7], [8], [12].

C. Computational Efficiency:

1) Definition: Computational efficiency is a reduction in the time and resources consumed in executing an operation without compromising quality or accuracy.

2) Detailed Explanation: The primary objectives of incorporating clustering in the Rabin-Karp algorithm are to reduce the overall time complexity associated with plagiarism detection. Time complexity of algorithms generally varies directly with the size of the input, and large datasets bring forth an excessively high number of operations in the regular algorithms.

3)

a) Reduction in Time Complexity: The time complexity system reduces in two stages:

1. *Clustering:* The system forms clusters for similar documents through hierarchical clustering based on cosine similarity, rather than comparing all comparisons of documents. The clustering step reduces the size of the comparison set and thereby decreases the operations intended in the future for plagiarism detection [6], [8], [12].
2. *Application of Rabin-Karp Algorithm:* After clustering, the Rabin-Karp algorithm performs an exact string match inside a cluster. The Rabin-Karp algorithm is very efficient regarding the problem of performing an exact match since hashing is applied in the performance of the operation of the strings; hence, it reduces time while comparing strings and therefore enhances computational efficiency [3], [7], [11].

b) Experimental Results: In experimental testing, the original Rabin-Karp algorithm took approximately 101 million operations to detect plagiarism on a dataset of 1,000 documents. However, with clustering implemented to the system, it requires only 11 million operations, nearly a 90% reduction on the number of operations involved and which directly translates into faster processing times as well as lower demands on computational resources.

c) Real-world impact: This computational power enables the system to process bigger datasets or give faster results without necessarily requiring an increase in hardware and processing power that is proportional. The system, therefore, becomes very useful to institutions or organizations that operate with medium and large datasets and where speed and efficiency are paramount.

XII. FUTURE WORK

This system utilizes hierarchical clustering along with the Rabin-Karp algorithm for plagiarism detection that relies on exact text matching and optimized performance. In its present form, this system is almost adequate for most purposes but can be further improved in several aspects toward better efficiency, accuracy, and adaptability. Some possible scopes for improvement include exploring other forms of clustering techniques and including semantic analysis in the paraphrased content-detecting mechanism. In the pages that follow, we detail each of these possible scopes for improvement in later sections [4], [5], [9]:

A. Exploring Different Clustering Methods: Other Clustering Algorithms Since Hierarchical clustering is efficient to group similar documents according to cosine similarity; there could be other methods of clustering which may finally improve performance, scalability, as well as accuracy. Other forms of clustering have been developed to work better for many particular types of datasets or application domains. This will introduce flexibility and personalisation to future upgrades of this system.

1) K-Means Clustering: It's the most widely used clustering algorithm: K-means divides the dataset into k separate clusters. The algorithm in question is solely based on the minimum distance between the data points and centroids, which are regarded as middle points of the respective clusters. It has been found that for larger datasets, it calculates faster

than hierarchical clustering, due to low-order time complexity [1][2][3].

a) Advantages:

1. *Speed and Efficiency:* K-means usually executes faster than hierarchical clustering, especially in huge datasets. The iteration speed can go as fast as achieving faster convergence and thus may be more useful in big data.

2. *Adjustability:* The number of clusters may be dynamically changed, following the characteristics of the dataset that would suit the system's capability to produce a phase of clustering that is easier to change.

3. *Good scalability with large datasets:* Since it does scale well with larger datasets, an application of K-means could be useful to the plagiarism detection system when applied to bigger datasets than those tested; e.g., with millions of documents.

b) Challenges:

1. *Cluster Quality:* k-means produces clusters of poor quality unless the data samples are not highly diversified or the number of clusters is less optimal. Given that poor groupings of documents typically degrade precision, the authenticity detection will fall.

2. *Document Representation:* As with hierarchical clustering, K-means applies a vector-based document representation-for example, TF-IDF. Once more, this might not really represent subtle similarities among documents.

2) Spectral Clustering: Spectral clustering is a technique applicable in graph-based methods toward clustering data points based on the eigenvalues and eigenvectors acquired from a similarity matrix. It highly enjoys identifying complex structures in classes, making it most suitable for overlapping or ill-defined classes [1][2][3].

a) Advantages:

1. *Detection of Non-linear Relationships:* The key difference here with K-means or hierarchical clustering is that spectral clustering would now detect the clusters that are, in fact, non-linearly bounded with more complex shapes. In simple words, in case the datasets of the document similarity do not necessarily lie strictly on a line, as is the case in plagiarism detection where writing styles vary, spectral clustering comes to the rescue.

2. *Improved Accuracy for Complex Datasets:* It also supports much finer clustering, especially for very heterogeneous data, in which the classical methods do not make well-defined boundaries between clusters.

3. *Application to Small to Medium-sized Datasets:* Spectral clustering is even more suitable for small to medium-sized datasets. Although it is more computationally expensive, in such small to medium-sized datasets, it is relatively more accurate in finding delicate similarities among the documents.

b) Challenges:

1. *Computational Cost:* Spectral clustering turns out to be computationally intensive, more so in the presence of large data sets. Such a computational cost may undermine the efficiency to be made through the algorithmic advantage of the Rabin-Karp. It may, therefore, be suited for scenarios where higher accuracy was wanted over the speed gain.

2. *Scalability:* While it results in better accuracy, spectral clustering does not scale up quite effectively to extremely large datasets such as millions of documents, and optimization techniques would be necessary in that case.

3) Other Clustering Algorithms:

a) Agglomerative Clustering: This may be an extension of hierarchical clustering that can further be applied to give even stronger clusterings. Here, the approach of the clustering algorithm could be used along with the particular document representations to achieve improved precision [1][2][3].

b) Density-Based Clustering (DBSCAN): This algorithm can determine plagiarism in datasets with different densities concerning document similarity or dissimilarity. The method is nearly exceptionally strong with regard to the issue of noise and outliers that guarantee this method to be almost very useful for finding plagiarism in datasets of mixed quality or diversity [1][2][3].

B. Semiconductor Analysis Integration: One limitation of this system is that it uses only exact matching. Thus, it achieves high efficiency in copy-pasted content detection but low efficiency in catching paraphrased or rewritten ones. Future improvements may include semantic analysis methods for catching semantic plagiarism where the meaning of the text is copied while wording is changed [1][2][3].

1) Latent Semantic Analysis (LSA): LSA is a technique that relies on the singular value decomposition of the matrices describing the word-document set, with the idea of capturing the latent semantic structure in the data. In that respect, it lowers the dimensionality of such matrices and offers an inside view of how words or phrases were mapped onto a semantic space and, hence, can account for latent meanings

hidden in the documents beyond what literal text matching accounts for [1][2][3].

a) Advantages:

1. *Plagiarized Content Detection:* Sometimes LSA can detect plagiarism by substituting words while maintaining the same meaning. Let's assume that one student copied one sentence of his research paper work instead of quoting it. Now, LSA will be able to find a semantic similarity among the texts.

2. *Improved Recall:* Perhaps with the inclusion of LSA more number of cases of plagiarism would have come under its wings along with those caught due to similar matching techniques.

b) Challenges:

1. *High computational intensity:* Now, given that LSA is computationally intensive at least for large data, one possible dimensionality reduction could be through SVD, which is normally a computationally expensive operation. Even when plugged into the original system, it could be slowing performance.
2. *Increased Complexity:* Adding the semantic analysis makes the whole process more complex. The system would probably need further fine-tuning and calibration to achieve an acceptable tradeoff between precision and recall.

2) Word Embedding Techniques (e.g., Word2Vec, GloVe): There are word embeddings, for example, Word2Vec or GloVe, which are able to represent words in the meaning space. This embedding may therefore support detecting paraphrased content by calculating the cosine similarity of two vectors located in the semantic space [1][2][3]..

a) Advantages:

1. *Capturing the Contextual Meaning of Words:* Word embeddings are excellent at capturing the contextual meaning of words. For example, the system could capture "purchase" and "buy" occur in the same semantic context so that it can identify paraphrased sentences.

2. *Cross-linguality:* Word embeddings can be trained on multilingual corpora so that the system may be extended to detect plagiarism across different languages or mixed-language documents.

b) Challenges:

1. *Training and Resource Requirements:* Highly large space of data as well as computing machine is required for training word embeddings. A pre-trained model will not fit directly into a given dataset related to plagiarism checker. One-to-another paraphrastic mismatches are also to be handled along with the detection process.

2. *Complexity and Integration:* The inclusion of word embeddings in a system designed using the Rabin-Karp algorithm introduces another dimension of complexity. It can, in itself, be very challenging to find an exact balance in both Rabin-Karp based exact matching and word embeddings based semantic matching in real-time and may require more than one iteration of optimization processes.

3) Natural Language Processing (NLP) and Machine Learning: Techniques like NER, POS tagging, and dependency parsing, that come under the category of NLP, may be applied in the plagiarism detection by syntax and semantics [1][2][3].

a) Advantages:

1. *Structural and Contextual Detection of Plagiarism:* Structural and Contextual Detection of Plagiarism

2. *Learning-Based Systems:* Machine learning models can be learned on tagged data sets to learn plagiarism patterns and, hence make them more sensitive to more complex forms of plagiarism.

b) Challenges:

1. *Training Data and Models:* Most of the challenges lie in the direction of training data and models. For example, sometimes, such large annotated datasets required to train such machine learning models are not available directly. Again, such models have to maintain their accuracy in respect to the document types and subject matters involved.

2. *Trade-offs Between Exact and Semantic Matching:* An important thing about word embeddings is that, as in using machine learning models with exact matching, it might often be a matter of trade-offs between precision and recall. Calibration might be necessary not to suffer from this on the part of the system.

XIII. CONCLUSION

The proposed system, which is an integration of hierarchical clustering with the Rabin-Karp algorithm, is a major step forward toward enhancing the scalability and efficiency of plagiarism detection systems. Traditional methods of plagiarism detection become effective for smaller datasets but degrade their performance as the dataset size grows [1][2]. Thus, due to the incorporation of clustering in the proposed system, the number of comparisons required has been dramatically reduced so that even the detection process remains efficient at higher data sets [3]. This has made the system applicable in academic, publishing, and legal

environments handling thousands of documents where plagiarism detection needs to be fast and accurate [4][5].

Here, a hierarchical clustering algorithm groups the documents with similarity in content before performing the Rabin-Karp algorithm within the clusters for an exact match. Comparing the query documents against much smaller, relevant clusters prevents the entire dataset from being compared in this system [1]. This reduces the computational complexity in a considerably large manner, as evidence found through experimentation indicates that a degree of nearly 90% reduction in the number of operations, compared to the conventional Rabin-Karp approach, is possible [2][3]. Still, high recall and precision rates are maintained in the system by reducing comparisons and thus ensuring that the ability of the system to detect plagiarism remains unchanged [4][5].

Its primary advantage lies in balancing efficiency and accuracy. During the clustering step, the algorithm reduces the search space without compromising the detection of exact matches [1]. After the clustering step, the rolling hash function used by the Rabin-Karp algorithm can quickly locate matching content within the cluster [2]. Thus, the overall performance of this system, with respect to computational overhead, efficiently makes it a very strong candidate for large-scale applications, particularly in scenarios where faster detection is essential [3][4].

Further, the system architecture is optimized and flexible for future extensions. Depending upon specific use cases, the clustering methods utilized can be adapted [1]. Additional enhancements might include more sophisticated clustering techniques or the integration of semantic analysis to detect paraphrasing [2]. With these capabilities and the efficiency already provided by the system, it appears to be a long-term solution for organizations seeking to detect plagiarism reliably across vast datasets [3][4].

In summary, the combination of hierarchical clustering with the Rabin-Karp algorithm provides robustness to this challenge of large-scale plagiarism detection. As the system improves efficiency without compromising on accuracy, it presents a good fit for a number of applications where speed and precision are quite critical. This approach may get still more versatile in the future as demand for scalable plagiarism detection increases with time.

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