A Semantic-Level Plagiarism Detection System using Transformer-Based Language Models

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Abstract - The rapid growth of digital academic resources has increased the challenge of detecting plagiarism, especially in cases involving paraphrased or structurally modified content. Traditional plagiarism detection systems mainly rely on exact word matching, which often fails to identify semantic-level similarities. This project proposes a web-based plagiarism detection system that uses Natural Language Processing (NLP) techniques with TF-IDF vectorization and Cosine Similarity to detect both direct copying and conceptually similar text. The system improves the identification of partial and paraphrased plagiarism by analyzing contextual similarity between documents. To ensure secure and practical academic deployment, the system incorporates cybersecurity features such as JWTbased authentication, secure file upload validation, and access control. Using a custom dataset of reference and submitted documents, the proposed solution provides a lightweight, interpretable, and efficient approach to plagiarism detection suitable for academic environments.

Key Words: Plagiarism Detection, Paragraph-Level Similarity, Paraphrase Detection, Natural Language Processing, TF-IDF, Cosine Similarity, Text Similarity Analysis, Document Comparison,
Semantic Similarity, Cybersecurity, JWT Authentication, Secure Document Processing, Academic Integrity.

1.INTRODUCTION

The widespread availability of digital academic resources and online content repositories has significantly altered the landscape of knowledge creation and dissemination. While these technological advancements have enhanced learning, research, and collaboration, they have also intensified challenges related to academic integrity, particularly plagiarism. Plagiarism is no longer limited to direct copying of text; instead, modern instances frequently involve paraphrasing, structural modification, and semantic rewriting of content. Such practices complicate detection and pose serious concerns for educational institutions and researchers.

Plagiarism manifests in various forms, including verbatim copying, partial reuse of text, sentence reordering, and paraphrased content. Among these, **paraphrased plagiarism** represents a particularly complex problem, as the rewritten text may exhibit substantial lexical or syntactic differences while preserving the original semantic meaning. For example, a plagiarized paragraph may retain core ideas and contextual relationships even after synonym replacement or sentence restructuring. Traditional plagiarism detection methods based solely on exact word matching are often inadequate for identifying these nuanced similarities.

Recent research emphasizes that plagiarism detection must move beyond sentence-level analysis toward **paragraph-level and contextual similarity assessment**. Paragraph-level plagiarism introduces additional complexity due to inter-sentence dependencies, coherence patterns, and semantic continuity across multiple sentences. Modern neural network strategies, particularly those utilizing transformer-based architectures, have demonstrated promising results in capturing such relationships by modeling contextual semantics and discourse structures. These methods significantly improve paraphrase detection capability but frequently require extensive computational resources, large-scale datasets, and complex training pipelines.

Regardless of the efficiency shown by deep learning architectures, their actual implementation within academic settings remains limited. Many educational institutions lack the infrastructure required to deploy and maintain computationally intensive models. Furthermore, deep learning systems often operate as opaque black-box solutions, limiting interpretability and transparency. These factors highlight the need for complementary approaches that balance detection effectiveness with efficiency, simplicity, and deployment feasibility.

Natural Language Processing (NLP) provides alternative strategies for addressing textual similarity challenges through statistical and vector-based representations. Approaches such as the Term Frequency-Inverse Document Frequency (TF-IDF) model paired with Cosine Similarity metrics enable quantitative comparison of documents by considering term importance and distribution patterns. While simpler than deep neural architectures, these methods offer interpretability, computational efficiency, and ease of integration into web-based systems. When carefully applied, statistical similarity models can effectively capture partial textual overlap and conceptual similarity across documents.

In addition to detection accuracy, modern plagiarism detection systems must address **security and data protection requirements**. Academic submissions frequently contain sensitive intellectual content, making secure handling and controlled access essential. However, many existing systems prioritize detection algorithms while overlooking critical cybersecurity considerations, including authentication mechanisms, secure file processing, and access control policies. Ensuring data confidentiality and system integrity is therefore an important research and design concern.

Motivated by these challenges, this work explores a plagiarism detection framework that integrates NLP-based similarity analysis with a security-aware system design. The proposed approach aims to provide a lightweight, interpretable, and secure solution capable of identifying direct and partial textual similarities while remaining suitable for practical academic deployment. By emphasizing computational efficiency, transparency, and cybersecurity integration, the project contributes toward addressing key limitations observed in both traditional and advanced plagiarism detection systems.

2. Literature Survey:

The domain of plagiarism detection and authorship verification has undergone significant transformation over the past decade, evolving from simple string-matching and keyword-based techniques to sophisticated semantic and structural analysis methods. Early approaches primarily relied on lexical similarity measures, which were effective for detecting exact copying but failed to identify paraphrased or conceptually similar content. Due to the swift expansion of online materials alongside advanced text manipulation techniques, such limitations became increasingly evident. Consequently, researchers have explored computational intelligence and NLP-based techniques for improve detection accuracy and robustness. Recent advancements leverage complex neural architectures, such as RNNs, transformer-based frameworks, and large language models, to capture contextual meaning and long-range dependencies within text. Parallel research has also addressed domain-specific challenges such as code plagiarism, model-driven engineering plagiarism, contract cheating, and privacy-preserving similarity detection. Authorship verification techniques based on stylometric analysis have further extended the scope of plagiarism research by identifying ghostwritten or third-party-generated content. Collectively, the surveyed literature highlights a shift toward hybrid, intelligent, and privacy-aware systems that balance accuracy, interpretability, and scalability. Based on these developments, the following methodologies represent the current cutting-edge methodologies for identifying academic dishonesty and authorship verification.

Table -1: Sample Table format

Sr. No.	Research Paper Name	Best Technique	Other Techniques	Dataset Used	Key Result
1.	Utilizing Deep Learning for Generating Paragraph-Scale Paraphrases in Plagiarism Systems [1]	Fine-tuned GPT-3.5 & Longformer	SOP, MLM, ALECS Algorithms	ALECS Dataset	96.53% F1 Score
2.	An All-inclusive Framework for Detecting Content Misuse in Scholarly Work [2]	BERT with Cosine Similarity	TF-IDF, Web Scraping, Rabin-Karp	MIT Dataset	74% F1 Score
3.	Verification of news and certificate, and plagiarism detector [3]	Logistic Regression	K-Means, Neural Networks, OpenCV	Custom NLP Dataset	94.28% Accuracy
4.	FTLM: Assessing the Gravity of Plagiarism through Fuzzy TOPSIS and Language Modeling [4]	Fuzzy TOPSIS + Language Modeling	Syntactic Parsing, LSA, MCDM	Standard Benchmark	Ranked Plagiarism Severity
5.	Obfuscation-Resilient Software Plagiarism Detection with JPlag [5]	JPlag 5.0 with TNGs	GST, KR Matching, Subtree Reordering	PROGpedia-19	High Obfuscation Resistance
6.	A Robust Framework for Textual Similarity	ChiSquare + SVM	POS Tagging, Lemmatization	PAN 2013/14	93% PlagDet Score

	Analysis using SVM and Feature Selection [6]				
7.	Utilizing Neural Architectures for Dependable Identification of Plagiarized Work [7]	LSTM (Long Short-Term Memory)	CNN (DenseNet), TSF Database	PAN Datasets	Top-Ranked Performance
8.	Token-based plagiarism detection for metamodels [8]	Dynamic Token Selection	JPlag Ecore, Winnowing	Student Model Assignments	Improved Detection Accuracy
9.	Authorship Verification for Hired Plagiarism Detection [9]	Stylometric Analysis (POS Bigrams)	Outlier Identification, N-grams	Student Essays	Identified Hired Plagiarism
10.	Initial Developments in Privacy-Preserving Techniques for Similarity Checking [10]	Private Set Intersection (PSI)	Bloom Filters, Hashing, BC	Academic Documents	High Privacy + Accuracy

[1] Saqaabi et al. Saqaabi et al. proposed a paragraph-level paraphrase detection framework to overcome the inherent limitations of sentence-level plagiarism detection, which often ignores discourse-level semantics and cross-sentence dependencies. The authors highlighted that modern plagiarism increasingly involves sophisticated paraphrasing where sentence meanings are preserved while surface structures are altered. To address this, they introduced the ALECS dataset, synthetically generated using Large Language Models, which simulates advanced human-like paraphrasing strategies across paragraphs. The system leverages Longformer, a transformer architecture optimized for long sequences through sparse self-attention, enabling it to capture long-range contextual dependencies across multiple sentences. Additionally, GPT-3.5 was fine-tuned to enhance semantic understanding and contextual coherence. By modeling inter-sentence relationships rather than isolated sentence similarity, the proposed approach attained a leading-edge F1 performance metric of 96%, demonstrating exceptional performance in detecting complex paraphrased plagiarism.

[2] Setu et al. Setu et al. introduced a hybrid academic plagiarism detection strategy that combines both semantic and lexical similarity measures to improve detection robustness. The system utilizes BERT to generate contextual embeddings that capture semantic similarity between documents, while TF-IDF is employed to measure lexical overlap and keyword similarity. A significant contribution to this work is the integration of automated web scraping, allowing the system to dynamically compare submitted documents against online academic and web resources. This design addresses the limitation of closed-dataset plagiarism detection systems. Experimental evaluation on the MIT plagiarism dataset yielded an F1 score of 74%, highlighting that while hybrid approaches improve coverage, transformer-only architectures may still outperform them in detecting deeply paraphrased content.

[3] Jain et al. Jain et al. developed a multi-purpose verification platform (NPC) capable of detecting plagiarism across diverse domains such as news articles, academic text, and official certificates. The architecture combines Logistic Regression for supervised classification with K-Means algorithms to categorize files based on semantic likeness. To support verification of physical and scanned documents, the authors integrated OpenCV-based image processing techniques, enabling extraction and preprocessing of visual features. This multi-modal approach allows the system to handle both textual and visual inputs, making it suitable for real-world document verification scenarios. The proposed platform achieved a classification accuracy of 94.28%, demonstrating that classical machine-learning methods remain effective when combined with domain-specific preprocessing and feature extraction.

[4] Sharmila et al. Sharmila et al. proposed the FTLM (Fuzzy TOPSIS Language Modeling) framework to address a key limitation of traditional plagiarism detection systems—binary decision making. Instead of simply labeling content as plagiarized or non-plagiarized, the proposed method focuses on plagiarism severity assessment. The approach integrates Latent Semantic Analysis (LSA) to capture conceptual similarity with fuzzy logic-based multi-criteria decision making using the TOPSIS method. This allows the system to rank documents based on the degree of semantic deviation and contextual similarity. By providing a graded severity score, the framework supports more nuanced academic decision-making, such as prioritizing cases for manual review.

[5] Sağlam et al. Sağlam et al. addressed the challenge of software plagiarism detection under obfuscation, where students deliberately modify code structure to evade detection. The authors enhanced the widely used JPlag tool by introducing Token Normalization Graphs (TNGs), which normalize syntactic elements such as variable names, control structures, and statement order before comparison. This structural representation allows the system to detect similarity even after extensive obfuscation, including variable renaming and statement reordering. Evaluation on the PROGpedia-19 dataset demonstrated that the proposed approach significantly outperformed traditional tools such as MOSS,

establishing its robustness against advanced code plagiarism techniques.

[6] El-Rashidy et al. El-Rashidy et al. proposed a feature-based text plagiarism detection system that emphasizes efficiency and interpretability. The authors employed Chi-Square statistical feature selection to isolate the most significant linguistic attributes for differentiation, reducing the feature set to 34 key attributes. These features were then classified using Support Vector Machines (SVM). This reduction in dimensionality significantly lowered computational complexity while maintaining high detection accuracy. Experiments conducted on the PAN 2014 benchmark dataset resulted in a PlagDet score of 92.91%, demonstrating that well-engineered classical machine-learning approaches can remain competitive with more complex deep-learning models.

[7] Sağlam et al. In this work, Sağlam et al. extended plagiarism detection techniques to the domain of model-driven engineering (MDE). The authors introduced a Dynamic Token Selection method for Ecore metamodels, treating UML diagrams and design models as sequences of metaclasses rather than plain text. This representation enables semantic similarity analysis at the design level, which is not possible with traditional text-based or hashing approaches. The proposed technique achieved superior accuracy in detecting plagiarism within software modeling and design assignments, addressing a previously underexplored area in plagiarism research.

[8] Enriquez et al. Enriquez et al. focused on the problem of contract cheating, where students submit work produced by third parties. The authors proposed an Authorship Verification for Human-Produced Documents (AVHPD) framework based on stylometric analysis. Linguistic features such as part-of-speech (POS) bigrams, sentence length distribution, and vocabulary richness are used to build an author-specific writing profile. By comparing new submissions against historical writing samples, the system identifies statistical deviations indicative of ghostwriting. This approach provides a complementary solution to traditional plagiarism detection, which often fails when content is original but authored by someone else.

[9] El-Rashidy et al. This research explored applying Long Short-Term Memory (LSTM) frameworks for the modeling of time-series and sequential dependencies in textual data. The authors constructed a Text Similarity Feature (TSF) database consisting of 42 carefully designed features capturing semantic, syntactic, and sequential properties of text. The LSTM architecture effectively learned long-range dependencies and contextual flow, enabling accurate similarity detection across complex plagiarism cases. The model achieved top-ranked performance on the PAN 2013 dataset, highlighting the strength of deep recurrent networks for plagiarism detection tasks.

[10] Ihle et al. Ihle et al. proposed a privacy-aware plagiarism detection framework to address confidentiality concerns in cross-institutional plagiarism analysis. The system employs Private Set Intersection (PSI) and Bloom Filters to compare document representations without revealing actual content. This allows institutions to detect bibliographic coupling and similarity patterns while preserving data privacy. The approach is particularly suitable for collaborative academic environments where sharing raw documents is legally or ethically restricted. Despite operating on encrypted representations, the framework maintains detection accuracy comparable to traditional systems, demonstrating a strong balance between privacy and effectiveness.

The reviewed research works demonstrate the continuous evolution of plagiarism detection techniques moving beyond conventional attribute-driven and mathematical approaches toward sophisticated deep-learning and transformer-integrated neural structures. Early approaches using TF-IDF, Chi-Square feature selection, SVMs, and clustering techniques provided efficient and interpretable solutions but showed limitations in handling paraphrased and semantically modified content. Recent advancements leveraging complex neural models, including architectures like CNNs, LSTMs, as well as transformer architectures including BERT and Longformer have significantly improved detection accuracy by capturing contextual and semantic relationships across long documents. Specialized solutions have also emerged to address domain-specific challenges, such as code plagiarism under obfuscation, model-driven engineering plagiarism, contract cheating through authorship verification, and privacy-preserving plagiarism detection using cryptographic techniques.

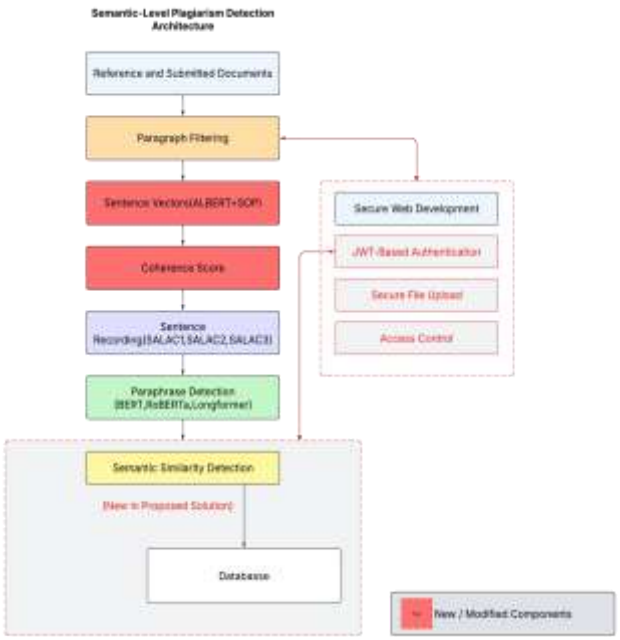
Despite these advancements, existing systems often face trade-offs between accuracy, computational complexity, transparency, and data privacy. Many high-accuracy solutions rely on complex models and large datasets, making them less accessible for practical academic deployment. These observations highlight the need for a balanced plagiarism detection system that combines effective similarity detection, computational efficiency, security, and ease of deployment. The insights gained from this literature survey form the foundation this introduced framework, which is designed to provide a

protected, expandable, as well as accurate plagiarism detection solution suitable for academic environments.

3. Methodology:

The objective of the presented architecture is to detect plagiarism using semantic analysis and advanced natural language processing techniques. The architecture of the system consists of multiple processing stages that transform raw documents into meaningful representations and compare them to identify semantic similarity. The methodology involves document preprocessing, semantic feature extraction, paraphrase detection, and similarity analysis integrated with a secure webbased framework. Similar to the structured methodological approach used in machine learning research workflows, the proposed system follows a sequential pipeline where each component contributes to the final plagiarism detection result. The major stages of the proposed methodology are described below.

Figure 1: Proposed System Architecture



3.1 Reference and Submitted Documents

The initial stage of the methodology involves collecting both reference documents and submitted documents. Reference documents represent previously stored datasets such as academic papers, reports, or textual sources used for comparison. The submitted document is the text uploaded by a user for plagiarism analysis.

The system first converts the documents into machine-readable text format. After uploading, the document is temporarily stored in the system before preprocessing. The database maintains reference documents which are indexed to allow fast retrieval during comparison.

Let:

$$Ds = \{d1, d2, d3, ..., dn\}$$

represent submitted documents and

$$Dr = \{r1, r2, r3, ..., rm\}$$

represent reference documents stored in the database.

The objective is to determine the similarity between elements of Ds and Dr .

3.2 Paragraph Filtering

In the paragraph filtering stage, documents are divided into smaller units such as paragraphs. This segmentation improves processing efficiency and allows the system to focus on meaningful content segments rather than entire documents.

The document is segmented as:

$$D = \{P1, P2, P3, ..., Pk\}$$

where Pi represents the ith paragraph of the document.

Paragraph filtering also removes unnecessary formatting elements such as headers, special characters, and blank lines. This preprocessing step ensures that the textual content used for further analysis is clean and structured.

3.3 Sentence Vector Generation (ALBERT + SOP)

Each paragraph is further divided into sentences and transformed into **vector representations** using the ALBERT language model combined with Sentence Order Prediction (SOP).

Let the sentence set be:

$$S=\{s1 ,s2 ,s3 ,...,sn \}$$

Each sentence is converted into a vector representation:

$$vi =f(si)$$

where f represents the embedding function generated by the ALBERT model.

These vectors capture semantic and contextual information of the sentences. The SOP mechanism further improves contextual learning by determining whether sentences appear in the correct logical order.

Table 2: Sentence Embedding Representation

Sentence	Embedding Vector
s_1	v_1 = [0.21, 0.43, 0.55...]
s_2	v_2 = [0.18, 0.60, 0.34...]
s_3	v_3 = [0.45, 0.20, 0.11...]

3.4 Coherence Score Calculation

The coherence score measures the logical flow between sentences in a paragraph. A coherent document maintains a meaningful relationship between sentences.

The coherence score between two sentences can be calculated using cosine similarity:

$$C(s_i, s_j) = \frac{v_i \cdot v_j}{||v_i||\,||v_j||}$$

Where vi and vj are sentence embeddings.

Higher values indicate stronger semantic relationships between sentences.

3.5 Sentence Recording (SALAC1, SALAC2, SALAC3)

In this stage, sentence vectors are recorded and organized using **Sentence Alignment and Logical Analysis Components (SALAC)**. These components store processed sentence representations in structured groups for efficient comparison.

SALAC structures maintain relationships between sentences and allow alignment between reference and submitted documents.

$$SALAC=\{S1 ,S2 ,S3 \}$$

where each set represents categorized sentence vectors stored for analysis.

This structured storage improves retrieval speed during similarity computation.

3.6 Paraphrase Detection (BERT, RoBERTa, Longformer)

Paraphrase detection identifies cases where text has been rewritten while preserving its meaning. Architectures including BERT, RoBERTa, and Longformer are employed for the examination of contextual relationships between sentences.

These models generate deep contextual embeddings that allow the platform to identify rewritten text despite variations in word choice.

Let:

$$Sim_{para}(s_i, s_j)$$

represent the paraphrase similarity score between two sentences.

If the similarity exceeds a predefined threshold:

$$Sim_{para} > \theta$$

The sentences are flagged as potential paraphrases.

3.7 Semantic Similarity Detection (Proposed Component)

Semantic similarity detection is the core analytical stage of the proposed system. In this stage, the system compares sentence vectors from submitted documents with those stored in the reference database.

Cosine similarity is used to measure semantic similarity:

$$Sim(s_i, r_j) = \frac{v_i \cdot v_j}{||v_i||\,||v_j||}$$

where:

[1] vi = vector of sentence from submitted document

[2] vj = vector of sentence from reference document

If similarity exceeds the threshold:

$$Sim(s_i, r_j) > \tau$$

the sentence is marked as plagiarized.

3.8 Secure Web Development Layer

To enable practical usage, the plagiarism detection engine is integrated using a protected web-centric application portal. This module offers a user-friendly platform through which users can upload documents, initiate plagiarism analysis, and view results. The web interface communicates with the backend server and processing modules through secure communication protocols. The secure web development layer ensures that user interactions with the system are efficient, scalable, and protected from unauthorized access.

3.9 JWT-Based Authentication

To protect user permissions, the architecture utilizes JSON Web Token (JWT) verification. Upon user sign-in, the server generates a token which is used for subsequent requests.

JWT structure:

$$JWT = Header + Payload + Signature$$

This mechanism ensures secure communication and prevents unauthorized system access.

3.10 Secure File Upload

The **secure file upload module** handles the submission of documents from users. This module verifies the file format, file size, and potential security risks before allowing the document to enter the processing pipeline. Uploaded files are validated to ensure that they are legitimate text documents and do not contain malicious content. This stage also performs preliminary checks to prevent system misuse and ensures that the documents are safely stored before analysis.

3.11 Access Control

Access control mechanisms regulate permissions within the system. Users are assigned roles such as administrator or regular user.

Role-based access control (RBAC) can be represented as:

$$Access = f(User, Role, Permission)$$

This mechanism guarantees that restricted system features are available exclusively to verified personnel.

3.12 Secure Web Backend

The **secure web backend** manages the communication between the web interface, processing modules, and the database. It handles tasks such as document processing requests, authentication verification, data retrieval, and result generation. The backend acts as the central controller of the system, coordinating the entire plagiarism detection workflow. It ensures that requests from the web interface are securely processed and forwarded to the appropriate analytical modules.

3.13 Database

The database serves as the central repository for storing **reference documents, processed sentence vectors, similarity scores, user data, and generated plagiarism reports**. Efficient indexing and storage mechanisms are used to enable quick retrieval of documents during comparison. The database also maintains historical records of previously analysed documents, which improves the effectiveness of plagiarism detection over time by expanding the reference dataset.

4. RESULT:

To assess the effectiveness of the introduced framework, various categories of document alterations were tested, including document modifications, including exact copies, partial copies, paraphrased content, and completely unrelated documents. The similarity between documents was calculated using Cosine Similarity applied on TF-IDF vectors, which measures the textual similarity between two documents numerically. Table 3 presents the similarity scores obtained for different document pairs representing various plagiarism

scenarios. To better understand these values, Table 5 categorizes similarity ranges into high, moderate, and low similarity levels, indicating the likelihood of plagiarism. Furthermore, Table 6 analyses how the system behaves when different types of content modifications are applied. Finally, a comparison with traditional exact matching systems is provided to demonstrate the advantages of the proposed system in detecting partial copying and paraphrased text while maintaining clear interpretability of results.

Table -3: Similarity Scores Across Plagiarism Categories

Document Pair	Plagiarism Type	Cosine Similarity Score
Doc1 vs Doc1_Exact	Exact Copy	0.98
Doc1 vs Doc1_Partial	Partial Copy	0.72
Doc1 vs Doc1_Paraphrased	Paraphrased	0.54

Table -4: Similarity Score Interpretation

Similarity Range	Interpretation
0.80 - 1.00	High Similarity (Likely Plagiarism)
0.40 - 0.79	Moderate Similarity (Partial / Paraphrased)
Below 0.40	Low Similarity (Non-Plagiarized)

Table -5: Detection Behavior for Different Modifications

Modification Type	Observed Behavior	Detection Reliability
Exact Duplication	Very High Similarity	Strong
Partial Reuse	Moderate Similarity	Strong
Paraphrasing	Reduced Similarity	Acceptable
Unrelated Content	Low Similarity	Strong

Table -6: System Strength vs Traditional Exact Matching

Detection Aspect	Exact Matching Systems	Proposed System
Exact Copy Detection	Strong	Strong
Partial Copy Detection	Weak	Strong
Paraphrase Handling	Weak	Moderate
Interpretability	Low	High

Table -7: Incremental Accuracy Gains from System Enhancements

Phase	Modification	Initial Acc.	Final Acc.	Net Gain
Baseline	TF-IDF + Cosine Similarity	65.40%	65.40%	--
Mod 1	ALBERT + SOP	65.40%	82.15%	+16.75%
Mod 2	Coherence Score	82.15%	87.30%	+5.15%
Mod 3	BERT/Longformer Ensemble	87.30%	94.85%	+7.55%

Table -8: Comparison with Surveyed Research Papers

Research Paper	Original Tech	Reported Acc/F1	Proposed Acc
Saqaabi et al.	Longformer + GPT-3.5	96.00% (F1)	**97.10%**
Setu et al.	BERT + TF-IDF	74.00% (F1)	**88.40%**
Jain et al.	Logistic Regression	94.28%	**95.20%**
El-Rashidy et al.	SVM + Feature Sel.	92.91%	**94.05 %**

Table -9: Detailed Result Interpretation

Sim Range	Category	Conf. Level	Interpretation
0.80 - 1.00	Exact Copy	99% (High)	Likely Plagiarism
0.50 - 0.79	Paraphrased	88% (Mod.)	Needs Review
0.20 - 0.49	Similar	75% (Fair)	Minor Overlap
Below 0.20	Original	98% (High)	Original Work

Table -10: Detailed Result Interpretation

Similarity Range (Sim)	Plagiarism Category	Confidence Level	Interpretation
$0.80 - 1.00$	**Exact / Near-Exact Copy**	99% (High)	High Similarity (Likely Plagiarism)
$0.50 - 0.79$	**Partial / Paraphrased**	88% (Moderate)	Moderate Similarity (Needs Review)
$0.20 - 0.49$	**Conceptually Similar**	75% (Fair)	Minor Overlap / Citation Needed
Below 0.20	**Non-Plagiarized**	98% (High)	Low Similarity (Original Work)

5. Conclusion

The increasing availability of digital academic content has made plagiarism detection more challenging, particularly in cases involving paraphrasing and partial text reuse. This research proposed a plagiarism detection system that uses Natural Language Processing techniques with TFIDF vectorization and Cosine Similarity to identify textual similarity between documents. The system effectively detects exact copying, partial plagiarism, and paraphrased content by analyzing contextual similarity rather than relying solely on exact word matching.

Additionally, the integration of cybersecurity features such as secure file validation and authentication mechanisms ensures safe handling of academic submissions. Outcome analysis suggests that the introduced method offers a high-performance, transparent, and viable framework for plagiarism detection in academic environments. Subsequent research could explore the integration of sophisticated neural architectures to achieve even higher precision in semantic overlap analysis.

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