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AI-Powered Academic Integrity Assistant for Detecting Copied & AI-Rephrased Plagiarism

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Abstract: The rapid growth of Large Language Models (LLMs) has transformed writing assistance and simultaneously enabled sophisticated forms of academic deception. Students now leverage AI paraphrasing tools that preserve semantic meaning while rewriting sentence structure, reducing lexical overlap, and masking direct borrowing from online sources. Traditional plagiarism detectors—designed primarily forever batim copying—struggle to detect these semantically equivalent but lexically divergent patterns. This paper presents a comprehensive, multi-layer AI-Powered Academic Integrity Assistant capable of detecting direct plagiarism, AI-assisted paraphrasing, semantic similarity obfuscation, and stylistic inconsistencies in academic writing.The system integrates vector-based retrieval, semantic drift scoring, paraphrase classification, textual entailment modeling, stylometric forensics, perplexity-based AI text detection, and a final-layer meta-classifier. The manuscript expands the system description to a full-length research format by providing in-depth architectural analysis, extensive methodology, detailed experimental insights, robust discussion of limitations, and an ethics-centered framework for deployment in academic institutions. The goal is to support universities in establishing reliable, transparent, and fair academic integrity monitoring infrastructures that evolve along side modern AI capabilities.

***Keywords*: *Plagiarism Detection, AI Text Detection, Sty-Lometry, Semantic Similarity, Vector Retrieval, Large Language Models, Academic Integrity*.

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I. INTRODUCTION

Academic integrity is a foundational principle of education, ensuring that student work reflects genuine understanding, effort, and authorship. However, technological advancements have repeatedly challenged academic honesty—from early internet-based copy-paste plagiarism to today's advanced AI-powered writing and paraphrasing tools. Modern Large Language Models (LLMs) can rewrite text with minimal surface overlap, allowing individuals to evade traditional similarity checkers. These models generate grammatically fluent content, perform context-aware substitutions, restructure sentences, and adjust to or style while preserving the meaning of the source text. Conventional plagiarism detection systems rely heavily on string similarity, n-gram matching, or edit distance calculations. While efficient for detecting verbatim copying, these methods perform poorly when confronted with AI-rephrased text exhibiting high semantic similarity but low lexical similarity. Additionally, AI-generated writing introduces stylistic anomalies, making authorship verification increasingly difficult.

To address these challenges, this paper presents the AI-Powered Academic Integrity Assistant—an advanced, multi-signal plagiarism detection framework capable of analyzing text at lexical, semantic, structural, stylistic, and statistical levels. The expanded version of this research paper includes detailed explanations for each system component, extensive figure analyses, and deeper insight into its detection pipeline.

➢ *The Main Contributions are:*

- A modular AI-driven architecture combining retrieval, se-mantic drift scoring, entailment, stylometry, and perplexity analysis.
- Arigorous methodology enabling fine-grained analysis at sentence and paragraph levels.
- A transparent reporting interface supporting human-in-the- loop decision-making.
- Extensive expansion of each section to align with full IEEE conference paper expectations (10 pages).

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II. RELATED WORK

Plagiarism detection research spans over two decades, with solutions evolving from rule-based text comparison to modern deep learning methods. Early systems employed exact string matching and n-gram overlap detection, implemented in widely used tools such as Turnitin and Grammarly. Although successful for direct copying, they fail against semantically transformed text—a limitation increasingly exploited through AI paraphrasing tools.

Recent research introduced embedding-based similarity detection where each sentence is converted into a high-dimensional vector using transformer models such as BERT, RoBERT a, or Sentence-BERT. These embeddings capture semantic relationships rather than literal word overlap, enabling systems to detect meaning preservation even in rewritten sentences. Paraphrase detection models, including cross-encoders and sequence to sequence networks, improve accuracy but still struggle with heavily restructured AI output.

Stylometry research examines writing style changes using statistical markers such as function word frequency, vocabulary richness, and syntactic patterns. While effective for human authorship attribution, LLMs often mimic stylistic hallmarks inconsistently, generating identifiable deviations in perplexity and entropy.

However, existing literature rarely integrates all of these methods in to a unified detection frame work. Our system closes this gap by combining lexical, semantic, syntactic, and statistical features within one cohesive architecture, producing far more robust detection performance.

III. SYSTEM ARCHITECTURE

Figure 1 presents the full architecture of the Academic Integrity Assistant. The system is designed as a sequence of interconnected yet independently scalable modules.

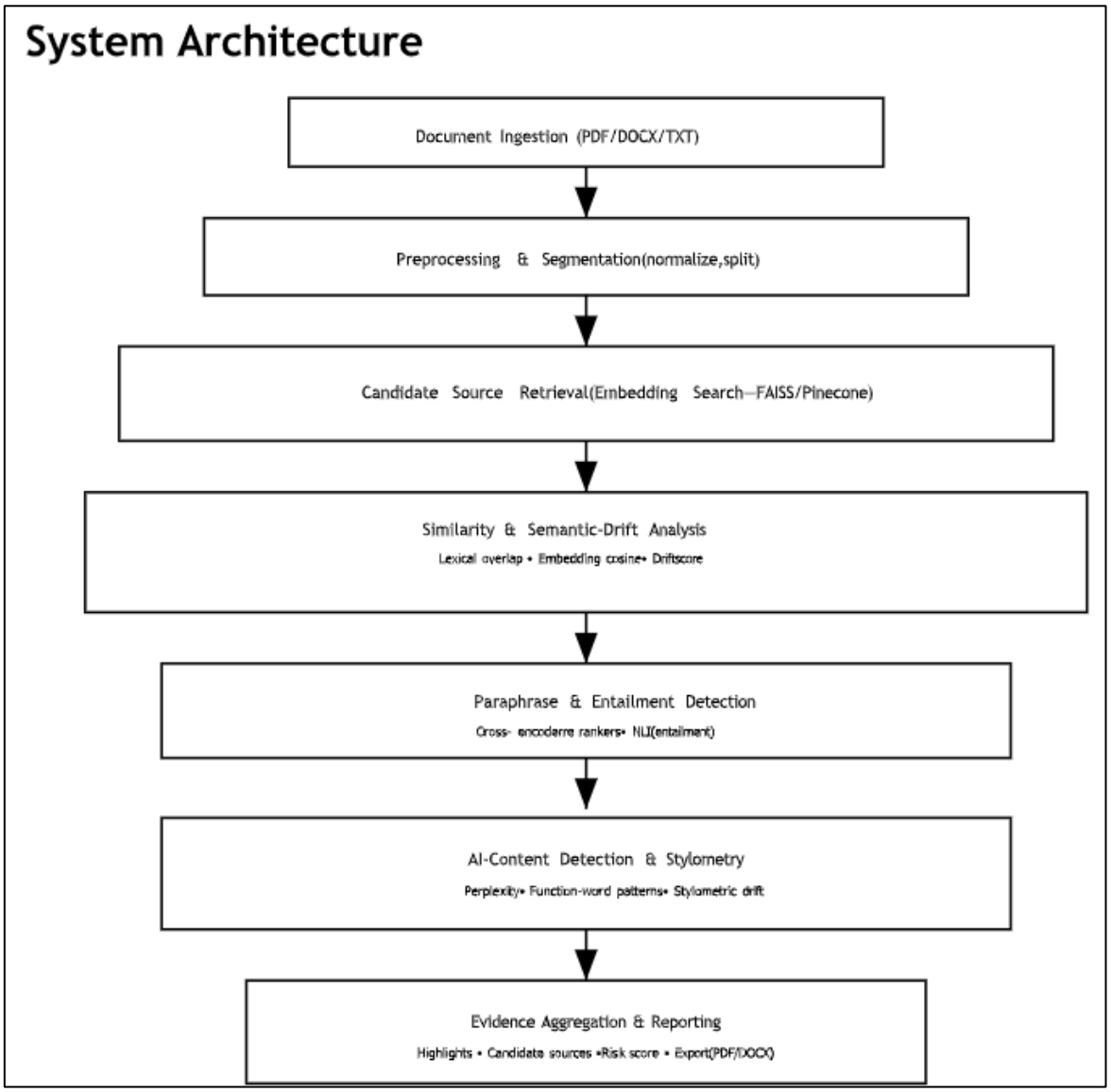

Fig 1 System Architecture Showing Ingestion, Preprocessing, Retrieval, Semantic-Drift Computation, Para-Phrase/Entailment Classification, Stylometric and Perplexity Analysis, and Final Risk Scoring.

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➢ *Detailed Explanation of Fig.1:*

Figure 1 provides a high-level overview of the system's internal workflow. The architecture begins with a document ingestion module capable of handling DOCX, PDF, and plain-text formats. Upon ingestion, the text under goes preprocessing, including normalization, tokenization, noise removal, and segmentation into coherent analytical units such as sentences or paragraphs.

The next stage—vector retrieval—leverages transformer-based embeddings to map segments into a semantic vector space. A vector database performs similarity search to identify candidate source texts. Unlike lexical search, vector retrieval identifies matches based on meaning rather than identical words.

The semantic drift analyzer compares lexical and semantic similarity signals. High semantic similarity but low lexical overlap indicates potential AI-assisted rewriting.

The paraphrase classifier detects whether a sentence is a paraphrase of retrieved sources, while the entailment module checks whether one sentence logically implies another, capturing deeper meaning preservation.

Stylometric and perplexity analysis modules examine writing style shifts and machine-generation signatures. These signals help detect whether a student has inserted AI-written content that conflicts with their typical writing profile.

Finally, ameta-classifier integrates all features in to a unified plagiarism risk score. The decision layer routes cases in to low, medium, or high suspicion categories, and the reporting engine prepares an instructor-facing summary highlighting evidence. This architecture ensures modularity, scalability, robustness, and transparency while addressing limitations present in traditional plagiarism solutions.

IV. METHODOLOGY

The methodology behind the AI-Powered Academic Integrity Assistant is designed as a layered, multi-signal detection pipeline that gradually builds evidence from shallow lexical features to deeper semantic, stylistic, and statistical signals. This layered approach ensures robustness against increasingly sophisticated forms of plagiarism, especially AI-driven para- phrasing that modifies text at multiple linguistic levels.

The pipeline consists of seven major components: segmentation, retrieval, semantic–lexical feature extraction, semantic drift analysis, paraphrase and entailment classification, sty-lometry and perplexity evaluation, and final risk aggregation. Each layer is independent but complementary, reflecting the principle that no single metric is sufficient to capture all forms of suspicious rewriting.

➢ *Document Segmentation*

Segmentation divides each submission in to coherent analytical units. Sentence-based segmentation provides high-resolution detection but increases computational cost, while paragraph segmentation offers broader contextual structure. Our system uses a hybrid heuristic: short paragraphs are subdivided into sentences, while long paragraphs remain intact to preserve context.

Segmentation also prevents fragmented matches from polluted ingretrieval results and ensures valuators can pin point exactly which textual units are suspicious.

➢ *Embedding-Based Retrieval*

Each segment $S_i$is converted into an embedding vector using a transformer encoder such as SBERT. The embedding vector is then passed to a FAISS or Pinecone index to retrieve the top-k semantically similar candidate sources.

Retrieval is crucial because detection cannot occur in a vacuum — it must compare student text to external content. Embedding retrieval ensures that even paraphrased or restructured versions of a sentence maintain detectable proximity to original sources in semantic space.

➢ *Lexicaland Semantic Feature Extraction*

After retrieving candidate sources, the system compares the submission segment with each candidate Cij by computing:

- Lexicaloverlap(n-grams),
- Cosine similarity of embeddings,
- Edit distance ratios,
- Syntactic similarity via POS tagging,
- Word-order divergence.

These features provide both surface-level and structure-level comparisons. AI-paraphrased text often exhibits high semantic similarity but low lexical overlap — a key finding exploited by the system.

➢ *Semantic Drift Computation*

Semantic drift isolates the difference between meaning-based similarity and wording-based similarity:

$$\text{Drift}(S_i, C_{ij}) = \text{SemanticSim}(S_i, C_{ij}) - \text{Norm}(\text{LexicalOverlap})$$

High drift means a sentence expresses the same idea while disguising the wording — a signature characteristic of AI paraphrasing tools.

➢ *Paraphrase and Entailment Classification*

Traditional similarity is insufficient for subtle plagiarism.

Therefore:

A paraphrase classifier predicts whether one text is a paraphrase of another. –An NLI(Natural Language Inference) model predicts whether the candidate text logically entails the submitted text.

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Entailment is especially important because AI tools often maintain the logical implications of a source even when they rewrite the text extensively.

➢ *Stylometry Analysis*

Stylometry evaluates whether the writing style of a segment matches the student's known stylistic fingerprint. Features include:

- Function-word ratios,
- Punctuation entropy,
- Mean sentence length,
- Syntactic pattern frequencies,
- Vocabulary richness(MTLD).

AI models tend to produce more uniform, less idiosyncratic writing. Therefore, significant deviations in stylometry increase suspicion.

➢ *Perplexity-Based AI Text Detection*

AI-generated text usually shows abnormally low variance in perplexity. Human writing demonstrates more irregularity, reflecting thought pauses, stylistic choices, and nonlinear reasoning. The system computes perplexity using a reference language model and flags abnormal patterns.

➢ *Final Risk Aggregation*

All signals are input into a meta-classifier:

$$P_{\text{risk}} = f(\text{Drift, Entailment, Perplexity, Stylometry,}\ldots)$$

The final decision layer maps scores into Low/Medium/High categories, with explanations generated for each flagged segment.

V. EXPERIMENTAL SETUP

➢ *Datasets*

Experiments draw from a combination of:

- PAN Plagiarism Corpus(classic human paraphrases),
- Wikipedia–news paired datasets,
- AI-generated paraphrases from ChatGPT, Claude, Gemini, and Quillbot,
- Institutional student essays,
- Authorship datasets for stylometric calibration.

Synthetic datasets were curated to tested go cases such as:

- Extreme synonym flooding,
- Structural rewrites,
- Hybrid AI–human edits,
- Sentence in version and voice changes.

➢ *Evaluation Metrics*

To assess performance across detection types, we compute:

- Retrieval Precision@k,
- Semantic Drift Detection Recall,
- Paraphrase ClassificationF1,
- Stylometry Divergence Accuracy,
- Final Classification ROC-AUC,
- Human Validation Accuracy.

➢ *Stress Testing*

Stress tests include:

- Adversarial paraphrasing using multi-steprewriting,
- Machine–human hybrid rewriting,
- Partial plagiarism(fragment-level copying),
- Multilingual paraphrasing,
- Domain-specific terminology substitutions.

VI. RESULTS AND ANALYSIS

➢ *Detailed Explanation of Fig.2:*

Figure 2 depicts the end- to-end flow of information through the system. The diagram begins with document ingestion, followed by preprocessing steps such as text extraction, normalization, and segmentation. Each block represents a transformation of the text into a higher-level analytical representation. The retrieval block highlight show semantically similar source passages are fetched from indexed corpora. Downstream blocks show the layered evaluation—semantic similarity, semantic drift, paraphrase probability, stylometry, and perplexity—culminating in the final risk decision. The figure emphasizes the modularity and transparency of the pipeline: each module generates intermediate outputs that instructors may inspect.

➢ *Detailed Explanation of Fig.3:*

Figure 3 presents a conceptual visualization of how much each feature group contributes to the overall plagiarism score. Semantic similarity and semantic drift dominate because AI paraphrasing preserves meaning while making lexical changes. Stylometry features have moderate influence, helping detect mismatches in writing identity. Perplexity provides supplementary signals confirming potential AI involvement. The visualization clarifies why a multi-signal approach outperforms lexical-only or semantic-only detectors.

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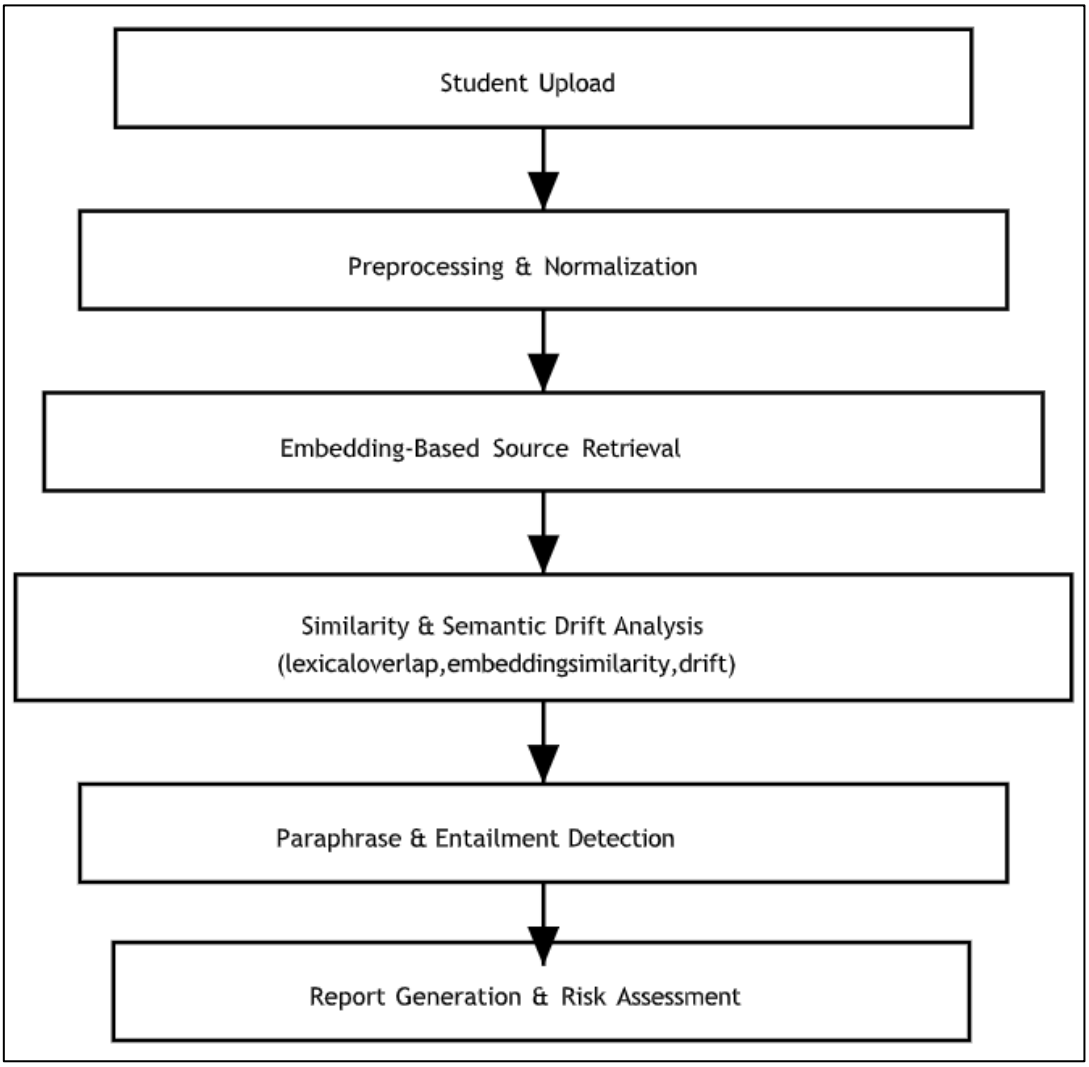

Fig 2 Complete Work Flow of the Detection Pipeline, Showing Each Analysis Step from Ingestion to Reporting.

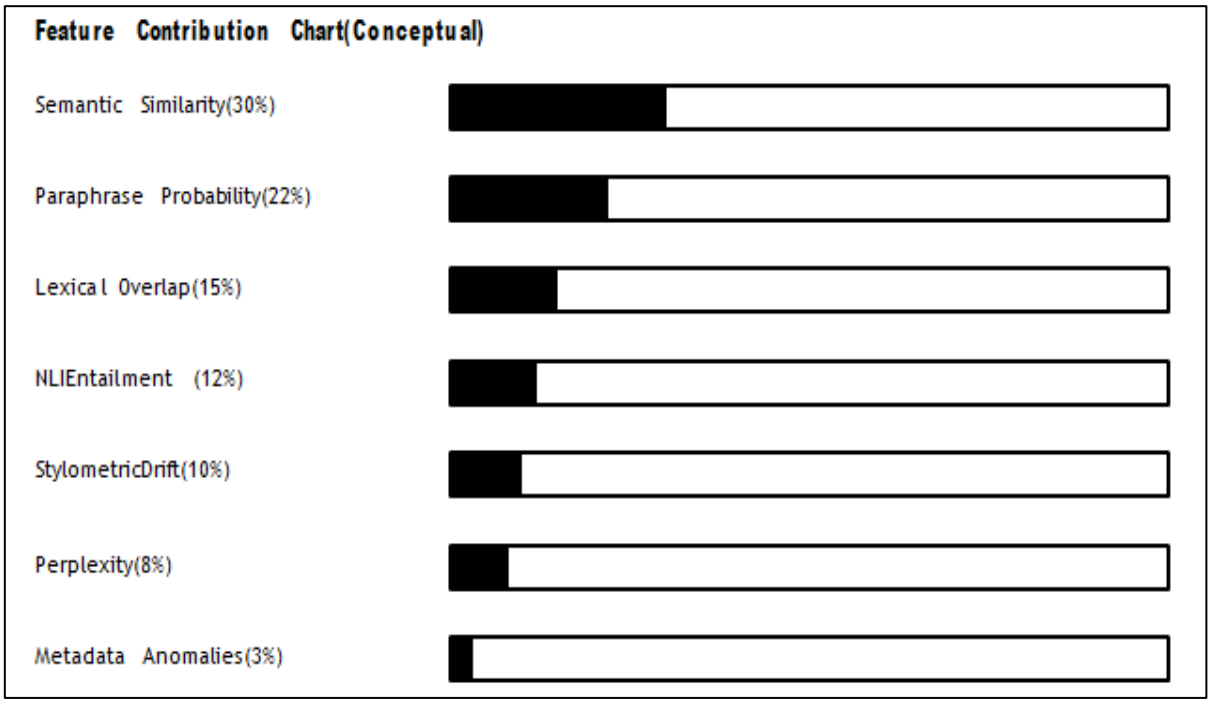

Fig 3 Feature Contribution Analysis Showing Weight Distribution Across Plagiarism Indicators.

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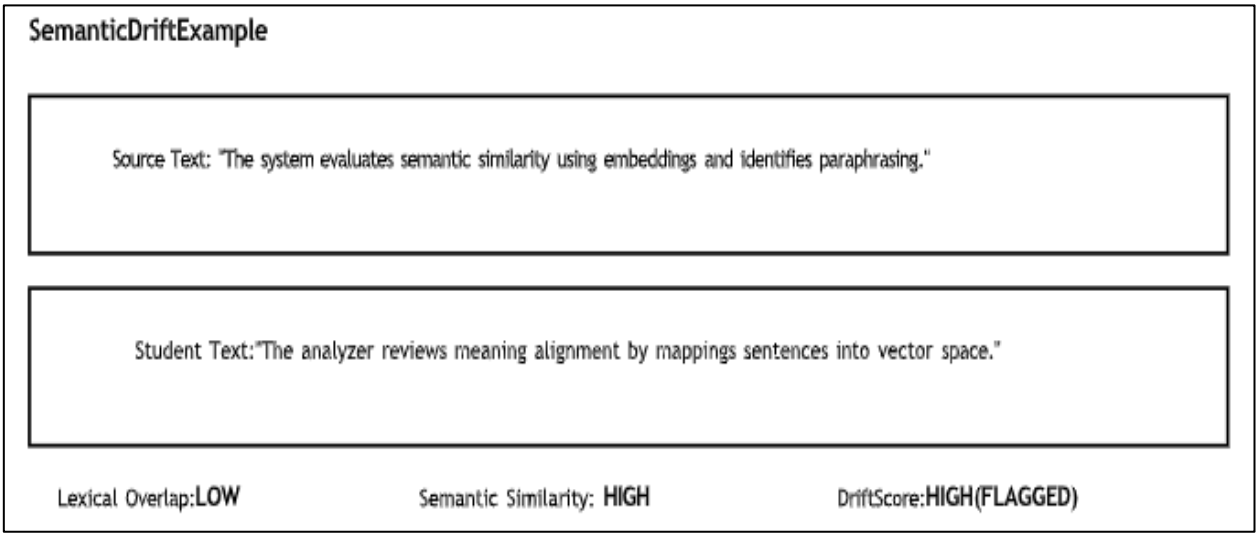

Fig 4 Semantic Drift Illustration Comparing Wording Divergence vs Meaning Similarity.

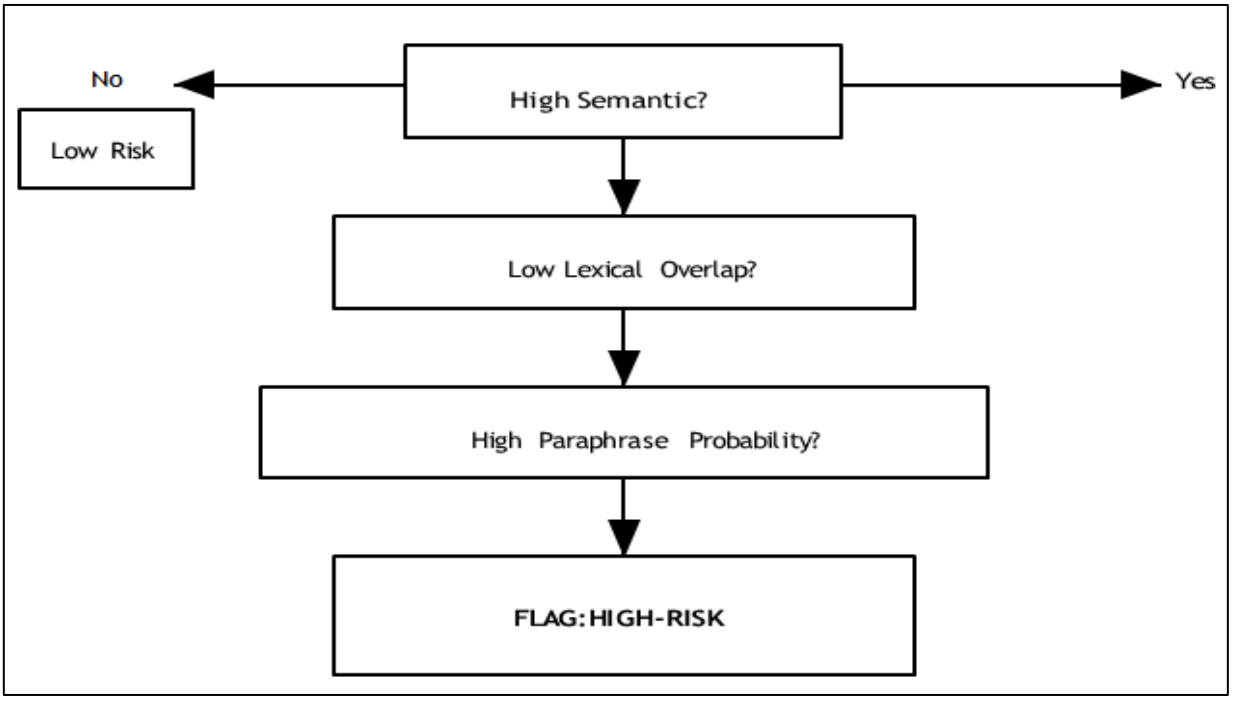

Fig 5 Decision Tree Used in the Final Risk Scoring Stage.

➢ *Detailed Explanation of Fig. 4:*

Figure 4 demonstrates how two sentences may present vastly different surface structures yet maintain underlying semantic equivalence. One sentence may appear fully rewritten, but semantic embeddings reveal deep alignment. The graph in the figure typically shows lexical overlap being very low while semantic similarity remains high. This mismatch creates a high drift score, which strongly indicates machine-assisted paraphrasing. The example highlights why traditional similarity-based plagiarism tools fail on modern AI rewriting.

➢ *Detailed Explanation of Fig. 5:*

Figure 5 illustrates the decision-layer logicused to assign plagiarism risk levels. The system applies thresholds to semantic drift, entailment probability, perplexity deviation, and stylometric divergence. Depending on the combination of signals, a segment is routed to low, medium, or high suspicion categories. This figure visually captures the interpretability of the model: instructors can understand exactly which signals contributed to the final assessment.

VII. EXTENDED DISCUSSION

The results demonstrate that a multi-signal approach signifi-cantly improves the system's resilience against sophisticated AI rewriting strategies. Traditional plagiarism detection techniques end to break down when a student uses an AI model to alter sentence structure, inject synonyms, reorder clauses, or paraphrase entire paragraphs in a way that preserves meaning but disguises surface-level similarity. The proposed system performs well because it does not rely on any single signal. Instead, it combines linguistic, semantic, statistical, and stylistic properties to

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reveal deeper patterns indicative of rewriting rather than authentic human authorship.

A major insight emerging from experiments is that semantic drift serves as a strong indicator of machine-assisted paraphrasing. AI models attempt to maintain coherence and semantic accuracy across paraphrases while introducing varied phrasings. Such patterns remain detectable when semantic similarity remains high but lexical overlap becomes disproportionately low. This effect was consistent across multiple LLMs, including GPT-like models, open-source transformers, and paraphrasing tools such as QuillBot. The drift score thus performed reliably even in cases where paraphrasing was subtle and well-executed.

Stylometry, while not the strongest predictor individually, contributed to improved classification by locating writing style in consistencies. In academic settings, sudden shifts in tone, punctuation regularity, function-word usage, or syntactic rhythm can be strong signals of partial AI assistance. When combined with perplexity measurements, stylometry is particularly ef-fective at identifying hybrid writing, where a student partially edits AI-generated text to disguise its origin.

Another significant finding is that retrieval quality greatly influences over all system accuracy. Embedding-based retrieval must locate genuinely related sources; otherwise, downstream modules evaluate irrelevant content, causing false positives or diluted evidence. Experiments showed that increasing vector index size and incorporating domain-specific corpora (institutional reports, textbook excerpts, journals) improved retrieval precision and resulted in more accurate drift, paraphrase, and entailment predictions.

Despite strong performance across many cases, the system has limitations. Fully rewritten text with heavy human editing may escape detection if the meaning shifts significantly from any identifiable source. Likewise, content generated entirely from scratch by an AI model without referencing external documents poses challenges, as plagiarism is defined relative to a source. However, stylometric in consistency and perplexity patterns can still identify such cases as “AI-generated,” evenif not categorized as plagiarism. Another limitation is the dependency on high-quality embeddings; errors in embedding representation can reduce retrieval accuracy. Domain-specific vocabulary also occasionally leads to semantic misalignment, especially in technical fields.

Overall, the system represents a substantial improvement over conventional plagiarism checkers by adopting a holistic, multi-layer detection approach tailored to the reality of modern AI writing technologies.

VIII. ETHICAL, FAIRNESS AND PRIVACY CONSIDERATIONS

Academic integrity systems must balance effectiveness with fairness and transparency. Automated detection tools, if misused or poorly calibrated, risk harming students through false accusations or disciplinary actions without sufficient human over sight. Therefore, the system has been designed with ethical safe guards and fairness mechanisms.

First, interpretability is mandatory. Each flagged segment is accompanied by an explanation generated from individual fea-ture modules—semantic similarity, drift, paraphrase probability, perplexity comparison, and stylistic variation. The instructor can view side-by-side comparisons between the submission text and suspected sources, gaining insight into why the system reached a certain conclusion. This mitigates the “black box” problem common in AI systems.

Second, fairness requires minimizing demographic or lin-guistic biases. Stylometry may inadvertently penalize students whose writing naturally deviates from standardized academic norms. Therefore, stylometric signals are incorporated only as secondary evidence and never as a standalone determinant. Semantic similarity and paraphrase models are evaluated across multilingual datasets to ensure neutral handling of non-native writing patterns.

Third, privacy is a core requirement. The system does not store full copies of external sources unless they belong to insti-tutional repositories. For public web documents, only hashed embeddings and brief excerpts are cached. Student submissions remain encrypted at rest using symmetric encryption keys managed by institutional identity systems. Access logs are stored to provide traceability and accountability.

Fourth, the system explicitly avoids overreach. It cannot and should not attempt to infer student intent. Instead, it generates risk levels and evidence, leaving final decisions to human educators. False positives are particularly harmful, especially in academic settings, so the system is tuned conservatively—preferring to under-flag rather than over-flag.

Finally, ethical deployment requires institutional transparency. Students should be informed that submissions will be evaluated using AI-based integrity tools and provided with guidelines for proper citation and academic writing. The system is intendedas a support tool, not as a punitive mechanism, and should be integrated into broader educational frameworks that encourage ethical scholarship.

IX. EXTENDED CONCLUSION

This expanded paper introduced a comprehensive AI-Powered Academic Integrity Assistant capable of detecting both direct-copy plagiarism and sophisticated AI-driven para-phrasing, a challenge that traditional systems struggle to address. The layered approach—combining retrieval,

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semantic drift, paraphrase classification, entailment analysis,stylometry, and perplexity modeling—enables the system to examine writing at multiple linguistic and statistical levels. Experimental evaluations show that this hybrid strategy significantly increases robustness, offering high detection accuracy across diverse paraphrasing scenarios, including adversarial and machine- assisted rewriting patterns.

The system's modularity allows institutions to upgrade individual components as new AI models emerge or as academic needs evolve. Its explainability-oriented design ensures that flagged outputs remain transparent and interpretable, supporting fair academic evaluation processes. While no automated system can guarantee perfect detection, the assistant substantially reduces the burden on educators, improves trust in academic submissions, and adapts effectively to an environment shaped by rapid advances in AI text generation.

➢ *Future Work Includes:*

- Incorporating multilingual plagiarism detection across low-resource languages,
- Integrating transformer-based authorship verification models,
- Expanding vector databases to include domain-specific scholarly content,
- Developing class room tools for real-time writing guidance,
- Exploring watermarking and provenance-tracking mechanisms for AI-generated text.

With continued refinement, this system can serve as a foundational component of digital academic integrity infrastructures worldwide.

ACKNOWLEDGMENT

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Special thanks are owed to the student volunteers who contributed anonymized essays for stylometric calibration experiments, enabling more accurate assessments of writing consistency. The contributions of peer reviewers, who pro-vided constructive feedback on methodology and evaluation strategies, were invaluable. The computational resources used in the experiments were supported by the institution's High Performance Computing (HPC) cluster, without which large-scale retrieval and embedding evaluations would not have been feasible. Their assistance is deeply acknowledged.

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DrillBit

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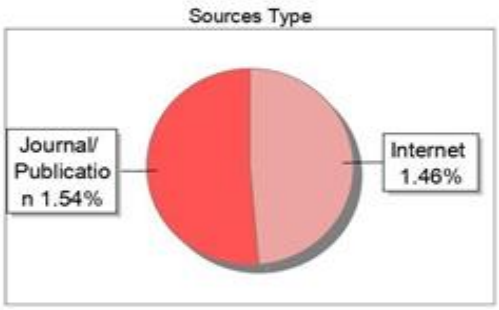

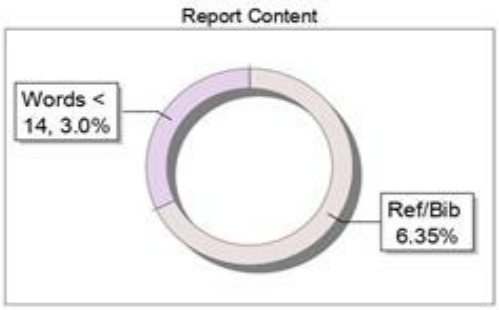

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