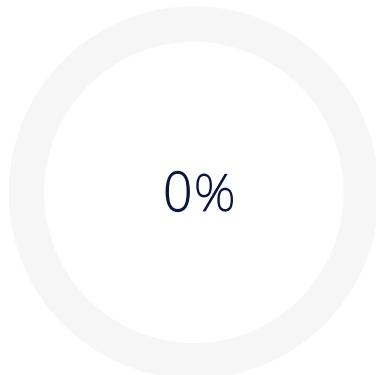


# Analysis Report

## Plagiarism Detection and AI Detection Report

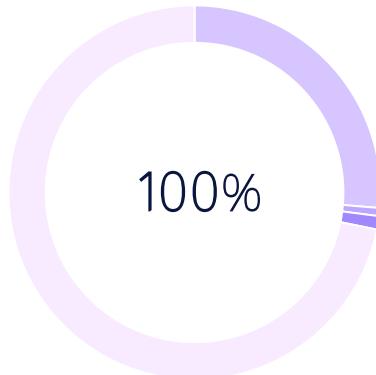
New Scans 12:29 AM

### Plagiarism Detection



Plagiarism types	Text coverage	Words
Identical	0%	0
Minor Changes	0%	0
Paraphrased	0%	0
<strong>Excluded</strong>		
Omitted Words	0	0

### AI Detection



	Text coverage	Words
AI Text	100%	433
Low Frequency		114
Medium Frequency		3
High Frequency		5
Human Text	0%	0
<strong>Excluded</strong>		
Omitted Words	0	0

# Plagiarism

0%

## Results (0)

\*Results may not appear because the feature has been disabled.

		
<b>Private Cloud Hub</b>	<b>Shared Data Hub</b>	<b>Filtered / Excluded</b>
0	0	0

		
<b>Internet Sources</b>	<b>AI Source Match</b>	<b>Current Batch</b>
0	0	0

### Plagiarism types

 Identical	0%	0
 Minor Changes	0%	0
 Paraphrased	0%	0
<b>Excluded</b>		
 Omitted Words		0

## About Plagiarism Detection

Our AI-powered plagiarism scans offer three layers of text similarity detection: Identical, Minor Changes, and Paraphrased. Based on your scan settings we also provide insight on how much of the text you are not scanning for plagiarism (Omitted words).

### Identical

One to one exact word matches. [Learn more](#)

### Minor Changes

Words that hold nearly the same meaning but have a change to their form (e.g. "large" becomes "largely"). [Learn more](#)

### Paraphrased

Different words that hold the same meaning that replace the original content (e.g. 'large' becomes 'big') [Learn more](#)

### Omitted Words

The portion of text that is not being scanned for plagiarism based on the scan settings. (e.g. the 'Ignore quotations' setting is enabled and the document is 20% quotations making the omitted words percentage 20%) [Learn more](#)

## Copyleaks Shared Data Hub

Our Shared Data Hub is a collection of millions of user-submitted documents that you can utilize as a scan resource and choose whether or not you would like to submit the file you are scanning into the Shared Data Hub. [Learn more](#)

## Filtered and Excluded Results

The report will generate a complete list of results. There is always the option to exclude specific results that are not relevant. Note, by unchecking certain results, the similarity percentage may change. [Learn more](#)

## Current Batch Results

These are the results displayed from the collection, or batch, of files uploaded for a scan at the same time. [Learn more](#)

# AI Content



	Text coverage	Words
AI Text	100%	433
Low Frequency		114
Medium Frequency		3
High Frequency		5
Human Text	0%	0
<b>Excluded</b>		
Omitted Words		0

## About AI Detection

Our AI Detector is the only enterprise-level solution that can verify if the content was written by a human or generated by AI, including source code and text that has been plagiarized or modified. [Learn more](#)

### AI Text

A body of text that has been generated or altered by AI technology.

[Learn more](#)

### Human Text

Any text that has been fully written by a human and has not been altered or generated by AI.

[Learn more](#)

## Copyleaks AI Detector Effectiveness

Credible data at scale, coupled with machine learning and widespread adoption, allows us to continually refine and improve our ability to understand complex text patterns, resulting in over 99% accuracy—far higher than any other AI detector—and improving daily. [Learn more](#)

## Ideal Text Length

The higher the character count, the easier for our technology to determine irregular patterns, which results in a higher confidence rating for AI detection. [Learn more](#)

## Reasons It Might Be AI When You Think It's Not

The AI Detector can detect a variety of AI-generated text, including tools that use AI technology to paraphrase content, auto-complete sentences, and more. [Learn more](#)

## User AI Alert History

Historical data of how many times a user has been flagged for potentially having AI text within their content. [Learn more](#)

## AI Logic

The number of times a phrase was found more frequently in AI vs human text is shown according to low, medium, and high frequency. [Learn more](#)

## AI Logic

Shows you the “why” behind AI detection with sources you can see and verify.

## AI Phrases

Detects phrases that appear with higher frequency in AI-written text than in human writing.

The frequency of a phrase in AI vs. human text.

3x  898x

898x **to further refine model performance.**

How frequently the phrase was found in our dataset:

AI Text	1.15 / 1,000,000 Documents
Human Text	0 / 1,000,000 Documents

224x **compared to existing baselines;**

How frequently the phrase was found in our dataset:

AI Text	16.09 / 1,000,000 Documents
Human Text	0.07 / 1,000,000 Documents

185x **significant improvement over baseline methods.**

How frequently the phrase was found in our dataset:

AI Text	3.08 / 1,000,000 Documents
Human Text	0.02 / 1,000,000 Documents

165x **while the paper explores**

How frequently the phrase was found in our dataset:

AI Text	1.47 / 1,000,000 Documents
Human Text	0.01 / 1,000,000 Documents

107x **paradigm that decomposes**

How frequently the phrase was found in our dataset:

AI Text	1.1 / 1,000,000 Documents
Human Text	0.01 / 1,000,000 Documents

65x **promising direction by**

How frequently the phrase was found in our dataset:

AI Text	3.18 / 1,000,000 Documents
Human Text	0.05 / 1,000,000 Documents

43x **approach moves beyond**

How frequently the phrase was found in our dataset:

AI Text	12.14 / 1,000,000 Documents
Human Text	0.28 / 1,000,000 Documents

461x **integrated with CoT.**

How frequently the phrase was found in our dataset:

AI Text	1.18 / 1,000,000 Documents
Human Text	0 / 1,000,000 Documents

224x **dataset generation pipeline**

How frequently the phrase was found in our dataset:

AI Text	14.92 / 1,000,000 Documents
Human Text	0.07 / 1,000,000 Documents

177x **the method demonstrates**

How frequently the phrase was found in our dataset:

AI Text	125.73 / 1,000,000 Documents
Human Text	0.71 / 1,000,000 Documents

148x **the image generation process. The**

How frequently the phrase was found in our dataset:

AI Text	5.3 / 1,000,000 Documents
Human Text	0.04 / 1,000,000 Documents

70x **CoT does not**

How frequently the phrase was found in our dataset:

AI Text	15.93 / 1,000,000 Documents
Human Text	0.23 / 1,000,000 Documents

44x **achieves a score of**

How frequently the phrase was found in our dataset:

AI Text	38.34 / 1,000,000 Documents
Human Text	0.87 / 1,000,000 Documents

42x **pipeline. To support this,**

How frequently the phrase was found in our dataset:

AI Text	1.46 / 1,000,000 Documents
Human Text	0.03 / 1,000,000 Documents

**42x increase in inference**

How frequently the phrase was found in our dataset:

AI Text	6.91 / 1,000,000 Documents
Human Text	0.17 / 1,000,000 Documents

**36x by employing a structured,**

How frequently the phrase was found in our dataset:

AI Text	4.28 / 1,000,000 Documents
Human Text	0.12 / 1,000,000 Documents

**32x generation process. To**

How frequently the phrase was found in our dataset:

AI Text	65.91 / 1,000,000 Documents
Human Text	2.06 / 1,000,000 Documents

**29x challenging benchmarks such as**

How frequently the phrase was found in our dataset:

AI Text	1.94 / 1,000,000 Documents
Human Text	0.07 / 1,000,000 Documents

**27x without a proportional increase in**

How frequently the phrase was found in our dataset:

AI Text	19.56 / 1,000,000 Documents
Human Text	0.73 / 1,000,000 Documents

**26x increased resource consumption.**

How frequently the phrase was found in our dataset:

AI Text	10.97 / 1,000,000 Documents
Human Text	0.43 / 1,000,000 Documents

**20x computational overhead in the**

How frequently the phrase was found in our dataset:

AI Text	6.32 / 1,000,000 Documents
Human Text	0.32 / 1,000,000 Documents

**17x the inference latency of**

How frequently the phrase was found in our dataset:

AI Text	2.5 / 1,000,000 Documents
Human Text	0.15 / 1,000,000 Documents

**16x approach suffers from significant**

How frequently the phrase was found in our dataset:

AI Text	1.45 / 1,000,000 Documents
Human Text	0.09 / 1,000,000 Documents

**13x these existing approaches?**

How frequently the phrase was found in our dataset:

AI Text	16.3 / 1,000,000 Documents
Human Text	1.23 / 1,000,000 Documents

**13x that distinguish your**

How frequently the phrase was found in our dataset:

AI Text	6.19 / 1,000,000 Documents
Human Text	0.47 / 1,000,000 Documents

**9x there are significant concerns regarding**

How frequently the phrase was found in our dataset:

AI Text	1.9 / 1,000,000 Documents
Human Text	0.2 / 1,000,000 Documents

**9x in performance. Specifically,**

How frequently the phrase was found in our dataset:

AI Text	1.81 / 1,000,000 Documents
Human Text	0.21 / 1,000,000 Documents

**8x model, which achieves**

How frequently the phrase was found in our dataset:

AI Text	7.38 / 1,000,000 Documents
Human Text	0.91 / 1,000,000 Documents

### 7x analysis of the underlying mechanisms

How frequently the phrase was found in our dataset:

AI Text	1.83 / 1,000,000 Documents
Human Text	0.27 / 1,000,000 Documents

### 6x Summary: This paper introduces

How frequently the phrase was found in our dataset:

AI Text	1.76 / 1,000,000 Documents
Human Text	0.28 / 1,000,000 Documents

### 6x thoughts and actions. This

How frequently the phrase was found in our dataset:

AI Text	6.19 / 1,000,000 Documents
Human Text	1 / 1,000,000 Documents

### 5x required for sophisticated

How frequently the phrase was found in our dataset:

AI Text	1.2 / 1,000,000 Documents
Human Text	0.25 / 1,000,000 Documents

### 3x approach and existing

How frequently the phrase was found in our dataset:

AI Text	1.25 / 1,000,000 Documents
Human Text	0.41 / 1,000,000 Documents

#### Paper Summary:

This paper introduces an interleaved reasoning trajectory that integrates thoughts and actions into the image generation process. The visualization results are compelling, and the method demonstrates certain gains on the GenVal benchmark. The overall presentation is well-structured. However, the approach suffers from significant inference latency without a proportional increase in performance. Specifically, the reported GenVal score (0.82) underperforms compared to existing baselines; for instance, a 1B generative model or Bagel with CoT already achieves a score of 0.88.

#### Paper Strengths:

This paper introduces process-driven image generation, a multi-step paradigm that decomposes the synthesis process into an interleaved reasoning trajectory of thoughts and actions. This innovative approach moves beyond single-step generation by employing a structured, multi-stage pipeline. To support this, the author present a robust dataset generation pipeline designed to construct the complex trajectories required for sophisticated visual reasoning

#### Major Weaknesses:

**Literature Comparison & Novelty:** We note that interleaved Chain-of-Thought (CoT) frameworks have been explored in recent literature [1, 2, 3]. Given the similarities in certain equations and figures, could you provide a rigorous technical analysis of the underlying mechanisms that distinguish your methodology from these existing approaches?

**Benchmark Breadth & Performance:** The current evaluation is limited in scope, relying solely on the GenVal benchmark. Furthermore, the reported performance (0.82) is underwhelming compared to the original Bagel model, which achieves 0.88 when integrated with CoT.

Additional benchmarking is required to demonstrate competitive advantage.

**Efficiency vs. Utility:** There is a significant increase in inference overhead without a commensurate gain in performance. Specifically, the proposed interleaved text-image CoT does not yield a statistically significant improvement over baseline methods. [1] Interleaving reasoning for better text-to-image generation [2] Thinking-while-Generating: Interleaving Textual Reasoning throughout Visual Generation[J]. arXiv preprint arXiv:2511.16671, 2025. [3] Beyond Textual CoT: Interleaved Text-Image Chains with Deep Confidence Reasoning for Image Editing”

#### Minor Weaknesses:

**RL Optimization:** We suggest incorporating Reinforcement Learning (RL) to further refine model performance. It would be valuable to verify whether an RL-based fine-tuning stage can bridge the current performance gap.

#### Justification For Recommendation And Suggestions For Rebuttal:

Overall, while the paper explores a promising direction by utilizing an interleaved reasoning trajectory (alternating thoughts and actions), there are significant concerns regarding the computational overhead in the text-to-image generation process. To strengthen the manuscript, the authors should explicitly address the inference latency of the proposed framework. Furthermore, it is critical to clearly delineate the technical distinction between this approach and existing interleaved text-image methods (such as [Reference [1,2,3]]), justifying whether the performance gains warrant the increased resource consumption. If feasible within the rebuttal scope, report results on more challenging benchmarks such as DPG-Bench.