# ImAgent: A Unified Multimodal Agent Framework for Test-Time Scalable Image Generation

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## Abstract

*Recent text-to-image (T2I) models have made remarkable progress in generating visually realistic and semantically coherent images. However, they still suffer from randomness and inconsistency with the given prompts, particularly when textual descriptions are vague or underspecified. Existing approaches, such as prompt rewriting, best-of-N sampling, and self-refinement, can mitigate these issues but usually require additional modules and operate independently, hindering test-time scaling efficiency and increasing computational overhead. In this paper, we introduce* `ImAgent`*, a training-free unified multimodal agent that integrates reasoning, generation, and self-evaluation within a single framework for efficient test-time scaling. Guided by a policy controller, multiple generation actions dynamically interact and self-organize to enhance image fidelity and semantic alignment without relying on external models. Extensive experiments on image generation and editing tasks demonstrate that* `ImAgent` *consistently improves over the backbone and even surpasses other strong baselines where the backbone model fails, highlighting the potential of unified multimodal agents for adaptive and efficient image generation under test-time scaling.*

## 1. Introduction

Text-to-Image (T2I) models [33–36, 44, 47] have made remarkable progress in generating visually realistic and semantically coherent images from natural language descriptions. Despite these advancements, the quality of generated results often exhibits randomness and inconsistency with the given prompts [18, 62]. This limitation primarily stems from the strong dependency of existing T2I models on the clarity and specificity of textual inputs. When the prompt is vague or underspecified, the models tend to overlook key semantic elements, leading to images that deviate from the intended meaning and fail to fully capture the user's intent.

To mitigate this problem, prior research has proposed various strategies, such as prompt rewriting [1, 25, 29], best-of-N sampling [21, 42], classifier-free guidance [11, 37, 39], and self-revision or iterative refinement [14, 19, 41]. These approaches aim to either clarify the textual prompt or reduce the model's inherent randomness rather than finetuning the models, reflecting the underlying principle of test-time scaling—improving generation quality through additional inference-time computation.

While effective, these methods typically require additional components, such as a language model for prompt enhancement, a generative model for image synthesis, and a vision-language model for evaluation, thereby increasing memory consumption and computational cost. Moreover, they are often applied independently, requiring human intervention to determine the optimal approach for a given case, which substantially limits the efficiency of test-time scaling and leads to unnecessary computational overhead.

In this paper, we aim to construct a universal agent for image generation that can adaptively select the optimal action for a given case, allocate computational resources accordingly, and execute the selected action within the agent itself without relying on any external models. This design enables more efficient test-time scaling. Thanks to recent advances in unified multimodal models [6, 34, 54, 54, 60], which integrate text generation, image generation, and visual understanding within a single framework, this assumption becomes attainable. Building upon this foundation, we introduce `ImAgent`, a training-free unified multimodal agent designed to perform efficient test-time scaling for image generation.

Specifically, `ImAgent` is built around a policy controller that serves as its "brain", determining whether an image requires refinement based on the observation history and deciding which action should be invoked in the next step. Under its coordination, multiple predefined generation actions, such as *Prompt Enhancement with CoT*, *Image Detail Refinement*, and *Best-of-N Sampling*, operate collaboratively within a unified framework. Notably, all these actions are executed internally through the agent itself. Through this dynamic interaction, `ImAgent` trans-

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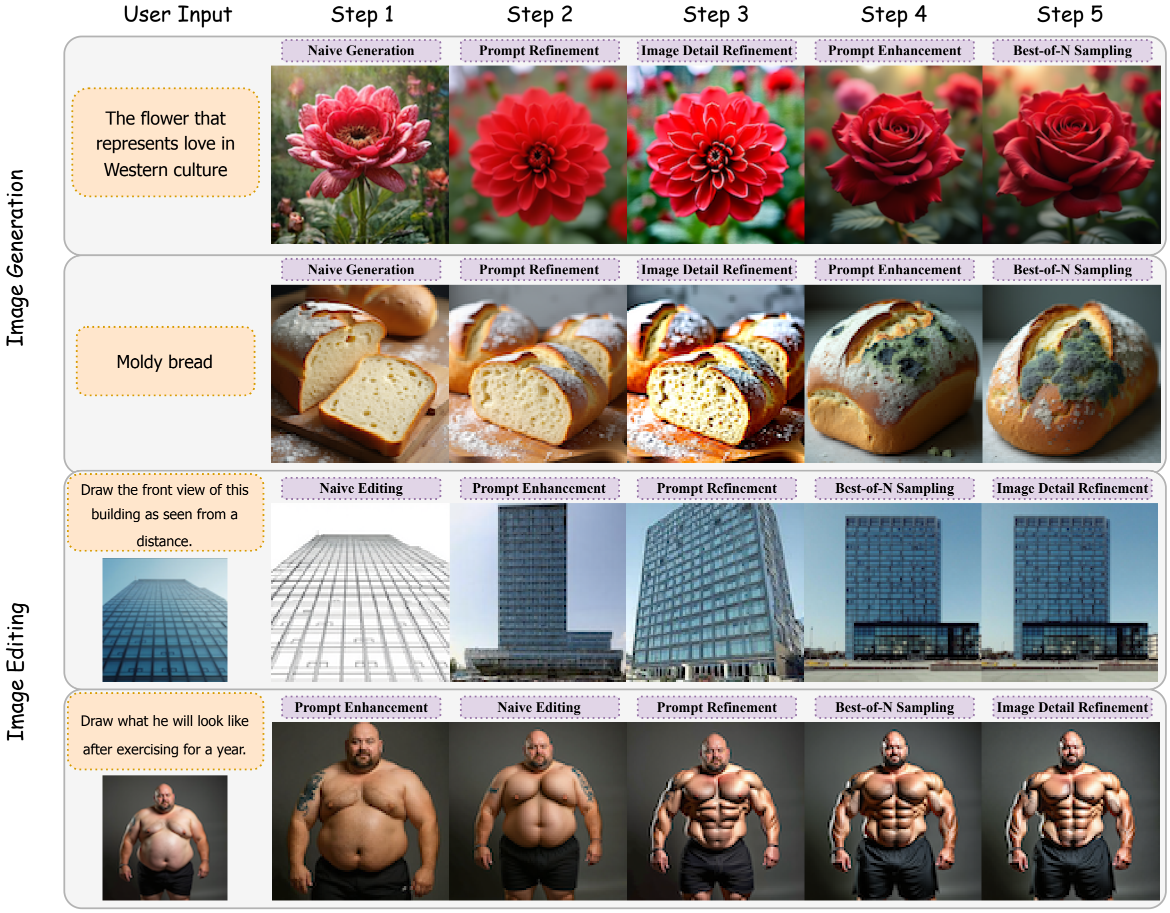


Figure 1. Qualitative examples of `ImAgent` built upon Bagel for image generation and image editing.

forms what was previously a manually assembled pipeline into a self-organizing agent capable of reasoning, generation, and self-improvement, thereby enhancing the efficiency of test-time scaling.

We conduct experiments on two popular tasks, image generation and image editing, to evaluate the effectiveness of the proposed `ImAgent`. Extensive experimental results show that `ImAgent` achieves significant improvements over the backbone model, demonstrating its strong capability and the effectiveness of test-time scaling in enhancing image generation performance. The contributions of this paper are summarized as follows:

- We propose a unified multimodal agent framework for image generation, `ImAgent`, which integrates multiple generation actions and dynamically coordinates them through a policy controller.
- Extensive experiments on image generation and editing tasks demonstrate that `ImAgent` achieves substantial improvements over the backbone model, even outperforming baselines that the backbone model fails to surpass, validating its effectiveness and in test-time scaling.

## 2. Related Work

### 2.1. Text-to-Image Generation

Text-to-Image (T2I) models have demonstrated remarkable ability in synthesizing visually realistic and semantically coherent images from natural language descriptions. The evolution of T2I models has followed several major paradigms, including diffusion-based models [7, 9, 33, 35, 36, 59], autoregressive models [44, 47, 52, 61, 69, 73], and more recently, unified multimodal models [6, 26, 49, 58, 60, 72, 74]. These approaches have significantly advanced image fidelity, diversity, and text-image alignment.

### 2.2. Unified Multimodal Models

Unified multimodal models refer to models that jointly possess multimodal understanding and generation capabilities within a single framework. Unlike traditional pipelines that rely on separate models for text or image understanding, image generation, and image editing, these models integrate vision and language processing into a shared architecture, enabling seamless information exchange across modalities [49, 54, 54, 58, 74]. This convergence of understanding and generation not only improves efficiency and coherence but also paves the way for building more general-purpose, human-like agents capable of reasoning, creating, and self-correcting.

## 2.3. Generation Optimization Strategies

Despite the remarkable progress of T2I models, the quality of generated images still depends heavily on the clarity of prompts and the randomness inherent in the generation process. To alleviate these issues, various optimization strategies have been proposed. *Best-of-N sampling* [21, 48, 50] generates multiple candidates and selects the best one, reducing the influence of stochastic variations in model sampling. *Prompt rewriting* [48, 53, 64] reformulates or enriches the input text to provide more explicit guidance for the generator, improving semantic alignment and visual coherence. *classifier-free guidance* [11, 37, 39] controls the conditioning strength to balance fidelity and diversity, and *iterative self-refinement* [14, 19, 28, 41, 63] enables models to assess and revise their outputs through multiple rounds of generation. Although these techniques significantly enhance performance, they typically operate as independent modules with limited interaction between reasoning, generation, and evaluation—highlighting the need for unified multimodal frameworks that integrate these capabilities into a cohesive pipeline.

# 3. Method

We construct ImAgent upon unified multimodal models, which inherently possess both understanding and generation capabilities. Motivated by the observation that multimodal understanding is generally more reliable and easier to achieve than multimodal generation [67, 70], ImAgent leverages the model's strong understanding ability to adaptively select the optimal action for a given case that enhances the overall generation quality. This design enables ImAgent to fully exploit the potential of a single unified multimodal model without any additional training or external modules, thereby achieving efficient test-time scaling. In this section, we first introduce the overall agent framework of ImAgent, followed by a detailed description of its action space.

## 3.1. Agent Framework Overview

As shown in Figure 2, ImAgent dynamically selects the next action based on the current observation and executes the selected action until either the STOP action is chosen or the maximum step limit is reached. Formally, we define the state at the current $t$-th time step as:

**Algorithm 1:** ImAgent for Image Generation.

```
Input: Initial user prompt $P_0$, action space
       $\mathcal{A} = \{a_1, \dots, a_n\}$, maximum step number
       $T_{\max}$
Output: Final image $I^*$
Initialize prompt $p \leftarrow p_0$; image $I \leftarrow \varnothing$;
  observation history $\mathcal{O} \leftarrow [\,]$
for $t = 1$ to $T_{\max}$ do
    // 1.  Reasoning and Action
        Selection
    Use the policy controller $\pi_\theta$ to determine the
      next action:
        $a_t \leftarrow \pi_\theta(a \mid s_t)$
    if $a_t = \mathit{STOP}$ then
        break // The model decides the
            generation is satisfactory
    // 2.  Action Invocation
    Execute the selected action $a_t \in \mathcal{A}$:
        $(P_{t+1}, I_{t+1}, o_t) \leftarrow f_{a_t}(P_t, I_t, \mathcal{O}_{t-1})$
    where $o_t$ is the new observation (e.g., quality
      evaluation)
    // 3.  State Update
    Append $o_t$ to the observation history:
      $\mathcal{O}_t \leftarrow \mathcal{O}_{t-1} \cup \{o_t\}$
return Final image $I^* \leftarrow I$
```

$$s_t = \{P_0, I_0, P_t, I_t, \mathcal{O}_{t-1}\}, \tag{1}$$

where $P_0$ and $I_0$ denote the initial user prompt and input image, $P_t$ and $I_t$ represent the current prompt and generated image at $t$-th step, and $\mathcal{O}_{t-1} = \{o_1, \dots, o_{t-1}\}$ denotes the history of past observations, i.e., action history.

Then, ImAgent dynamically selects an action $a_t$ from the defined action space $\mathcal{A} = \{a_1, \dots, a_n\}$ (detailed in Section 3.2) using a policy controller $\pi_\theta$ conditioned on the current state at $t$-th step:

$$a_t \sim \pi_\theta(a \mid s_t). \tag{2}$$

Upon selecting $a_t$, the corresponding action function $f_{a_t}$ is invoked to produce an updated prompt $P_{t+1}$, an updated image $I_{t+1}$, and a new observation $o_t$:

$$(P_{t+1}, I_{t+1}, o_t) = f_{a_t}(P_t, I_t, \mathcal{O}_{t-1}). \tag{3}$$

Then, the observation is updated as follows:

$$\mathcal{O}_t \leftarrow \mathcal{O}_{t-1} \cup o_t. \tag{4}$$

Unlike conventional agent-based frameworks where observations directly influence state updates, in ImAgent the

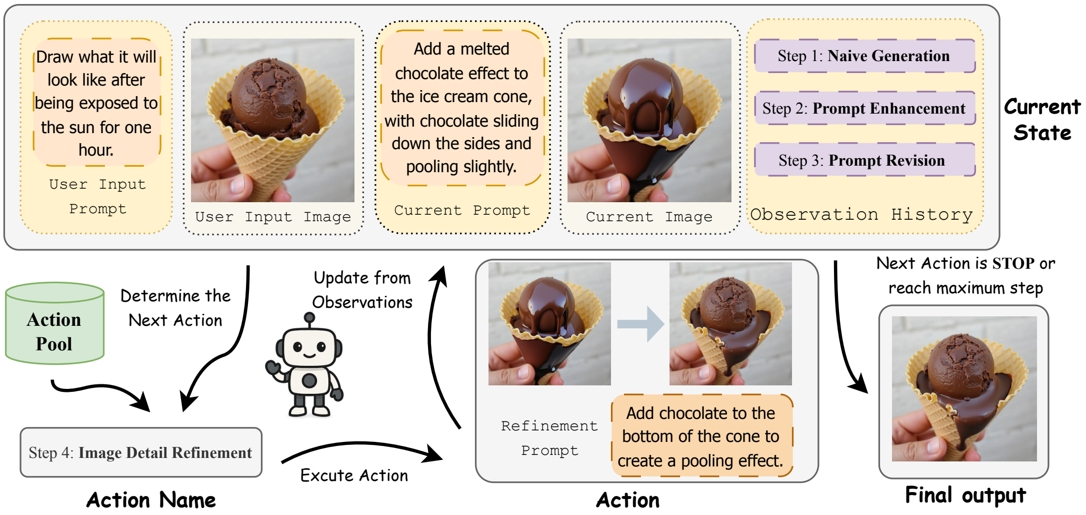

Draw what it will look like after being exposed to the sun for one hour.
User Input Prompt
User Input Image
Add a melted chocolate effect to the ice cream cone, with chocolate sliding down the sides and pooling slightly.
Current Prompt
Current Image
Step 1: Naive Generation
Step 2: Prompt Enhancement
Step 3: Prompt Revision
Observation History
Current State
Action Pool
Determine the Next Action
Update from Observations
Step 4: Image Detail Refinement
Action Name
Excute Action
Refinement Prompt
Add chocolate to the bottom of the cone to create a pooling effect.
Action
Next Action is STOP or reach maximum step
Final output

Figure 2. The overall architecture of ImAgent.

observation history is primarily used for action selection, while prompt and image updates are determined by the selected generation actions.

This iterative process continues until the agent selects the STOP action, which indicates that the generated result is satisfactory, or until the maximum number of steps $T_{\max}$ (set to 5 by default) is reached. Notably, both the policy controller and the action execution are implemented within a single unified multimodal model. The detailed algorithm for image generation is presented in Algorithm 1, while the algorithm for image editing follows a similar procedure and is provided in the Appendix.

## 3.2. Action Space

In this section, we introduce the action space $\mathcal{A}$ of ImAgent. The detailed definitions and usage of each action are provided in the Appendix.

**Naive Generation/Editing.** This action performs a one-shot image generation or editing operation directly based on the current prompt. It is typically used when the input description is simple, unambiguous, and requires no iterative refinement.

**Prompt Enhancement with CoT.** This action refines the input prompt by enriching vague or underspecified user queries with additional contextual and descriptive details. Since text-to-image (T2I) models are highly sensitive to prompt wording [1, 25, 29], more elaborate and specific prompts typically lead to higher-quality visual outputs. However, most T2I backbones are trained on simple captions or surface-level image descriptions, which limits their ability to reason over complex or compositional instructions. To address this limitation, we leverage the language reasoning capability of the model's understanding module through Chain-of-Thought (CoT) prompting. By explicitly performing intermediate reasoning and elaboration, the agent transfers structured linguistic insights from the understanding domain to the generation process, thus producing more semantically aligned and visually coherent outputs.

**Prompt Revision Based on the Generated/Edited Image.** This action is triggered when the generated or edited image indicates that the current prompt is suboptimal. In this case, the unified multimodal model is prompted to analyze the discrepancy between the visual output and the intended semantics, and to self-revise the prompt accordingly. This self-correction mechanism allows the agent to iteratively refine textual descriptions based on visual feedback, thereby enhancing both semantic alignment and generation quality over successive iterations.

**Image Detail Refinement.** This action aims to correct minor imperfections in the generated or edited image when the input instruction is already satisfactory and the remaining issues stem from the generation module itself. It refines local visual details—such as textures, lighting, or small artifacts—without modifying the current prompt. By enhancing fine-grained fidelity while maintaining semantic consistency, this action improves the overall perceptual quality and realism of the generated results.

**Best-of-N Sampling.** This action mitigates the inherent stochasticity of text-to-image (T2I) generation. Unlike language models that typically produce stable, low-entropy outputs through supervised fine-tuning (SFT) and reinforcement learning (RL) optimization, T2I models exhibit substantial variance across different samples [21, 48, 50]. To

| Types | Model | Comm. | Comp. | Logical | Numerical | Causal | Overall |
|---|---|---|---|---|---|---|---|
| *Gen* | SD3-medium | 0.54 | 0.64 | 0.55 | 0.50 | 0.18 | 0.53 |
| | Sana-1.5 | 0.49 | 0.67 | 0.49 | 0.48 | 0.21 | 0.49 |
| | Lumina-T2I | 0.38 | 0.49 | 0.38 | 0.45 | 0.18 | 0.39 |
| | Omnigen | 0.43 | 0.60 | 0.51 | 0.47 | 0.34 | 0.48 |
| | LLM4GEN$_{SD1.5}$ | 0.55 | 0.48 | 0.55 | 0.39 | 0.45 | 0.51 |
| | ELLA$_{SD1.5}$ | 0.40 | 0.44 | 0.40 | 0.32 | 0.29 | 0.39 |
| | LlamaGen | 0.38 | 0.39 | 0.38 | 0.35 | 0.12 | 0.36 |
| | DALL-E-3 | 0.78 | 0.76 | 0.69 | 0.69 | 0.64 | 0.73 |
| | gpt-image-1 | 0.83 | 0.87 | 0.81 | 0.88 | 0.71 | 0.83 |
| *Unified* | EMU3 | 0.44 | 0.59 | 0.55 | 0.61 | 0.41 | 0.52 |
| | Show-o | 0.42 | 0.59 | 0.42 | 0.57 | 0.30 | 0.46 |
| | Lumina-Image 2.0 | 0.49 | 0.65 | 0.56 | 0.43 | 0.40 | 0.52 |
| *Bagel* | Vanilla | 0.47 | 0.65 | 0.53 | 0.68 | 0.40 | 0.54 |
| | `ImAgent` | **0.58** | **0.68** | **0.62** | **0.71** | **0.53** | **0.62** |
| *Janus-Pro-7B* | Vanilla | 0.45 | **0.60** | 0.46 | 0.46 | 0.36 | 0.47 |
| | `ImAgent` | **0.47** | 0.58 | **0.52** | **0.54** | **0.44** | **0.51** |

Table 1. Experimental results on **R2I-Bench** [4]. *Comm.* and *Comp.* denote the Commonsense and Compositional categories, respectively. Due to the inaccessibility of parts of the Mathematical and Concept-Mixing categories, these two categories are omitted. Vanilla represents the backbone model, while `ImAgent` denotes our agent built upon this model. The best performance between vanilla and `ImAgent` is highlighted in **bold**.

reduce this randomness, the agent generates $N$ candidate images and employs the unified multimodal model to evaluate their visual and semantic alignment. The image with the highest alignment score is selected as the final output.

**Termination (STOP).** This action signals the end of the iterative reasoning process when the agent determines that the current image and prompt have achieved satisfactory alignment. Instead of relying on a fixed number of steps, the agent autonomously decides to terminate based on its internal evaluation of visual quality.

# 4. Experiments

## 4.1. Experimental Setting

**Models.** We build our `ImAgent` on two of the most recent and powerful unified models, Bagel [6] and Janus-Pro-7B [5]. Both models possess versatile multimodal capabilities, including image understanding, image generation, which collectively form the foundation of our framework. For image generation, we leverage both Bagel and Janus-Pro-7B. However, since Janus-Pro-7B does not support image editing, we employ Bagel exclusively for the image editing tasks.

**Benchmarks.** We evaluate `ImAgent` on multiple benchmarks, including 3 benchmarks on image generation and 4 benchmarks for image editing tasks. For image generation, we use R2I-Bench [4], which is designed to rigorously assess reasoning-driven T2I generation; WISE [30], which covers six categories of image generation scenarios; and T2I-ReasonBench [43], which assesses the models' reasoning ability in generative tasks. For image editing, we adopt GEdit-Bench [23], which contains both Chinese and English instruction-based editing tasks; RISEBench [71], which focuses on reasoning-informed visual editing across diverse reasoning types; KRIS-Bench [57], which evaluates reasoning capabilities over factual, conceptual, and procedural knowledge; and ImgEdit-Bench [65], which is used to evaluate image editing performance in terms of instruction adherence, editing quality, and detail preservation.

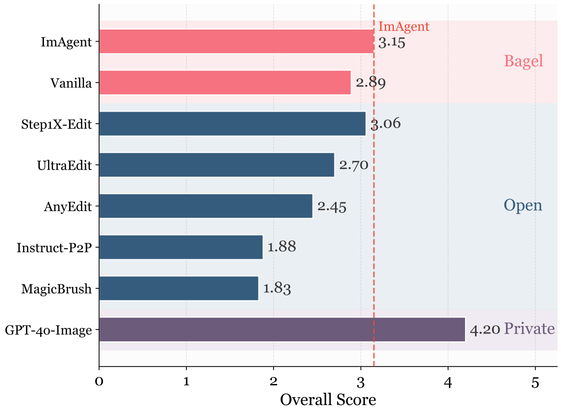


Figure 3. Experimental results on **ImgEdit-Bench** [65].

**Baselines.** For image generation, we employ SDv1.5 [36], SD3-Medium [36], SDXL [33], SD3.5-Medium [7], SD3.5-Large [7], PixArt-Alpha [3], FLUX.1-Dev [15], Sana-1.5 [59], Lumina-T2I [34], LLM4GEN$_{SD1.5}$ [22], ELLA$_{SD1.5}$ [12], LlamaGen [44], DALL-E-3 [27], gpt-image-1 [13], Omnigen [58], FLUX.1-schnell [16], andPlayground-v2.5 [20], as generation-based models. We also include Janus [54], VILA-U [56],

| Types | Model | Cultural | Time | Space | Biology | Physics | Chemistry | Overall |
|---|---|---|---|---|---|---|---|---|
| *Gen* | SDv1.5 | 0.34 | 0.35 | 0.32 | 0.28 | 0.29 | 0.21 | 0.32 |
| | SDXL | 0.43 | 0.48 | 0.47 | 0.44 | 0.45 | 0.27 | 0.43 |
| | SD3.5-large | 0.44 | 0.50 | 0.58 | 0.44 | 0.52 | 0.31 | 0.46 |
| | PixArt-Alpha | 0.45 | 0.50 | 0.48 | 0.49 | 0.56 | 0.34 | 0.47 |
| | playground-v2.5 | 0.49 | 0.58 | 0.55 | 0.43 | 0.48 | 0.33 | 0.49 |
| | FLUX.1-dev | 0.48 | 0.58 | 0.62 | 0.42 | 0.51 | 0.35 | 0.50 |
| *Unified* | Janus | 0.16 | 0.26 | 0.35 | 0.28 | 0.30 | 0.14 | 0.23 |
| | VILA-U | 0.26 | 0.33 | 0.37 | 0.35 | 0.39 | 0.23 | 0.31 |
| | Show-o | 0.28 | 0.40 | 0.48 | 0.30 | 0.46 | 0.30 | 0.35 |
| | Emu3 | 0.34 | 0.45 | 0.48 | 0.41 | 0.45 | 0.27 | 0.39 |
| | MetaQuery-XL | 0.56 | 0.55 | 0.62 | 0.49 | 0.63 | 0.41 | 0.55 |
| | GPT-4o | 0.81 | 0.71 | 0.89 | 0.83 | 0.79 | 0.74 | 0.80 |
| *Bagel* | Vanilla | 0.44 | 0.55 | 0.68 | 0.44 | 0.60 | 0.39 | 0.52 |
| | `ImAgent` | **0.63** | **0.63** | **0.72** | **0.59** | **0.69** | **0.53** | **0.63** |
| *Janus-Pro-7B* | Vanilla | 0.30 | 0.37 | 0.49 | 0.36 | 0.42 | 0.26 | 0.35 |
| | `ImAgent` | **0.44** | **0.46** | **0.55** | **0.45** | **0.50** | **0.27** | **0.44** |

Table 2. Experimental results on **WISE** [30]. Vanilla represents the backbone model, while `ImAgent` denotes our agent built upon this model. The best performance between vanilla and `ImAgent` is highlighted in **bold**.

| Types | Model | Idiom | | Textual | | Entity | | Scientific | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Acc. | Qual. | Acc. | Qual. | Acc. | Qual. | Acc. | Qual. | Acc. | Qual. |
| *Gen* | FLUX.1-dev | 39.1 | 83.4 | 56.9 | 76.5 | 45.1 | 90.6 | 46.7 | 80.9 | 47.0 | 82.8 |
| | FLUX.1-schnell | 40.9 | 83.1 | 65.1 | 74.5 | 44.8 | 91.5 | 50.7 | 83.0 | 50.4 | 83.0 |
| | playground-v2.5 | 43.9 | 87.8 | 38.5 | 72.1 | 48.4 | 92.4 | 50.8 | 83.3 | 45.4 | 83.9 |
| | SD-3-Medium | 35.9 | 81.4 | 60.9 | 71.3 | 42.4 | 90.1 | 50.9 | 81.7 | 47.5 | 81.1 |
| | SD-3.5-Medium | 34.4 | 80.6 | 58.0 | 70.1 | 44.8 | 92.1 | 49.9 | 83.0 | 46.8 | 81.4 |
| | SD-3.5-Large | 35.6 | 85.3 | 62.2 | 75.4 | 46.6 | 92.6 | 52.9 | 84.5 | 49.3 | 84.4 |
| | gpt-image-1 | 75.7 | 94.5 | 86.9 | 97.6 | 77.5 | 96.6 | 74.7 | 94.3 | 78.7 | 95.8 |
| *Unified* | Emu3 | 33.1 | 82.9 | 33.7 | 68.7 | 33.8 | 85.2 | 40.1 | 77.0 | 35.2 | 78.5 |
| | Janus-Pro-7B | 25.5 | 78.0 | 37.2 | 70.9 | 38.5 | 87.6 | 44.9 | 77.8 | 36.5 | 78.6 |
| | show-o | 33.1 | 82.5 | 35.3 | 80.3 | 34.9 | 87.4 | 41.6 | 76.6 | 36.2 | 81.7 |
| | GoT | 29.7 | 76.4 | 30.6 | 70.7 | 31.0 | 86.2 | 36.8 | 76.3 | 32.0 | 77.4 |
| | Gemini-2.0 | 52.4 | 87.8 | 73.0 | 83.3 | 67.0 | 94.3 | 66.7 | 89.3 | 64.8 | 88.7 |
| *Bagel* | Vanilla | 30.2 | 85.7 | 36.6 | 68.4 | 45.0 | 94.7 | 54.4 | 87.5 | 41.6 | 84.1 |
| | `ImAgent` | **37.7** | **90.0** | **54.2** | **79.1** | **52.6** | **96.6** | **61.2** | **90.3** | **51.4** | **89.0** |
| *Janus-Pro-7B* | Vanilla | 25.5 | 78.0 | **37.2** | **70.9** | 38.5 | 87.6 | 44.9 | 77.8 | 36.5 | 78.6 |
| | `ImAgent` | **27.9** | **86.0** | 35.3 | 68.8 | **40.7** | **89.7** | **51.2** | **84.2** | **38.8** | **82.2** |

Table 3. Experimental results on **T2I-ReasonBench** [43]. Vanilla represents the backbone model, while `ImAgent` denotes our agent built upon this model. The best performance between vanilla and `ImAgent` is highlighted in **bold**.

Show-o [60], Janus-Pro-7B [5], Emu3 [52], Lumina-Image 2.0 [34], show-o [60], GoT [8] and MetaQuery-XL [32] as unified multimodal models.

For image editing, we evaluate both private and open baselines. The private baselines include Gemini-2.0 [10], Doubao [40], GPT-4o [31], and Gemini-2.0-Flash-pre [46]. The open baselines include Step1X-Edit [24], InstructPix2Pix [2], MagicBrush [68], AnyEdit [66], OmniGen [58], EMU2 [45], Qwen-Image-Edit [55], FLUX.1-Kontext-Dev [17], Ovis-U1 [51], and Seedream-4.0 [38].

### 4.2. Quantitative Results

**Image Generation.** As shown in Table 2, `ImAgent` achieves outstanding performance on the WISE benchmark. Compared to their respective backbone models, `ImAgent` built upon Bagel and Janus-Pro-7B consistently surpasses the vanilla counterparts, with performance improvements of 21.2% and 25.7%, respectively, demonstrating the effectiveness of our approach in enhancing image generation quality through coordinated reasoning and refinement. Notably, the vanilla Janus-Pro-7B underperforms compared to SDXL and EMU3 and performs on par with Show-o. In contrast, `ImAgent` constructed on Janus-Pro-7B surpasses all of them, highlighting its strong test-time scaling capability and generalization potential. Furthermore, on the reasoning benchmarks, `ImAgent` consistently delivers strong results. As shown in Tables 1 and 3, `ImAgent` outper-

| Types | Model | Temporal | Causal | Spatial | Logical | Overall |
|---|---|---|---|---|---|---|
| *Private* | Gemini-2.0-Flash-pre | 10.6 | 13.3 | 11.0 | 2.3 | 9.4 |
| | Gemini-2.0 | 8.2 | 15.5 | 23.0 | 4.7 | 13.3 |
| | GPT-4o | 34.1 | 32.2 | 37.0 | 10.6 | 28.9 |
| *Open* | EMU2 | 1.2 | 1.1 | 0.0 | 0.0 | 0.5 |
| | OmniGen | 1.2 | 1.0 | 0.0 | 1.2 | 0.8 |
| | Step1X-Edit | 0.0 | 2.2 | 2.0 | 3.5 | 1.9 |
| | Qwen-Image-Edit | 4.7 | 10.0 | 17.0 | 2.4 | 8.9 |
| | FLUX.1-Kontext-Dev | 2.3 | 5.5 | 13.0 | 1.2 | 5.8 |
| | Ovis-U1 | 1.2 | 3.3 | 4.0 | 2.4 | 2.8 |
| | Seedream-4.0 | 12.9 | 12.2 | 11.0 | 7.1 | 10.8 |
| *Bagel* | Vanilla | 2.4 | 5.6 | 14.0 | 1.2 | 6.1 |
| | `ImAgent` | **17.6** | **15.6** | **16.0** | **2.4** | **13.1** |

Table 4. Experimental results on **RISEBench** [71]. Vanilla represents the backbone model, while `ImAgent` denotes our agent built upon this model. The best performance between vanilla and `ImAgent` is highlighted in **bold**.

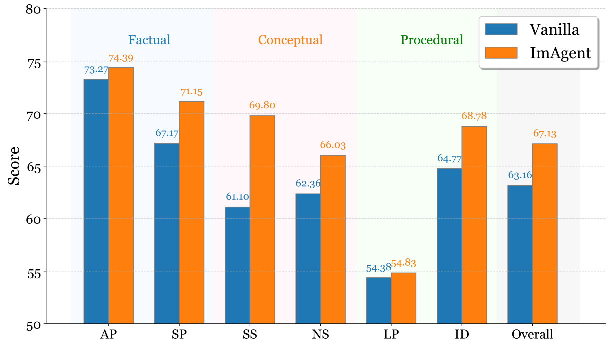


Figure 4. Experimental results on **KRISBench** [57].

forms the vanilla models across both backbone architectures. For instance, `ImAgent` achieves improvements of 14.8% and 7.5% across both backbones on R2I-Bench, respectively. Moreover, `ImAgent` built upon Bagel surpasses the commercial model Gemini-2.0 in overall quality on the T2I-ReasonBench, further demonstrating its effectiveness in reasoning-based image generation.

**Image Editing.** As shown in Table 4, vanilla Bagel achieves only 6.1 on RISEBench, underperforming compared to Qwen-Image-Edit and Seedream-4.0. In contrast, `ImAgent` achieves a 114.8% improvement over vanilla and surpasses both Qwen-Image-Edit and Seedream-4.0. Remarkably, `ImAgent` performs on par with Gemini-2.0, demonstrating its effectiveness and strong test-time scaling capability. This indicates that open-source models enhanced with `ImAgent` can achieve competitive performance with commercial models.

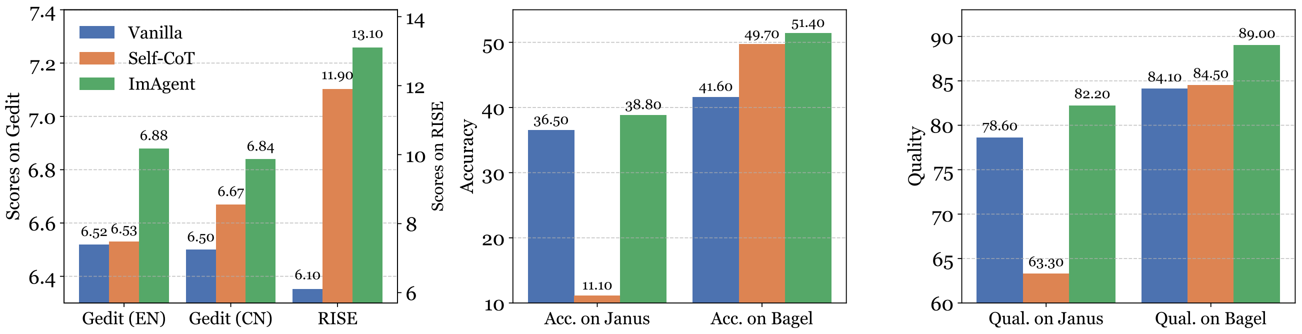
Furthermore, as shown in Figure 4, `ImAgent` also achieves excellent performance on KRISBench, attaining an overall score of 67.13, surpassing vanilla Bagel which scores 63.16. `ImAgent` performs well on ImgEdit-Bench (shown in Figure 3) as well, with vanilla achieving 2.89 and underperforming compared to Step1X-Edit, while `ImAgent` reaches 3.15, outperforming Step1X-Edit and achieving the best performance among open-source models. This further demonstrates the effectiveness of `ImAgent` in test-time scaling.

Moreover, `ImAgent` outperforms vanilla Bagel across both English and Chinese settings in GEdit-Bench, achieving improvements of 5.5% and 5.2%, respectively. Detailed results are provided in the Appendix.

### 4.3. Qualitative Analysis

**Image Refinement Flow.** As shown in Figure 1, we present several qualitative examples, including two for image generation and two for image editing, each executed for five steps. From an overall perspective, we can observe that the image quality improves progressively with each step, demonstrating that `ImAgent` refines the image gradually.

Specifically, consider a case where the user aims to generate an image based on the prompt “moldy bread.” In the first step, `ImAgent` performs the *Naive Generation* action and produces an image containing fresh bread, which clearly deviates from the prompt. The policy controller then selects the *Prompt Refinement* action to improve the prompt using both the generated image and the user’s original input. Although the updated image shows slight improvement, it remains unsatisfactory. To address this, the controller chooses the *Image Detail Refinement* action, leading to the appearance of mold on the bread. Subsequently, `ImAgent` applies the *Prompt Enhancement* action to further strengthen the textual guidance, resulting in an image that better aligns with the user’s intent. Finally, recognizing that the prompt is now sufficiently clear but the visual result could still be improved, `ImAgent` executes the *Best-of-N Sampling* action to generate multiple candidates and select the most aligned one. The final output successfully captures the desired “moldy bread” concept.

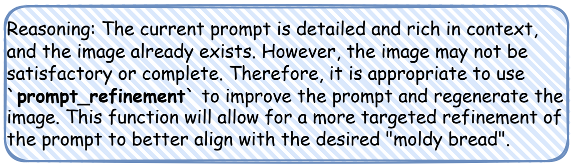


(a)

(b)

(c)

Figure 5. Comparison among the vanilla model, self-CoT, and `ImAgent`. (a) Results on Gedit-Bench (English and Chinese) and RISEBench using the Bagel backbone. (b) Accuracy and (c) Quality on Janus-Pro-7B and Bagel evaluated with T2I-ReasonBench.



Reasoning: The current prompt is detailed and rich in context, and the image already exists. However, the image may not be satisfactory or complete. Therefore, it is appropriate to use `**prompt_refinement**` to improve the prompt and regenerate the image. This function will allow for a more targeted refinement of the prompt to better align with the desired "moldy bread".

Figure 6. An example of the policy controller making a decision.

**Detailed Policy Controller Decision.** We present a detailed case study of the policy controller's output to illustrate how it makes action decisions. As shown in Figure 6, which visualizes the decision-making process for the case discussed earlier, the policy controller selects the `prompt_refinement` action to enrich the textual prompt and improve semantic clarity for subsequent generation steps. We present more examples in the Appendix.

### 4.4. Ablation Studies

**Comparison with Self-CoT.** Since the vanilla Bagel model already incorporates self-CoT capabilities, we further compare `ImAgent` with self-CoT to evaluate the effectiveness of our approach. For the image editing task, as shown in Figure 5(a), `ImAgent` significantly outperforms both the vanilla and self-CoT variants on the Gedit-Bench across both English and Chinese settings. Furthermore, `ImAgent` also surpasses self-CoT in the image generation task. As illustrated in Figures 5(b) and (c), under the Janus-Pro-7B backbone, the performance of self-CoT notably drops compared to the vanilla model, whereas `ImAgent` consistently achieves superior results. Similarly, under the Bagel backbone, `ImAgent` maintains clear advantages over both the vanilla and self-CoT models. These findings suggest that the improvements brought by `ImAgent` stem not only from self-CoT–like reasoning refinement, but also from the different actions coordination enabled by the strong policy controller.

| Method | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ | Random | `ImAgent` |
|---|---|---|---|---|---|---|---|
| Score | 0.54 | 0.58 | 0.57 | 0.56 | 0.56 | 0.59 | **0.62** |

Table 5. Comparison of different action selection policies on R2I-Bench. $a_1$–$a_5$ represent the five actions (Section 3.2) in order.

**Effectiveness of the Whole `ImAgent`.** To evaluate the effectiveness of `ImAgent` in coordinately selecting and executing appropriate actions, we compare its performance with that of single-turn actions and a random action selection policy, where the $T_{\max}$ for random selection is set the same as in `ImAgent`. As shown in Table 5, experiments are conducted on R2I-Bench [4]. All single-turn actions perform well compared to the naive generation action, which serves as the lower bound (0.54). Moreover, the random action selection policy achieves a score of 0.59, higher than all single-turn actions, indicating that naively constructing an agent is beneficial. Finally, `ImAgent` outperforms the random policy with a score of 0.62, demonstrating that it effectively and efficiently boosts test-time scaling in image generation.

## 5. Conclusion

In this paper, we presented `ImAgent`, a training-free unified multimodal agent designed to enhance image generation through efficient test-time scaling. By integrating multiple generation actions within a single framework and coordinating them via a policy controller, `ImAgent` dynamically selects and executes the most appropriate action for a given case. Extensive experiments on image generation and editing benchmarks demonstrate that `ImAgent` consistently improves over the backbone models and surpasses strong baseline methods, including scenarios where the backbone fails. These results highlight the potential of unified multimodal agents for adaptive, efficient, and high-quality image generation without relying on additional external models.

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