# Programming with Pixels: Computer-Use Meets Software Engineering

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## Abstract

Recent advancements in software engineering (SWE) agents have largely followed a *tool-based paradigm*, where agents interact with hand-engineered tool APIs to perform specific tasks. While effective for specialized tasks, these methods fundamentally lack generalization, as they require predefined tools for each task and do not scale across programming languages and domains. We introduce `Programming with Pixels` (`PwP`), an agent environment that unifies software development tasks by enabling *computer-use agents*—agents that operate directly within an IDE through visual perception, typing, and clicking, rather than relying on predefined tool APIs. To systematically evaluate these agents, we propose `PwP-Bench`, a benchmark that unifies existing SWE benchmarks spanning tasks across multiple programming languages, modalities, and domains under a task-agnostic state and action space. Our experiments demonstrate that general-purpose computer-use agents can approach or even surpass specialized tool-based agents on a variety of SWE tasks without the need for hand-engineered tools. However, our analysis shows that current models suffer from limited visual grounding and fail to exploit many IDE tools that could simplify their tasks. When agents can directly access IDE tools, without visual interaction, they show significant performance improvements, highlighting the untapped potential of leveraging built-in IDE capabilities. Our results establish `PwP` as a scalable testbed for building and evaluating the next wave of software engineering agents.[1]

## 1. Introduction

Human software developers possess a remarkable ability to work across a wide range of programming tasks, seamlessly adapting to new languages, tools, and problem domains. Realizing a single, general-purpose agent with similar versatility is the overarching goal of many recent efforts in code generation and software engineering automation (Jiang et al., 2024; Jin et al., 2024; Wang et al., 2024b). However, most software engineering agents (SWE agents) still rely on a *tool-based paradigm*, where an agent takes actions using hand-engineered functions (e.g., search repository, run Python code) exposed through a text API (Yang et al., 2024a;b; Wang et al., 2024a;b). This fundamentally limits generalization, since tool-based agents can only perform tasks using the predefined actions. For example, an agent designed to manage GitHub pull requests lacks debugging abilities unless it is programmed into the agent's API. Furthermore, the tool-based paradigm lacks scalability, as hand-engineering complex tools requires significant human effort and may not be bug-free. As a result, it remains unclear whether the tool-based paradigm scales to the diversity of software engineering tasks, which spans multiple languages, modalities, and task types.

Our motivating hypothesis is that achieving general-purpose SWE agents requires a shift to *computer-use agents* (Anthropic, 2024) that interact with computers as humans do: by observing the screen, typing, and clicking. To this end, we recast agentic software engineering as interacting directly with an *integrated development environment (IDE)* by observing its visual state and using basic actions such as clicking and typing. This allows the agent to perform any task possible in an IDE and leverage all of the IDE's tools—from debuggers to web browsers—without requiring specialized APIs. However, despite promising results in web navigation (Anthropic, 2024) and open-ended computer tasks (Xie et al., 2024), the ability of computer-use agents to perform software engineering remains underexplored and we lack a dedicated environment for software engineering.

To close this gap, we introduce *Programming with Pixels (`PwP`)*, the first software engineering agent environment aimed at general-purpose computer-use agents. The `PwP` environment is a VSCode-based IDE where agents perceive the screen and use primitive actions such as typing, pointing, and clicking. `PwP` fulfills two key properties. First, the environment is *expressive*, allowing agents to complete any software engineering task achievable in an IDE, with-

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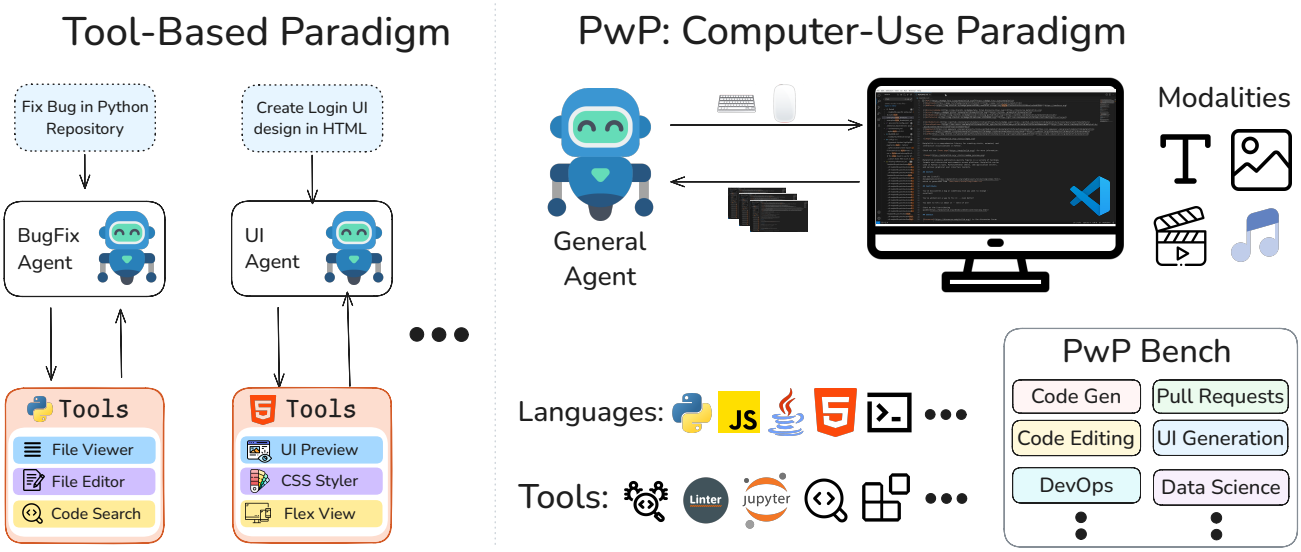


Figure 1: Comparison between the traditional tool-based paradigm (left) and our proposed `Programming with Pixels` (`PwP`) framework (right) for software engineering (SWE) agents. Instead of relying on specialized hand-engineered tools, `PwP` enables agents to interact directly with an IDE through basic computer interactions and screen observations. The framework naturally allows agents to take advantage of existing IDE capabilities across multiple languages and tools. Furthermore, `PwP-Bench` is a comprehensive benchmark to evaluate agent performance across different SWE domains.

out language- or domain-specific modifications. Second, agents naturally interact with *any tools available in the IDE*–including debuggers, linters, and code suggestions while handling diverse data types such as images, videos, and PDFs–through basic actions such as clicking and typing. This notion of tool use fundamentally differs from hand-engineered tool APIs, offering scalability and reducing the effort needed to hand-engineer tools for AI agents. Namely, `PwP` lets agents take advantage of the rich tools already accessible to humans in an IDE, rather than reinventing the wheel. Finally, computer-use agents reduce the need for complex tool pipelines (e.g., tool-specific prompts), opening up a simplified approach to general-purpose SWE agents.

To further evaluate agents developed for computer-use we construct `PwP-Bench`, a unified benchmark of 15 tasks spanning a variety of software engineering activities, including code generation, pull request resolution, UI development, and DevOps workflows. We show for the first time that general-purpose computer-use agents achieve non-trivial performance on a wide variety of SWE tasks, often approaching or exceeding state-of-the-art tool-based agents.

However, our analysis reveals substantial opportunities for future work. First, even state-of-the-art computer-use agents suffer from visual grounding issues. Second, we show that current agents lack the ability to use many of the tools available in the IDE, including ones that could make their tasks trivial. This suggests that training agents to explore and use the tools available in the IDE is a fruitful future direction. Finally, we find that only one model, Claude (Anthropic, 2024), performs well, highlighting the need for further research into training and improving computer-use agents.

In summary, our contributions are as follows. First, we introduce `Programming with Pixels` (`PwP`), the first software engineering-focused environment for evaluating computer-use agents. Second, we introduce `PwP-Bench`, a benchmark spanning 15 diverse SWE domains, allowing for systematic comparison of software engineering agents. Third, we demonstrate, for the first time, that computer-use agents can perform a wide variety of software engineering tasks without additional hand-engineering of their action or observation spaces. Fourth, we analyze the limitations of current computer-use agents, identifying the need for models that better leverage IDE tooling and highlighting agent training as a key future direction. Finally, both existing agents and benchmarks can be easily incorporated into our unified environment, positioning `PwP` to serve as a common platform for developing future SWE agents. Overall, `PwP` challenges the prevailing tool-based paradigm for SWE agents and provides a platform for developing more general agents that interact directly with IDEs.

## 2. Related Work

### 2.1. Task-specific SWE benchmarks

Early neural code generation approaches were typically evaluated on fixed input-output pairs—for example, gen-

erating code from docstrings (Chen et al., 2021) or from general textual descriptions (Austin et al., 2021). Subsequent benchmarks extended these evaluations to interactive settings, such as resolving GitHub pull requests or writing unit tests for real-world code repositories (Jimenez et al., 2023; Zan et al., 2024; Mündler et al., 2025). More recently, efforts have broadened the scope of code generation to include multimodal tasks, where vision models must interpret images to generate correct code or edits (Si et al., 2024; Shi et al., 2024; Jing et al., 2024; Yang et al., 2024b). However, each of these benchmarks is confined to specific languages, modalities, or task types. In contrast, our proposed `PwP-Bench` unifies these diverse evaluations into a single framework, encompassing multimodal and multilingual challenges that require interaction with a broad suite of IDE tools. Using this unified approach we reproduce the performance of established benchmarks and encourage the development of general-purpose agents capable of handling a variety of new software engineering tasks. We further compare our work with previous efforts in Tables 1 and 2.

### 2.2. Software Engineering (SWE) Agents

Recent work has explored "code agents" that move beyond single-step neural code generation toward interactive methods, where intermediate feedback from tools informs subsequent actions. However, many of these approaches specialize in particular tools or programming languages (Jin et al., 2024; Yang et al., 2024b), limiting their broader applicability. For example, Agentless (Xia et al., 2024) relies on a tool that parses files into Python-specific class and function structures. This fails to perform well in other languages or settings (Yang et al., 2024b) without manual modifications. Similarly, the SWE-agent requires modifications to adapt to different tasks (Abramovich et al., 2024; Yang et al., 2024b). In contrast, agents designed for `PwP` are inherently task and language-agnostic due to the expressive action and observation spaces mandated by our environment. Moreover, the diverse tasks in `PwP-Bench` require agents to generalize across a wide range of SWE challenges rather than excel in one narrowly defined area such as resolving pull requests.

Many existing agents also depend on hand-engineered tools that require human effort to implement and are susceptible to bugs. For instance, Agentless (Xia et al., 2024) leverages tools for parsing files into Python-specific structures; CodeAct relies on an IPython kernel (Wang et al., 2024a); SWE-Agent uses dedicated search and file editing tools (Yang et al., 2024a); AutoCodeRover requires a linter (Zhang et al., 2024); SWE-Agent EnIGMA develops specialized tools for CTF-style competitions (Abramovich et al., 2024); and SWE-Bench-MM (Yang et al., 2024b) implements a browser view. In `PwP`, these tools are inherently available within the IDE (as detailed in Table 7), and the agent's task is to effectively use them rather than being explicitly guided on which tool to use for each specific task.

Finally, current approaches often blur the line between the agent and the environment, as each agent is designed with its own specified action and observation spaces within a self-created environment. `Programming with Pixels` addresses this issue by unifying existing environments into a single, general-purpose platform on which agents operate. This clear separation of environment design from agent design standardizes evaluation and also allows any existing agent to be modeled within our framework, making it an important testbed for both current and future SWE agents.

### 2.3. Visual Agents and Computer-Use Agents

A family of recent multimodal agent benchmarks require agents to operate user interfaces using a predefined, limited set of actions (e.g., `new_tab`, `go_back`, `click [element id]`) (Koh et al., 2024a; Deng et al., 2023; Zheng et al., 2024) . These *visual agents* typically rely on additional prompting—such as set-of-marks techniques that supply an HTML accessibility tree containing textual and positional information—to overcome their inherent poor visual grounding capabilities (Yang et al., 2023b). Despite such aids, these agents often fail when faced with the complex and dense IDE interfaces found in our environment.

A separate family of *computer-use agents* (Anthropic, 2024; OpenAI, 2025; Gou et al., 2024) are trained to operate with an expressive action and observation space using primitive operations like clicks and keystrokes, without the need for external accessibility elements. However, there is no SWE-specific environment for evaluating and further training these agents. `PwP` fills this gap by providing a unified, expressive IDE platform that challenges computer-use agents with realistic and diverse SWE tasks.

### 2.4. Expressive Agent Environments

Prior work on expressive agent environments has predominantly targeted the web domain (Koh et al., 2024a; Deng et al., 2023), entire operating systems (Xie et al., 2024; Bonatti et al., 2024; Rawles et al., 2023), or other general scenarios (Xu et al., 2024). Some of these environments, such as OSWorld (Xie et al., 2024), feature general action and observation spaces similar to ours. However, although these benchmarks are capable of expressing a wide range of tasks, they do not focus on the unique challenges inherent to software engineering within an IDE. For example, while OSWorld offers a broad set of tasks, it is not specifically designed for SWE, resulting in increased computational overhead. Software engineering is a diverse and important domain that merits its own dedicated environment.

Additionally, we design `PwP` so that existing tool-based software engineering agents can be readily incorporated into our

framework. Specifically, we modify the source code of the IDE to open up API calls that let us test current tool-based agents. Furthermore, `PwP-Bench` is tailored specifically for multimodal SWE tasks within an IDE, encompassing activities such as pull-request handling, debugging, and image-based code generation across multiple programming languages. We also observe that existing agents built for generic UI control often struggle in the `PwP` environment, as they must interact with a richer set of tools and achieve precise visual grounding within a complex interface containing a large number of interactive elements. We further distinguish `PwP` from other environments in Table 1.

## 3. `Programming with Pixels` (`PwP`)

Modern software engineering (SWE) requires using multiple programming languages, tools, and modalities. Furthermore, it relies on a wealth of tools that required tremendous human effort to create—from linters, to visual code debuggers, to project management tools. Motivated by these observations, we create `Programming with Pixels`, an IDE environment that satisfies two properties: (i) it is *expressive*, meaning that an agent can perform any task that is achievable through a sequence of primitive operations (e.g., typing or clicking) within an IDE; (ii) an agent has access to any tool implemented within the IDE since using a tool amounts to performing a sequence of primitive actions.

### 3.1. PwP environment

We represent the `PwP` environment as a partially observable Markov decision process (POMDP). We define the PwP POMDP $\langle S, A, O, T, R \rangle$ as:

- **S** is the set of states describing the IDE and the operating system context, including open files, active editor panels, and cursor positions.
- **A** is the action space, encompassing all possible keyboard and mouse events. The atomic actions in PwP are provided by the `xdotool` library (Sissel), which allows specifying all possible keyboard and mouse events in a simple syntax. The specific action space varies based on the agent setting, described in (§5).
- **O** is the observation space. The observation space varies based on the agent setting, described in (§5).
- **T** is the transition function. Actions like inserting a character typically lead to deterministic changes in the IDE state, whereas background processes can introduce stochasticity in timing and responses.
- **R** is the reward function that measures performance on a given task. For instance, after the agent finishes editing code to fix a bug, the environment can run a test suite on the updated files to compute a reward.

Trajectories in `PwP` can thus resemble real-world development work: an agent can fix a bug in a repository, use a suggestion tool to help with writing code, or create documentation. The IDE and its operating system environment track changes, run tests and return reward signals.

### 3.2. Key Features of `Programming with Pixels`

**Expressive observation and action space.** A typical approach to building agents is to engineer a set of high-level actions for operations like "open file" or "list symbols in file", and then engineer an environment that supports each action (Xia et al., 2024; Yang et al., 2024b; Wang et al., 2024b). Furthermore, agents receive textual outputs that are manually reformatted for each action. The key difficulty is that such engineering does not scale to a large number of actions or to the full range of software engineering tasks, and the agent may be specialized to the observation and action space. In contrast, `PwP` preserves standard screen-based user interaction. The agent can navigate IDE menus visually, move the cursor, and press keys. This makes the environment expressive: an agent can achieve any task that can be achieved through primitive actions in an IDE.

**Full Spectrum of Developer Tools.** A modern IDE offers debuggers, linters, version control, refactoring utilities, integrated terminals, and many extensions. In particular, PwP is developed on top of VSCode, which has a rich set of built-in functionalities and extensions. Implementing each of these into an agent or environment would require significant human effort. However, `PwP` provides these capabilities out-of-the-box within a single environment. Agents can set breakpoints, execute code, use language-specific extensions, review error messages, or run tests in a consistent interface.

**Multimodality and Language Agnosticism.** Because the IDE supports numerous programming languages through extensions and built-in modules, `PwP` naturally covers tasks across Python, Java, JavaScript, Lean, and more without requiring separate integrations. For instance, agents can use the same debugger interface for all languages, or use pre-existing linters provided by IDE extensions. Beyond screenshots, the environment provides video streams and audio, though we leave exploring these for future work.

**Rich Feedback and State Access.** `PwP` can evaluate performance immediately using testing frameworks or compilation checks. For instance, if the agent modifies a file, the IDE can automatically trigger a build, update diagnostics, or run tests, generating real-time feedback. In cases requiring deeper inspection—such as verifying that a bug is

Table 1: **Comparison of PwP with existing environments** across different dimensions. PwP uniquely combines comprehensive IDE tool support with full multimodal support, general action space, and execution-based evaluation, while maintaining software engineering specificity.

| Environment | Multi-modal | General Action Space | Observation Space | State Checkpointing | Tools | Execution-Based Reward | SWE Specific |
|---|---|---|---|---|---|---|---|
| GAIA (Mialon et al., 2023) | ✗ | ✗ | Text | ✗ | Limited | ✗ | ✗ |
| SWE-Bench (Jimenez et al., 2023) | ✗ | ✗ | Text | ✗ | Limited | ✓ | ✓ |
| SWE-Bench-MM (Yang et al., 2024b) | Text, Image | ✗ | Text | ✗ | Limited | ✓ | ✓ |
| OpenHands (Wang et al., 2024b) | Text, Image | ✗ | Tool Output + Browser | ✗ | SWE | ✓ | ✓ |
| TheAgentCompany (Xu et al., 2024) | Text, Image | ✗ | Tool Output + Browser | ✗ | SWE | ✓ | ✗ |
| WEBSHOP (Yao et al., 2023) | ✗ | ✗ | Text | ✗ | Browser | ✗ | ✗ |
| WEBARENA (Zhou et al., 2024) | ✗ | ✗ | Text | ✗ | Browser | ✓ | ✗ |
| VWEBARENA (Koh et al., 2024a) | Text, Image | ✓ | Screen | ✗ | Browser | ✓ | ✗ |
| BrowserGym (Chezelles et al., 2024) | Text, Image | ✓ | Tool Output + Browser | ✗ | Browser | ✓ | ✗ |
| OSWORLD (Xie et al., 2024) | Text, Image | ✓ | Screen | ✗ | OS | ✓ | ✗ |
| WindowsAgentArena (Bonatti et al., 2024) | Text, Image | ✓ | Screen | ✗ | OS | ✓ | ✗ |
| PwP (Ours) | Text, Image, Video, Audio | ✓ | Screen | ✓ | All IDE Tools | ✓ | ✓ |

truly fixed—the environment can reveal file-system changes, process states, or test results.

**Future Adaptability.** As agents continue to evolve, PwP provides a unified environment for incorporating new benchmarks and training. For example, PwP is amenable to reinforcement learning due to its use of the standard gymnasium (Towers et al., 2024) interface and its checkpointing functionality. We show an example of how to interact with PwP in Figure 2. Checkpointing also allows for backtracking in search-based methods (Koh et al., 2024b; Putta et al., 2024). As software engineering practices progress and new IDE tools emerge, PwP incorporates them without additional engineering overhead. Further, as agents become more ubiquitous, it is imperative to evaluate their capabilities in pair-programming scenarios with human developers. PwP supports concurrent user-agent interaction, potentially enabling new kinds of pair programming or real-time collaboration studies. Finally, adding new tasks requires only minimal modification to configuration and evaluation files.

### 3.3. Infrastructure and Implementation

PwP is deployed in a secure sandboxed environment. In particular, we run a modified version of Visual Studio Code (VSCode) and a minimal operating system inside a Docker container, ensuring a secure and isolated environment. We chose VSCode for its extensive language support, rich ecosystem of extensions, widespread adoption in the developer community, and open-source nature that enables customization and modification of its core functionality. Each container instance maintains its own file system and processes, preventing interference between experiments, facilitates reproducibility, and ensuring parallelization of evaluation. We further provide the ability to checkpoint the environment state, which is especially useful for backtracking in search algorithms or while training RL agents.

The environment interfaces with VSCode through multiple channels: 1.) A controller that manages Docker container lifecycle and configuration, 2.) A port-forwarding system for real-time screen and video capture, 3.) A modified VSCode codebase that exposes DOM state information, and 4) The VSCode Extension API for accessing fine-grained IDE state. This multi-channel approach enables both high-level environment control and detailed state observation.

Screen capture is handled via `ImageMagick` for static screenshots and `ffmpeg` for streaming video output. These tools were selected for their low latency and ability to handle various screen resolutions and color depths. For actions, a lightweight controller executes `xdotool` commands within the container, which in turn simulates keyboard and mouse events on the IDE. Agents can thus insert code, open new files, or navigate menus using the same actions that a human developer would.

As shown in 2, a Python API is provided for interaction, following a style similar to common reinforcement learning libraries such as gymnasium (Towers et al., 2024). The API abstracts away the complexity of container management, benchmark management, and handling observations and actions, allowing researchers to focus on agent development. Users can query the environment for the latest screenshot, issue an `xdotool` command, and receive updated states or rewards. The environment's container configuration is flexible, allowing for software installations, customizable CPU/memory limits, and display settings (e.g., resolution). This versatility is crucial for large-scale evaluation, especially when tasks vary in complexity and resource needs.

## 4. PwP-Bench

We introduce PwP-Bench, a benchmark comprising 15 diverse software engineering tasks that span 8 programming languages and multiple modalities. Each task provides agents with access to the complete suite of tools available in the PwP environment. The purpose of PwP-Bench is to

```python
bench = PwPBench(dataset='swebench')
# Replace with any dataset from PwP-Bench
dataset = bench.get_dataset()

# Set up environment and get initial observation
env = bench.get_env(dataset[0])
observation: PIL.Image = env.get_observation()['screenshot']

# Generate and execute action
action = agent.get_action(observation)
print(action)
# Output: xdotool mousemove 1000 1200
# click 1 && xdotool type 'hello world'
observation, info = env.step(action)

env.render()

# Environment control
env.pause()
env.resume()

# Get reward and reset
is_success = env.get_reward()
env.reset()

```

Figure 2: Example demonstrating interaction with PwP environment, including keyboard/mouse actions, checkpointing, and state management. The code shows basic initialization, action execution, environment control, and reward handling.

evaluate how well agents handle a broad range of software engineering (SWE) activities, thereby testing the generality of their code generation and SWE capabilities.

**Tasks.** `PwP-Bench` contains 5400 instances covering 15 tasks, sourced from 13 existing code-generation datasets and 2 newly created by us. These tasks are designed to be representative of the breadth of software engineering—including tasks beyond conventional code generation to capture real-world complexities—and can be expanded as models excel in newer tasks. We followed three guiding principles: (1) tasks should require significant interaction with various SWE tools, (2) each task should necessitate multiple steps to complete, and (3) the overall benchmark should span multiple programming languages and modalities. Based on these principles, we collected diverse tasks and grouped them into four categories:

- **Code Generation and Editing:** Evaluates the ability of agents to generate and edit code. This category includes datasets such as HumanEval for code completion, SWE-Bench (Jimenez et al., 2023) and SWE-Bench-Java (Zan et al., 2024) for resolving pull requests, DSBench (Jing et al., 2024) for data science tasks, and Res-Q (LaBash et al., 2024) or CanITEdit (Cassano et al., 2024) for code editing. Each dataset benefits from different tools. For example, SWE-Bench can take advantage of debuggers and linters, while DSBench may leverage an IPython kernel and tools for analyzing large data files. Code editing tasks can leverage refactoring utilities and repository searches, covering varied input-output formats and end goals.

- **Multimodal Code Synthesis:** Involves creating code based on input images or other visual data. Examples include Design2Code (Si et al., 2024) for UI development, Chart2Mimic (Shi et al., 2024) for generating Python code from chart images, SWE-Bench-MM (Yang et al., 2024b) for multimodal code editing, and DSBench tasks that rely on images or PDF documents during data analysis.

- **Domain-Specific Programming:** Focuses on specialized fields such as ethical hacking (CTF) (Yang et al., 2023a) and interactive theorem proving (miniCTX) (Hu et al., 2024). These tasks demand significant interactivity with IDE components. For example, theorem proving requires continuously inspecting states via the IDE, while CTF tasks often involve analyzing images, running executables, or installing VSCode extensions (e.g., hexcode readers).

- **IDE-Specific and General SWE Tasks:** Recognizing that code generation is only one aspect of software engineering, we introduce two novel task sets to evaluate broader SWE skills. The first, **IDE Configuration**, evaluates an agent's ability to modify IDE settings—such as themes, extension installations, and preferences—that are critical for effective tool use in a complex environment. The second, which we term **General-SWE**, targets non-code activities such as profiling, designing UI mockups, managing Kanban boards, and project refactoring. These tasks capture essential operational skills typically required by human developers but largely absent from conventional code generation benchmarks.

Figure 3 shows the distribution of tasks across all categories. An agent that succeeds across these tasks demonstrates strong potential for automating a wide range of software engineering activities. For instance, `PwP-Bench` covers Python, Java, JavaScript, HTML, CSS, Bash, SQL, and Lean, and requires agents to work with text, images, data files, and other data types. Furthermore, effective interaction with IDE tools is essential.

**Benchmarking Design and Task Setup.** Every task is evaluated within the `PwP` environment. Unlike traditional benchmarks that provide structured, well-formatted context (for example, supplying all relevant schemas in text-to-SQL), `PwP-Bench` presents agents with an IDE containing

Table 2: **Comparison of existing software engineering benchmarks**. PwP-Bench provides the largest dataset (5400 instances) and uniquely covers all aspects: multiple languages and modalities, real IDE interaction, interactive coding, and both code generation and general software engineering tasks.

| Benchmark | #Instances | Multiple Languages | Multiple Modalities | Real IDE Env | Interactive Coding | Non-Code SWE Tasks | Code-Generation SWE Tasks |
|---|---|---|---|---|---|---|---|
| SWE-Bench (Jimenez et al., 2023) | 2K | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ |
| SWE-Bench-MM (Yang et al., 2024b) | $\leq 1K$ | ✗ | ✓ | ✗ | ✓ | ✗ | ✓ |
| LiveCodeBench (Jain et al., 2024) | $\leq 1K$ | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ |
| Aider Polyglot (Aider, 2024) | $\leq 1K$ | ✓ | ✗ | ✗ | ✓ | ✗ | ✓ |
| TheAgentCompany (Xu et al., 2024) | $\leq 1K$ | ✗ | ✓ | ✗ | ✓ | ✓ | ✗ |
| VisualWebArena (Koh et al., 2024a) | $\leq 1K$ | ✗ | ✓ | ✗ | ✗ | ✗ | ✗ |
| OSWORLD (Xie et al., 2024) | $\leq 1K$ | ✗ | ✓ | ✓ | ✗ | ✓ | ✗ |
| WindowsAgentArena (Bonatti et al., 2024) | $\leq 1K$ | ✗ | ✓ | ✓ | ✗ | ✓ | ✗ |
| PwP-Bench (Ours) | 5.4K | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

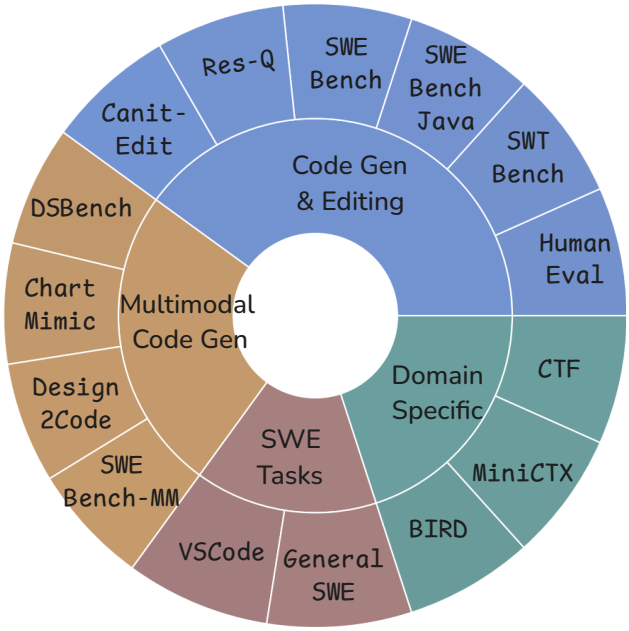


Figure 3: Distribution of tasks in PWP-Bench across four main categories: Code Generation and Editing, Multimodal Code Synthesis, Domain-Specific Programming, and General SWE Tasks. The inner ring shows the main categories while the outer ring shows specific datasets and tasks within each category.

a codebase rich in information. Specifically, an agent is provided with an initial environment state $S_i$ and an instruction $I$. The agent's goal is to update the codebase to satisfy $I$ and transition to a final state $S_f$. Only $S_f$ is evaluated, using execution-based criteria (e.g., running unit tests). This setup requires agents to autonomously discover and extract relevant information from files, directories, and other resources—mirroring the challenges faced in real-world software development.

Many tasks in PwP-Bench require extensive multi-turn interactions and can be time-consuming. To support large-scale evaluations, PwP enables parallelized testing in a sandboxed environment, ensuring both security and reproducibility. Tasks can also be configured to restrict or partially allow internet access based on experimental needs.

Furthermore, as software engineering tasks evolve with advancements in model capabilities, our benchmark is designed to grow over time. New tasks can be incorporated by creating simple setup scripts that define the IDE's initial state and evaluation logic, ensuring that PwP-Bench remains modular and adaptable.

**PwP-Bench-Lite.** Because PwP-Bench contains more than 5400 instances in total, running a full evaluation can be computationally expensive. To address this, we also provide PwP-Bench-Lite—a smaller subset of 300 instances, made up of 20 random samples per task. This subset preserves the overall difficulty and distribution while ensuring equal representation for each task, thereby making rapid experimentation more accessible.

## 5. Agents in Programming with Pixels

The primary objective of Programming with Pixels is to enable general-purpose SWE agents. We evaluate state-of-the-art agents based on vision-language models in our environment. Each agent operates in a turn-based manner, receiving a screenshot each turn and returning an action (keyboard or mouse action) to progress toward the goal. This design is the same as used in previous works (Xie et al., 2024; Koh et al., 2024a) and we refer them to as *computer-use agents*. In practice, most vision-language models struggle with raw image inputs. To mitigate this, we incorporate *Set-of-Marks (SoM)* (Yang et al., 2023b), in which the agent receives both the raw image and a parse of available interface element (e.g., buttons, text fields). The

Table 3: Performance Evaluation of Different Agents on PwP-Bench by Task Categories

| Inputs | Outputs | Model | Code Generation & Editing | Multimodal Code Generation | Domain-Specific Code Generation | General SWE Tasks | Overall Avg |
|---|---|---|---|---|---|---|---|
| Screenshot + SoM | Keyboard + Mouse | GPT-4o | 0.8% | 12.4% | 1.7% | 10.0% | 5.3% |
| | | GPT-4o-mini | 0.8% | 3.7% | 0.0% | 2.5% | 1.7% |
| | | Gemini-Flash | 0.0% | 4.3% | 0.0% | 0.0% | 1.2% |
| | | Gemini-Pro | 2.5% | 5.7% | 0.0% | 7.5% | 3.% |
| | | Claude-Sonnet | 10.0% | 8.2% | 5% | **20.0%** | 10.2% |
| Screenshot + SoM + Tool Output | Keyboard + Mouse + Tool Call (File, Bash) | GPT-4o | 37.0% | 41.9% | 28.3% | 5.0% | 32.3% |
| | | GPT-4o-mini | 23.6% | 17.5% | 15.0% | 5.0% | 17.8% |
| | | Gemini-Flash | 9.5% | 11.7% | 8.3% | 2.5% | 8.9% |
| | | Gemini-Pro | 30.9% | 16.7% | 3.3% | 5.0% | 18.1% |
| | | Claude-Sonnet | **52.1%** | **55.1%** | **43.3%** | **20.0%** | **46.8%** |

agent then interacts with element IDs instead of raw pixel coordinates.

We evaluate two categories of computer-use agents. The first category only outputs keyboard and mouse clicks. That is, the agent uses the following observation and action space:

- **O**: a screenshot and set-of-marks annotations.
- **A**: keyboard and mouse clicks with set-of-marks.

The second category of computer-use agents has access to file and bash commands supplied by the environment through an API. Furthermore, a screenshot is received only when the screenshot action is called, instead of receiving it every turn. These actions are provided in PwP in a similar design principle as Anthropic computer-use (Anthropic, 2024) which consists of file operations such as 'read file', 'create file', and 'string replace'. In summary, these agents use the following observation and action space:

- **O**: a screenshot and set-of-marks annotations and text output from tools if used.
- **A**: keyboard, mouse, and file and bash operation actions.

Finally, in Analysis 6.2, we create a tool-based agent design compatible with PwP. Specifically, we provide agents with domain-specific API calls that represent high-level actions (such as getting file structure) instead of UI interactions. Each high-level action is implemented as a sequence of low-level actions executed in PwP. This setting lets us test current state-of-the-art SWE agent patterns (e.g., Wang et al. (2024b)) within the PwP environment.

## 6. Experiments

**Experimental setup.** We evaluate two categories of baseline agents as described in Section 5. For each configuration, we test five state-of-the-art vision-language models (VLMs): Gemini-Flash-1.5, Gemini-Pro-1.5, GPT-4o, GPT-4o-mini, and Claude-3.5 Sonnet. With the exception of Claude—which is natively trained for UI interaction—the remaining models are provided with SoM.

At each timestep, an agent receives an observation (with the observation space determined by its category) and returns an action. The complete history of observations and actions is incorporated into the model's context. For each task instance, the maximum number of iterations is capped at 20 steps; if the agent either exhausts these steps or issues a stop command, the environment's final state is evaluated using task-specific metrics (see Appendix B for full details). Notably, the agent design remains the same throughout all tasks. Due to computational and budget constraints, we evaluate on PwP-Bench-Lite, which has 300 task instances.

### 6.1. Results

Table 3 summarizes performance across different agent architectures and base models over the four categories of PwP-Bench. As seen in the top half of the table, when using only primitive keyboard and mouse actions most agents have poor performance, with a maximum overall average of 10.2%. We attribute this poor performance primarily to limited visual grounding and an inability to interact effectively with the IDE—particularly for file editing and tool usage (see Section 6.2 for further analysis).

In contrast, when agents are granted access to file editing and bash operations through API calls rather than relying solely on UI interactions, we observe consistent improvements across all categories, with maximum average accuracy reaching 46.8%. Among the evaluated models, the Claude computer-use agent performs best, likely because it is specifically trained for UI interactions. We found that this agent is able to leverage basic IDE tools—such as HTML live preview, chart visualization, and file navigation—to boost performance on tasks requiring visual understanding and IDE navigation. Importantly, we find for the first time that a

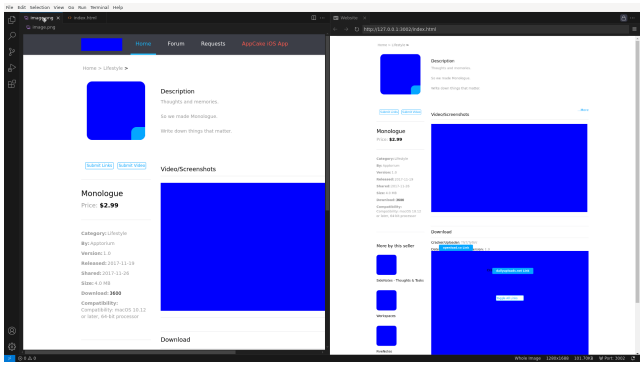

Figure 4: **Example of Successful Use of Live Preview Tool in the UI Replication Task** The agent successfully uses the live preview tool in the VSCode browser to compare the UI design it made versus the reference design.

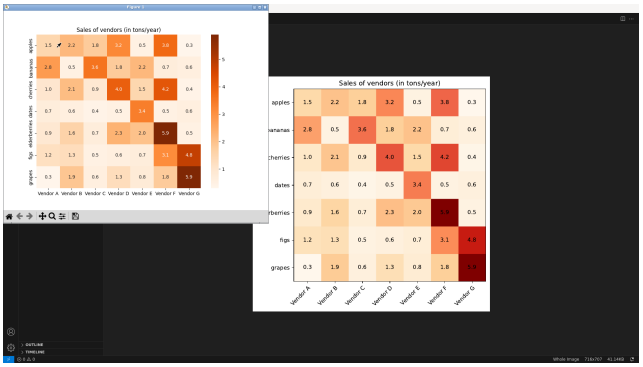

Figure 5: **Example of Successful Use of Tool in the Chart Generation Task** The agent can compare the generated chart with the reference chart side by side and refine its code accordingly.

single computer-use agent can achieve performance comparable to and often surpassing (See Appendix C) state-of-the-art methods across a wide variety of software engineering (SWE) tasks—encompassing multiple languages, modalities, and domains—while operating within a single unified environment and interface, and no specific hand-crafted tools, unlike existing SoTA methods.

Nonetheless, as detailed in Section 6.2, the models struggle to fully take advantage of the IDE tooling. This is evidenced by the poor performance on the 'General SWE' dataset, where tasks are often as simple as editing IDE settings and often require fewer than four clicks to complete. As we show in Section 6.2, these tasks become simpler if the models could use the IDE tooling more effectively.

Overall, while the results point toward a promising direction for developing general computer-use SWE agents, significant improvements are still needed in visual grounding, tool usage, and planning. We analyze these next.

### 6.2. Analysis

**Agents Demonstrate Poor Visual Grounding Capabilities.** Our qualitative analysis across multiple VLMs on `PwP-Bench` reveals significant limitations in visual understanding—even for basic IDE interactions. We identify two primary failure modes. First, models frequently fail to correctly identify the UI elements intended for interaction, as demonstrated in Figure 7, 8. In agents using set-of-marks (SoM), this issue manifests as incorrect element selection, while without SoM it leads to inaccurate mouse positioning. Second, models struggle to comprehend the current UI state. As shown in Figure 9, 10, they consistently fail to recognize highlighted elements, cannot detect linter errors indicated by wavy underlines (Figure 11), and often confuse active panels—resulting, for example, in typing into search bars rather than file editors (Figure 9). While similar issues have been documented in web and OS domains (Koh et al., 2024a; Xie et al., 2024), these limitations were primarily observed in models without UI-specific training. However, our work, shows even models explicitly trained for UI interaction (Anthropic, 2024), including Claude-Computer Use, exhibit these issues in `PwP`—likely due to the increased complexity of the IDE interface.

**Agents Fail to Edit Files.** File editing is a basic capability required in most SWE tasks. However, we find that the deficiencies in visual grounding significantly impact the file editing capabilities of current agents that use basic actions (clicking and typing). For example, even when provided with cursor location information in textual form, these models struggle to interpret such data amid complex UI elements. Models fine-tuned for UI interactions still commit basic editing errors—such as incorrect indentation and text misplacement—and are unable to recover from these errors (see Appendix for examples). We speculate these limitations could stem from two factors: (i) model overfitting to user interfaces in their training domains, or (ii) the increased complexity of the `PwP` IDE interface, which contains substantially more interactable elements than typical web or OS environments. Addressing these limitations represents an important direction for future work. Although direct file access via tool operations is available, UI-based editing confers unique advantages for tasks such as editing Jupyter notebooks, comparing changes, or modifying specific sections of large files. These results underscore two limitations: (i) current VLMs are challenged by complex UI interactions beyond simple web/OS interfaces (Xie et al., 2024; Koh et al., 2024a), and (ii) the inability to effectively perform UI-based editing prevents agents from leveraging valuable IDE features that could have improved their performance.

**Claude Computer-Use Agent Demonstrates Basic IDE Tool Proficiency.** Our analysis shows that the Claude

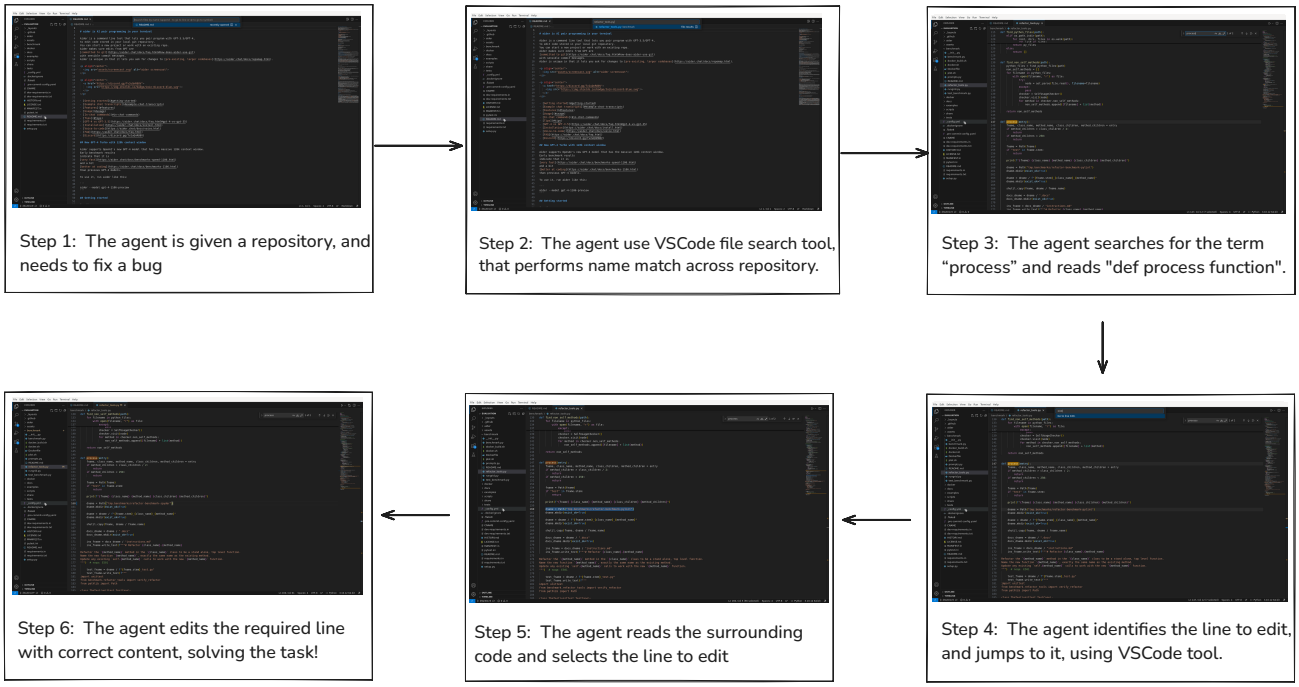


Figure 6: Example of the Claude Computer-Use agent successfully using multiple IDE tools to complete a repository level code-editing task.

Computer-Use agent successfully uses fundamental IDE functionalities, including file explorer navigation, file editing, search, browser-based live preview, and image generation and visualization capabilities. Figure 4 demonstrates the agent's effective use of browser tools in UI replication tasks. Similarly, Figure 6 illustrates the agent's ability to coordinate multiple tools while editing specific lines in a repository, relying solely on screenshot observations and primitive keyboard/mouse actions.

Second, we hypothesize that the agent has additional abilities to use tools that can be uncovered through prompting or fine-tuning. To investigate this, we considered the symbol renaming task in our 'General-SWE' benchmark, in which Claude initially achieves 0% accuracy when attempting the task. However, when explicitly instructed to use the renaming tool, its accuracy improves to 50% (see Appendix C).

**Agents Struggle to Use IDE Functionality.** Despite these successes with basic IDE functionality, computer-use agents demonstrate significant limitations when interfacing with more complicated IDE tools. We observe no successful instances of debugger usage or symbol listing operations. Models without specific UI interaction training struggle even with fundamental tools such as HTML live preview, image visualization, and graph generation capabilities. While Claude demonstrates competency with basic tools, it fails to effectively use advanced tools like profilers or debuggers.

To further evaluate these capabilities, we developed the 'General-SWE' dataset, which focuses on software engineering activities (e.g., profiling, refactoring, debugging) that can be completed without direct code modification. Although these tasks sometimes require only 4-5 steps when using appropriate IDE tools, agents achieve minimal performance, highlighting substantial room for improvement.

**Training Models to Use IDE Tools Better Would Improve Performance.** While a single computer-use agent design can perform well across a wide variety of tasks, our results indicate that these models do not fully exploit domain-specific tools. As an indication of the potential for performance gains *if* the agent was able to effectively use the IDE, we perform an "assisted" experiment.

For the assisted experiment, we manually engineer a set of API calls that are useful for the tasks. For example, in Design2Code, the assisted agents have an API call for a live HTML preview, while for SweBench it has API calls for retrieving repository structure and symbol outlines. Importantly, each API call is achievable using basic operations in the IDE, meaning that in principle an agent could learn to perform it. To ensure that each API call is achievable in the IDE, we implement each API call by executing a fixed sequence of low-level IDE actions, with the details abstracted away from the agent. A complete list of tools available in different environments is in Table 7 (see Appendix C).

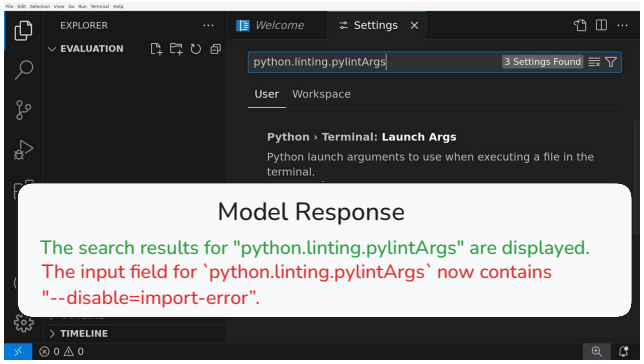


Figure 7: **Example of Agent Hallucinating Screen Contents** While the agent correctly mentions, search results are displayed (green text), it hallucinates an input field containing "disable import error" (red)

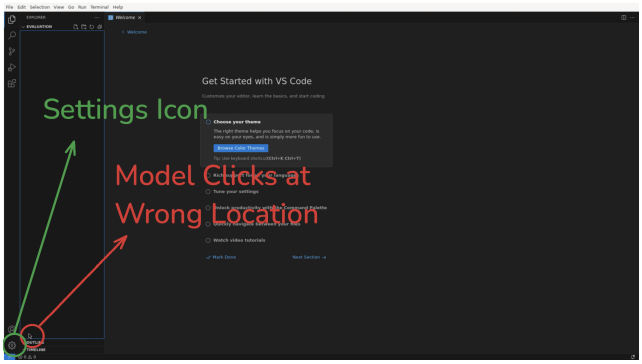


Figure 8: **Example of wrong mouse click by Claude-Computer Use Agent** The agent attempted to click Settings icon but clicked at the wrong location.

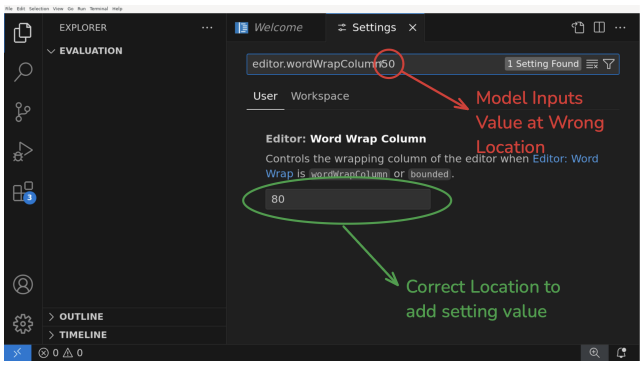


Figure 9: **Example of Agent Misidentifying UI Elements** The agent fails to identify the correct input field, typing '50' into the settings search bar instead of the word wrap column setting field (red arrow).

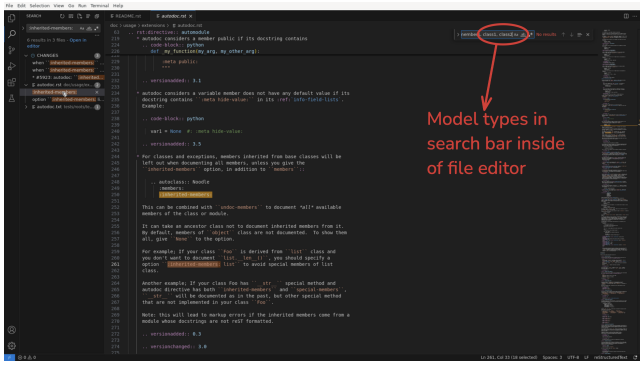


Figure 10: **Example of Agent Misidentifying Active Panel** The agent fails to recognize the active editor panel, incorrectly typing into the search bar (red arrow) instead of the file editor.

Table 4: Comparison of Different Agent Types Across Selected Tasks

| | SWE-Bench | Design2Code | Chartmimic | BIRD (T2 SQL) |
|---|---|---|---|---|
| Primitive Agents | 0% | 23.5% | 2.7% | 0% |
| Computer Use | 15% | 48.1% | 25.3% | 7% |
| Assisted | **19%** | **79.5%** | **61.6%** | **17%** |

Table 4 compares the performance of these assisted agents with that of standard computer-use agents across four datasets for which we manually created tools. The assisted agents achieved up to a 13.3% improvement in average scores relative to the non-assisted agents. This suggests that training agents to explore and use the built-in IDE functionality would yield performance gains. It also suggests that in the near term, we can get performance gains by introducing hand-engineered tools into the computer-use agent and incorporating existing agent designs in our PwP environment.

**Agents Are Incapable of Recovering from Errors.** Next, we find that current agents show limited error recovery capabilities. When an action fails to execute correctly, models tend to persistently repeat the same failed action without exploring alternatives. Similarly, if an agent selects an incorrect action, it continues along an erroneous solution path without recognizing or correcting the mistake. In an experiment designed to probe this behavior, we deliberately suppressed one of the model's actions. Despite the environment's screenshot clearly showing an unchanged state, the models proceeded with their planned action sequence as though the suppressed action had succeeded. This behavior suggests a heavy reliance on memorized action sequences rather than dynamic responses to visual feedback, resulting in exponentially increasing errors and poor performance.

## 7. Conclusion

In this work, we introduce PwP, a unified environment that challenges the prevailing tool-based paradigm by enabling

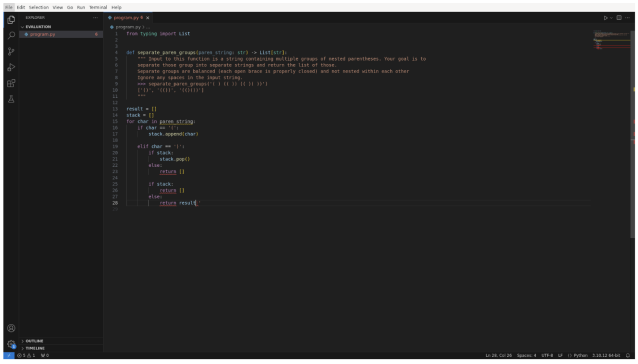

Figure 11: **Example of Agent Missing Visual Error Indicators** The agent fails to recognize linter error indicators (wavy underlines).

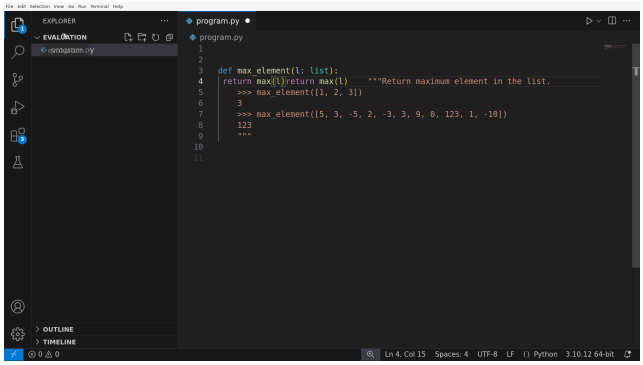

Figure 12: **Example of Agent's Inability to Perform File Editing** The agent incorrectly positions new content in the file editor.

direct interaction with IDEs through basic computer-use actions like typing and clicking. This approach allows for a wide range of tasks to be modeled without language- or domain-specific modifications. Second, we introduce PwP-Bench, a unification of existing SWE datasets evaluated in PwP. We find that general-purpose computer-use agents can approach or outperform previous state-of-the-art results, without any task-specific modifications. This suggests that the dominant paradigm of building specialized text-based tools for SWE agents may be superseded by end-to-end computer-use agents. However, our analysis reveals that state-of-the-art agents are still incapable of using the extensive set of tools available in PwP, and could perform better if they could use them. Our work opens up an exciting new direction of development of computer-use agents for SWE tasks, an important step towards reaching truly general-purpose SWE agents. Finally, PwP provides a common platform that supports existing agents and benchmarks, making it a foundation for future research on SWE agents.

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Table 5: Comparison of Hand-engineered Tools across Methods versus PwP. PwP natively supports all tools.

| Method | Hand-engineered Tools | Supported in PwP |
|---|---|---|
| Agentless (Xia et al., 2024) | File Edit, Repository Structure, File Structure | ✓ |
| CodeAct (Wang et al., 2024a) | File Edit, IPython, Bash | ✓ |
| SWE-agent (Yang et al., 2024a) | Search File, Search Text, File Edit | ✓ |
| EnIGMA (Abramovich et al., 2024) | SWE-agent Tools + Debugger, Terminal, Connection Tool | ✓ |
| swebench-mm (Yang et al., 2024b) | SWE-agent Tools + View Webpage, Screenshot, Open Image | ✓ |

# A. Programming with Pixels (PwP) Environment

## A.1. Tools

Previous methods have proposed use of various hand-engineered tools. However, as shown in Table 5, PwP natively supports all these tools.

## A.2. Comparison with Other Environments

In Table 1, we compare PwP with existing environments across multiple dimensions. We focus on environments designed for software engineering agents as well as those developed for web agents and operating system interaction. Since many prior code agent efforts do not explicitly separate their agent and environment architectures, we evaluate their environments based on their published interfaces (e.g., SWE-Bench, SWE-Bench-MM). We evaluate environments along the following dimensions:

- **Multi-modal support**: The ability to process diverse input modalities including text, images, video, and audio
- **General action space**: Whether the environment provides a general-purpose interface for tool interaction. For instance, OSWorld, WindowsAgentArena, and BrowserGym enable keyboard/mouse interactions through visual inputs, creating a general action and observation space. In contrast, environments like SWE-Bench and OpenHands restrict interactions to predefined tool-specific APIs. While OpenHands does allow BrowserGym interface, which in turns allows for general action and observation space, the generality is limited to browser interactions and does not apply to other SWE-related tools.
- **Observation space**: The range of environmental states and feedback accessible to an operating agent
- **State Checkpointing**: Native support for preserving file system and process states, a capability unique to PwP
- **Tools**: The set of available tools and capabilities accessible to agents
- **Execution-based evaluation**: Use of runtime execution to verify the correctness of agent actions
- **SWE-specific**: Whether the environment is purposefully designed for software engineering tasks

While some environments offer general action and observation spaces, they are not specifically designed for software engineering tasks. Programming with Pixels uniquely combines SWE-specific design with general-purpose interaction capabilities, enabling the development of general-purpose computer-use agents for software engineering.

# B. PwP-Bench

**Metrics** We use individual metrics mentioned in the original datasets. When reporting results on PwP-Bench, we report marco average of all these metrics. In particular, 11/15 used Accuracy as their metric. However, due to complexity of dataset, these often goes beyond simple accuracy metrics and in some cases, the dataset is evaluated on multiple orthogonal metrics, instead of one. We detail, these metrics for each of the datasets.

- **SWT-Bench** evaluates generated tests by the agent, and reports 6 different metrics: Applicability, Success Rate, F- X, F- P, P- P, and Coverage. We report the average of all 6 metrics.

Table 6: Performance Evaluation of Different Models Across Task Categories. Leged: HE: HumanEval, SB: SWEBench, SJ: Swebench-Java, RQ: ResQ, CI: CaniteEdit, ST: SWTBench, DC: Design2Code, CM: ChartMimic, DS: DSBench, SM: Swebench-MM, IC: Intercode-CTF, BD: Bird SQL, MC: Minictx, VS: VSCode, GS: No-Code SWE Tasks. *Much more costly method, ** Estimated Value since only Pass@8 is reported.

| | **Code Generation & Editing** | | | | | | **Multimodal Code Generation** | | | | **Domain-Specific Code Generation** | | | **No-Code SWE Tasks** | | **Overall** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Model** | HE | SB | SJ | RQ | CI | ST | DC | CM | DS | SM | IC | BD | MC | VS | GS | **Avg** |
| **Computer-Use Agents** (Screenshot + SoM) | | | | | | | | | | | | | | | | |
| GPT-4o | 5% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 48.7% | 0.7% | 0.0% | 0.0% | 5.0% | 0.0% | 0.0% | 20.0% | 0.0% | 5.3% |
| GPT-4o-mini | 0.0% | 0.0% | 0.0% | 0.0% | 5.0% | 0.0% | 14.8% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 5.0% | 0.0% | 1.7% |
| Gemini-Flash | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 15.2% | 2.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 1.2% |
| Gemini-Pro | 10.0% | 0.0% | 0.0% | 0.0% | 5.0% | 0.0% | 14.5% | 8.1% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 15.0% | 0.0% | 3.5% |
| Claude-Sonnet | 20.0% | 0.0% | 0.0% | 15.0% | 25.0% | 4.2% | 18.1% | 0.0% | 5.0% | 10.0% | 15.0% | 0.0% | 0.0% | 35.0% | 5.0% | 10.2% |
| **Computer-Use Agents** (Screenshot + SoM + File/Bash Operations) | | | | | | | | | | | | | | | | |
| GPT-4o | 85% | 25% | 15% | 30% | 50% | 17.0% | 70.2% | 65.5% | 11.9% | **20%** | 70% | 10% | 5% | 10% | 0.0% | 32.3% |
| GPT-4o-mini | 60% | 10% | 5% | 20% | 30% | 16.7% | 41.3% | 5.5% | 8.4% | 15% | 40% | 5% | 0% | 10.0% | 0.0% | 17.8% |
| Gemini-Flash | 0 | 5% | 5% | 15% | 15% | 17.1% | 19.9% | 13.5% | 3.2% | 10% | 25% | 0% | 0% | 5% | 0.0% | 8.9% |
| Gemini-Pro | 85% | 10% | 15% | 15% | 40.0% | 20.2% | 25.6% | 24.7% | 1.6% | 15% | 5% | 5% | 0% | 10% | 0.0% | 18.1% |
| Claude-Sonnet | **95%** | 25% | **35%** | **55%** | **65%** | **37.4%** | 83.4% | 71.2% | 55.7% | 10% | **100%** | 15% | 15% | **35%** | 5.0% | **46.8%** |
| **Previous State of the Art Reported*** | | | | | | | | | | | | | | | | |
| | 98.8% | 55%* | 9.9% | 58% | 63.3% | 37.1% | 90.2% | 71.4% | 39.4% | 12.2% | 72% | 30.2% | $\approx 25\%$** | 35.0% | 5.0% | 46.8%* |

- **ChartMimic** evaluates generated code on various metrics such as accuracy of text, colors used, legend etc. We average all metrics similar to the original dataset.

- **Design2Code** evaluates generated code on various metrics such as accuracy of text, position, clip score, etc. We average all metrics similar to the original dataset.

- **DSBench** has two categories, one containing MCQ questions, while the other containing generating code for Kaggle Competitions. We use 10/10 instances from each category in `PwP-Bench`-Lite. While MCQ questions are evaluated using Accuracy, the code generation part is evaluated using linear normalization between the baseline score (of the competition) and the score of the winner of competition.

## C. Results

Table 6 presents comprehensive results for all agent designs across 15 datasets in `PwP-Bench`. For comparison, we include previously reported state-of-the-art results, which represent the best performance achieved on individual datasets through various specialized approaches including finetuned models, custom tool interfaces, specific pipelines, prompts, inference strategies, and verifiers.

It is important to note that direct comparisons on individual datasets may not provide a complete picture, as state-of-the-art results often utilize different model versions, computational budgets, and domain-specific tools. For example, the 55% performance on SWE-Bench was achieved using significantly longer agent trajectories compared to `PwP`'s 20-iteration limit. Given statistical variations and differing evaluation conditions, we emphasize evaluating agents across the full range of tasks rather than focusing on individual dataset performance, as this better aligns with our goal of developing general-purpose SWE agents. We make our best effort to include the latest publicly available results, however, there may be minor discrepancies.

Notably, on the Intercode dataset (Capture the Flag), the computer-use agent significantly outperforms the state-of-the-art method despite the latter (SWE-Agent-Enigma) employing numerous specialized tools for static analysis, dynamic analysis, and networking (See Table 5). This improvement is statistically significant (p-value = 0.014, McNemar's test). While the agent did not rely on specific IDE tooling, this result highlights the advantages of a simple, general agent design and suggests the potential benefits of allowing agents to automatically identify optimal tools rather than imposing human priors on the system.

Table 7: **Tools available in different environments.** The table shows the various tools provided by different environments for assisted analysis. Common tools like file manipulation and bash operations are shared across environments, while specialized tools cater to specific tasks like web design and chart replication.

| Category | Tool | Description |
|---|---|---|
| Common Tools | bash | Perform bash operations |
| | file_edit | Perform file manipulation operations |
| SWEBench | search_repository | Search the repository for a string in the entire repository |
| | file_name_search | Search for a file by its name |
| | view_structure | View the structure of the current directory |
| Design2Code | view_html_preview | Get a preview of the index.html page as rendered in the browser |
| | view_original_image | Get a screenshot of the html image for replication |
| | zoom_in | Zoom in on the current rendered html page |
| | zoom_out | Zoom out on the current rendered html page |
| ChartMimic | view_python_preview | Get a preview of the graph generated by python file |
| | view_original_image | Get a screenshot of the graph for replication |
| BIRD | test_sql | Test a SQL query against the database |
| | get_relevant_schemas | Get relevant descriptions of the relevant database tables |

## D. Additional Results

**Training models to use IDE tools better would improve performance.** In Section 6.2, we demonstrate that models can achieve superior performance when effectively utilizing IDE tools. However, our analysis reveals two primary limitations in current models' tool usage: (1) poor visual grounding and inability to handle complex tool interfaces, and (2) failure to prioritize IDE tool-based solutions over manual approaches.

To evaluate the second limitation specifically, we developed refactoring tasks within our 'General-SWE' dataset. These tasks require agents to rename symbols across a project repository—an operation that cannot be reliably accomplished through simple search-and-replace due to potential naming conflicts and contextual variations. The IDE provides a robust solution through its rename feature, which leverages the complete AST to ensure accurate symbol renaming across the codebase. This operation requires only pressing F2 on a symbol and entering the new name. In our evaluation, the Claude agent initially achieved 0% accuracy across four tasks when given no tool guidance. However, when explicitly prompted with "You can utilize the rename feature in VSCode to perform this task," its accuracy improved to 50%.

We observed similar patterns across other tasks designed to evaluate tool usage. For instance, tasks that could be efficiently solved using the debugger showed limited success. While agents could sometimes set breakpoints, their poor visual grounding prevented them from effectively interpreting the debugging interface—particularly in understanding the current execution state and paused line location. These findings suggest significant potential for improving agent performance through better training on IDE tool utilization.

**Successful Use of Tools** We further show a couple of examples of successful tool use in Figure 4 5. However, we do note that while the agent is able to use the IDE tool through UI interaction, it still may not be able to make optimal use of it as shown in Figure 13.

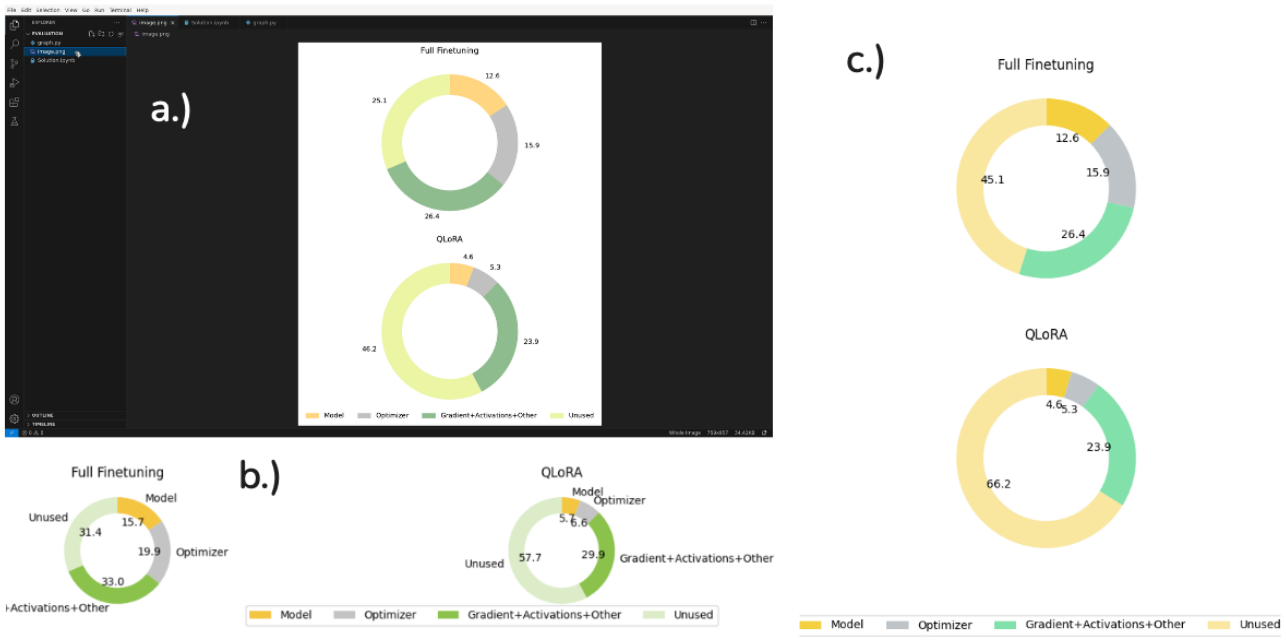


Figure 13: Performance comparison of GPT-4 agent in Computer-Use and Assisted settings on the ChartMimic dataset. a) Image as seen by the Computer-Use agent. b) Replication in Computer-Use setting. c) Replication in Assisted setting. The Assisted agent demonstrates superior performance despite seeing the same image but in different context and state.