TinyClick: Single-Turn Agent for Empowering GUI Automation

Anonymous ACL submission

Abstract

We present a single-turn agent for graphical user interface (GUI) interaction tasks, using Vision-Language Model Florence-2-Base. The agent's primary task is identifying the screen coordinates of the UI element corresponding to the user's command. It demonstrates strong performance on Screenspot and OmniAct, while maintaining a compact size of 0.27B parameters and minimal latency. Relevant improvement comes from multi-task training and MLLM-based data augmentation. Manually annotated corpora are scarce, but we show that MLLM augmentation might produce better results. On Screenspot and OmniAct, our model outperforms both GUI-specific models (e.g., SeeClick) and MLLMs (e.g., GPT-4V).

1 Introduction

Vision-language models (VLMs) have many applications in working with GUIs (Nakano et al., 2022; Rawles et al., 2024). Single-turn agents perform actions specified by the user in the UI environment, e.g. clicking on appropriate icons or entering text into appropriate fields. Examples of such commands are "choose first item in product list", "close the application" or "open cart". The agent can perform actions based on such commands and the current GUI screenshot captured from the user's device.

Currently, UI agents demonstrate moderate accuracy. Moreover, as shown in Table 2 of (Liu et al., 2024), standard multimodal language models (MLLMs) exhibit poor performance in single-turn agent tasks (only 0-11% accuracy), despite high computational cost.

We present single-turn agent based on Florence-2 (Xiao et al., 2023) model, which offers state-of-the-art performance, while being only 0.27B model.

[1]The code for TinyClick inference is included in the supplementary materials.

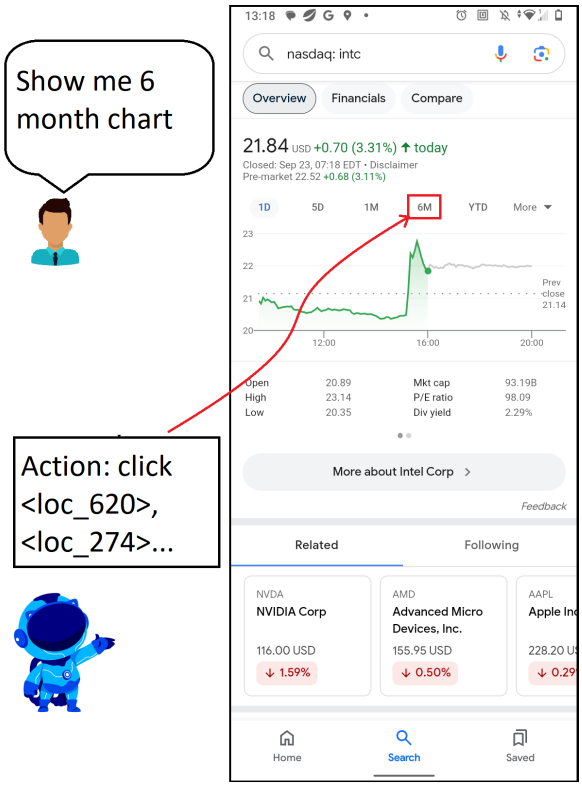

Figure 1: Example command of the downstream task. TinyClick receives a screenshot and user command and predicts bounding box of the UI element [*].
[*]Stickers from flaticon.com

When finetuning the model we investigated multiple approaches, public datasets and data preparation techniques. High-level diagrams are provided in Figure 1 (agent inference) and Figure 2 (agent training). Most important improvements come from multitask training. It uses multiple purpose-oriented objectives to reinforce more efficient UI representation in the model. Our key contributions are as follows:

- TinyClick significantly outperforms the baselines, achieving 73.8% accuracy on Screenspot and 58.3% on OmniAct.
- Training on multitask data (such as generate

captions and explanations) outperforms training on click-commands alone.

- MLLM-based augmentation of corpora with commands and boxes significantly improves model performance.

In addition, our contribution fills important niche, as tiny 0.27B model greatly outperforms state-of-the-art MLLM (GPT4, Gemini etc) on UI location task.

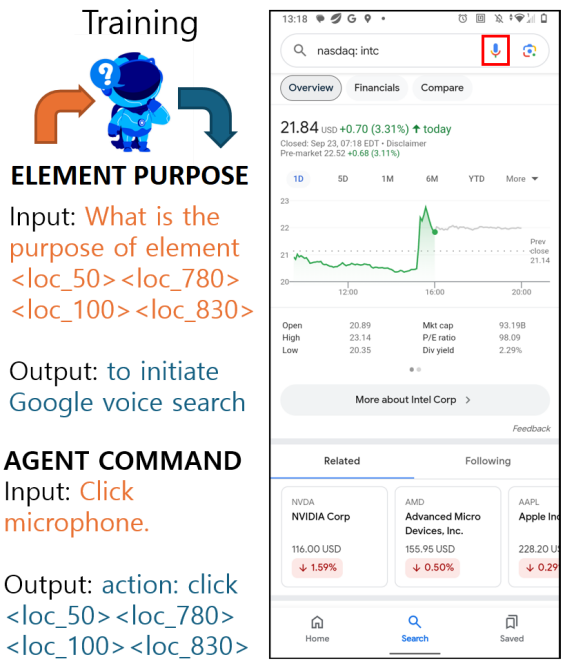

Figure 2: During the training, the model receives a question and generates an answer. Both question and answer can consist of location tokens of specific UI element. In this example, the first question is about element description and the second one is a command to click specific item. Multiple different tasks can be associated with a single UI element, allowing the model to gain a better understanding of the UI*.

*Stickers from flaticon.com

2 Related Works

In recent years there is much interest in Vision-Language Models (VLMs) and Multimodal Large Language Models capable of UI understanding (Rahman et al., 2024; Baechler et al., 2024; Gur et al., 2018; Li and Li, 2023).

Our focus are autonomous agents navigating UIs according to natural language commands of the user: such as AppAgent (Zhang et al., 2023), MobileAgent (Wang et al., 2024), CogAgent (Hong et al., 2024), Auto-UI (Zhang and Zhang, 2024), V-Zen(Rahman et al., 2024). A related problem is grounding, which involves finding UI elements corresponding to a given phrase (Ferret (You et al., 2024), Ferret v2 (Zhang et al., 2024a)). Also, language-only LLM are used as agents for web, using primarily HTML representation (Deng et al., 2024; Gur et al., 2024). Pix2Struct (Lee et al., 2023) was pretrained to reproduce simplified HTML representation of screenshot (including that for masked parts of the UI). SeeClick, one of best agent models so far, (Cheng et al., 2024) uses HTML data for grounding-style pretraining. Among multitask training approaches (Gao et al., 2024) utilizes 10 pre-training tasks that resemble real-world tasks. Tree-of-Lens was proposed to interpret screen content based on a user-indicated point (Fan et al., 2024).

3 Method

In this work, we use Florence-2 Base(Xiao et al., 2023), a 0.27B vision transformer with language modelling head trained for different vision tasks. The model latency is approximately 250 ms, allowing for cheaper inference as well. Vision encoder uses 768x768 image resolution, larger than in other related works (AutoUI (Zhang and Zhang, 2024) uses 224x224), which might be important for large screenshots. While Florence-2 uses text transformer, it is designed to handle detection and grounding tasks, encoding coordinates as single tokens.

3.1 Multitask Training

It was demonstrated that performance of transformer models can be improved by training on many related tasks (Chung et al., 2022), including Florence-2 (Xiao et al., 2023)), and models trained on UI (Gao et al., 2024; Zhang et al., 2024b; Lee et al., 2023). (Hsieh et al., 2023; Zhang et al., 2024b) also demonstrate training small model to predict natural language explanations of training data. Florence-2 is pretrained on object recognition, phrase grounding, captioning, segmentation and similar vision tasks. It was also trained for OCR, but not on UI data. To adapt Florence-2 for single-turn agent we investigated multitask training for UI, using tasks such as:

- Element captioning - generating descriptions or purposes or action expectations of UI elements based on their location on the screen.

	Size	Screenspot[1]	OmniAct
AutoUI-Base	0.41B[2]	1.97	1.25
Qwen-VL	9.6B	5.2	-
GPT-4V	-	16.2	-
SeeClick	9.6B	53.4	36.8
Florence-2 (vanilla)[3]	0.27B	0	0
TinyClick (ours)	0.27B	**73.8**	**58.3**
w/o multi-task FT		69.4	50.4

Table 1: TinyClick achieves the best results and significantly outperforms other known methods. Goal here is choosing location to click based on user command (point prediction). The metric presented in this table is accuracy as presented in Section 4.3. All values are in percentage (%).

- Element location - locating UI elements based on their visual description.
- Object detection - detection of all clickable UI elements.
- Agent action - locating an UI element to click or point to click based on user command.
- Question answering, based on screen content.

We used publicly available corpora for single-turn agent training, consisting mainly of commands and locations (bounding boxes). To prepare our training data, we used available MLLM annotations or software-based metadata and also re-annotated the data with own MLLM pipeline. Element captioning, expectation, location and purpose were mainly based on MLLM annotations, while for object detection we used Android XML UI metadata. Experiments confirm the viability of our approach, beating present baselines with much smaller and faster model.

4 Experiments

4.1 Training Datasets

We use following public datasets: WaveUI (Daniel Jeffries, 2024) (we do not use WebUI due to license issue and remove Screenspot and OmniAct as these are benchmarks), AMEX (Chai et al., 2024), Mind2Web (Deng et al., 2024), GUI Odyssey (Lu et al., 2024) (it is not included in our final training), GUI Course (Chen et al., 2024), AndroidControl (Li et al., 2024), ScreenQA (Hsiao et al., 2024). For WaveUI we use commands (for agent action task) as well as provided MLLM-generated expectation (expected outcome), purpose and captions of UI elements. We use similar approach to augment AMEX and GUI Course, where commands or functionalities of UI elements are provided with UI elements location. We use InternVL2-26B to annotate these data with purposes, captions or expectations. For AMEX, we use 'functionality' field (manually annotated purpose of UI element) as well as Android XML annotations (if available for specific element).

Information about our trainset that produced results in Table 1 can be found in Appendix A, Table 5, showing that training uses 845k rows in total.

4.2 Benchmarks

We use two standard benchmarks: Screenspot (Cheng et al., 2024) and OmniAct (Kapoor et al., 2024). The first one contains 1200 test cases divided into 3 groups: mobile, web and desktop. The second one contains 3000 examples mainly related to the use of desktop operating systems.

4.3 Results Analysis

The accuracy shown in Table 1 is calculated as average of binary outcomes, whether predicted click point (or bounding box center) falls within the original ground-truth bounding box (1 if it does, 0 otherwise). For Screenspot, we report the arithmetic mean accuracy achieved on 3 data subgroups (see Chapter 4.2), according to SeeClick publication (Cheng et al., 2024).

The results show strong performance improvement over other approaches, such as SeeClick (Cheng et al., 2024), AutoUI (Zhang and Zhang, 2024), and other MLLMs (see Table 1).

4.4 Methodology

We verified that presented claims are supported by statistically significant results. Smallest significant (2σ) difference in accuracy is 1.8% for OmniAct and 2.6% for Screenspot (calculated from Beta conjugate prior). This also accounts for observed variance of repeated experiments (about 1% for Screenspot). Results below significance threshold are deemed not conclusive. We used 3 epochs as initial setting and tested training up to 5 epochs, which did not produce statistically significant improvement (albeit appears to work minimally better). We trained models on 4xA100 GPU (except Table 3, which used 1xA100). Training the best checkpoint required about 56 GPU-hours (18h on 4xA100). The best checkpoint result in Table 1 is

[1] OmniAct included as validation set

[2] 0.22B for base model and 0.19B for Blip2 for features

[3] Florence-2 was not pretrained on GUI data, so it is almost impossible for it to predict correct locations.

average accuracy for 3 training runs. Other results were calculated for single training run.

4.5 Dataset insights

We performed ablation study, removing numerically largest AMEX, multitask data and MLLM multitask data (see Table 4). Multitask data seems more important than larger amount of commands, and MLLM data more important than metadata. AMEX produces only small gain, despite large number of examples. Some of multitask data (as WaveUI's) can be used either as grounding objectives (generate location given phrase) and annotation objectives (generate phrase given location). The latter appears to provide stronger performance gain. To corroborate this, we used GUI Course Web single-action commands and annotated each example with expectation and caption using InternVL2-26B MLLM (method analogous to WaveUI). For training with 51k commands, 6k MLLM generated annotations of each type improved result (see Table 3), but only for annotation objective.

Similar ablation was performed on AMEX with metadata multitask (based on Android XML annotations) compared to MLLM multitask (generated by us) and 50% of commands (functionality) (see Table 2). All multitask approaches yield 59% on Screenspot, but MLLM multitask is better on OmniAct, outperforming software-based metadata. Training on 100% command data produces worse result than baseline. Other MLLM annotation approaches were investigated (using InternVL2). We tested labelling screenshots without manual supervision, this however did not outperform smaller high quality corpora on present benchmarks.

4.6 Fail analysis

30% of failed examples suggest spurious signals that were taught to produce right answer for wrong reasons. One such example is positional bias: model clicks on the left and the top of the screen, where various menus are often found. Other is misinterpretations of similar icons. 20% of failed examples are "missed" clicks: model clicks very closely to correct button, but slightly off-mark. Both of these problems might be mitigated by multitask training, with model trained to reason about the UI and attend to specific parts of screenshot.

[4]Trainset like Table 5 but only 10% of GUI course and 10% of AMEX OD used.

	Screenspot	Omniact
AMEX alone, 50% commands	51.4	19.6
+ *metadata and MLLM multitask*	59.6	25.0
+ *metadata multitask*	59.2	25.0
+ *MLLM multitask*	**59.7**	**31.2**
+ *50% commands*	47.6	14.0

Table 2: Annotation and multitask training on AMEX

	Screenspot
TinyClick on 50% GUI Course web single	52.0
+ *6k annotations - text output*	**55.9**
+ *6k annotations - box output*	53.1
100% GUI Course web single	53.2

Table 3: Annotation and multitask training on GUI Course web single turn data.

	Screenspot
TinyClick[4]	72.5
w/o AMEX	71.9
w/o multitask	**67.3**
w/o multitask except metadata	68.1

Table 4: Training data ablation study of TinyClick model.

5 Conclusions

TinyClick model strongly improves present baselines, achieving 73.8% on Screenspot and 58.3% on OmniAct, while being much smaller than competing solutions and small enough to work with sub-second latency. Furthermore, we confirmed that augmenting manually annotated agent data with MLLM for multitask training improves the performance.

6 Future Research

The presented contribution suggests a few new research problems to investigate.

- TinyClick can be used as a component for multi-turn agent.
- MLLMs, thus far showing weak performance on UI control, might benefit from training strategy similar to ours.
- Florence2, as a grounding and detection model, allows to adapt out-of-domain by simultaneous use of annotated images and natural language explanations (fostering novel approach to grounding and detection).

Limitations

From user perspective, TinyClick should be considered a research artifact. It is limited to supporting only single-turn commands and does not achieve the level of accuracy or functionality needed to serve as a full-fledged assistant. Many device-specific actions, such as hardware buttons or touch gestures are not supported. Some of model predictions show biases, such as clicking unrelated elements on top of screen, where menus are found.

Furthermore, the results show a large difference between training on full suite of data and training on smaller datasets, suggesting importance of representative training dataset. Thus, user might experience much worse real-world accuracy when testing model on new apps and systems.

While TinyClick beats prior baseline by 20 percentage points with 35 times smaller model, our understanding of this improvement is not yet complete. Multitask training accounts for part of the improvement and also quality and diversity of training data is important. Other factors might be involved, such as Florence2 multitask pretraining on vision corpora, or Florence2 architecture (high resolution vision backbone, or use of location tokens), or favorable proportion of compute resources to model size. Answer to these questions requires further experiments, and possibly large investment for training new models from scratch. Other important yet poorly understood area is composition of datasets: with results strongly conditional on data distribution, it is not clear what this data distribution should be in general, in regard to tasks, apps and systems and how robust are the default proportions we used. Similarly, the robustness of most training parameters has not been tested (on the other hand presented configuration is fairly robust: dozens of similar experiments yield results over 70% on Screenspot).

Ethics

Model uses language-modelling architecture similar to MLLM, which could in principle expose it to output personal information or offensive, or misleading content. However, the model is trained to predict agent actions and uses only 0.27B parameters, which makes its language capabilities very poor. It is meant to be used only with predefined prompt, with its output parsed by the software layer as agent command. For similar reasons, it is unlikely that any personally identifiable information (such as photographs) are learned from the images, or produced in the output.

Relevant risk comes from unsupported real-world usage, which could lead to loss of data or even more serious damage, if the model wrongly executes commands. We recommend to test the model only on emulator, virtual machine or other controlled environment. Any risk-sensitive application (such as banking, decision-making, controlling machines...) should be strictly avoided.

Florence2 model is available under MIT license, while the datasets use open licenses that explicitly allow research use (CC BY, Apache 2.0 etc). We have made our model checkpoint and code accessible under the MIT license, ensuring easy and unrestricted use for research purposes.

During our works LLM assistants were used for code auto-completion and text proofreading.

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A Data Stack

In Table 5 we show summary of datasets used for training. AMEX OD is object detection data, for detecting all annotated UI elements. The data was processed from Android XML annotations, with long strings or URL removed. AMEX Functionality is command dataset, provided by dataset creators, while Purpose and Expectations were created by us using MLLM. GUI Course web-single refers to commands extracted from web single-action part. For two fields, "command" and "thought", we include both as commands (unless they are identical). Thought is often more detailed and explicit command. For Wave UI we removed Web UI (as there are concerns regarding copyright and use of personal data in this dataset), as well as Screenspot and Omniact, used for testing and validation. MLLM annotations, provided by dataset authors, are used for multitask training.

B Training procedure

We use industry-standard training procedure. For results in Table 1 we train model for 3 epochs, performing validation every quarter of epoch. Learning rate is $2.5 \cdot 10^{-5}$, optimizer is AdamW with 1% decay. Batch size is 8 per GPU. We use OneCycleLR scheduler from PyTorch (Ansel et al., 2024). We developed our code using Transformers (Wolf et al., 2020) and PyTorch Lighting (Falcon and The PyTorch Lightning team, 2019). We did not perform hyperparameter search for presented training configuration. According to common procedure, we apply augmentations to images during the training, using Albumenations library(A. Buslaev and Kalinin, 2018):

```
import albumentations as A
import cv2

augmentations = [
    A.SafeRotate(limit=(-10, 10),
        p=0.5, border_mode=cv2.
        BORDER_CONSTANT),
    A.ColorJitter(0.05, 0.5, 0.4,
        0.5, p=0.7),
    A.ToGray(p=0.4),
    A.GaussianBlur(sigma_limit
        =0.4, p=0.2),
    A.CoarseDropout(
```

Dataset	Rows	Use	Type
AMEX OD	98.5k	30%	object detection (metadata)
AMEX Functionality	296k	50%	commands
AMEX Purpose	296k	50%	multitask (MLLM)
AMEX Expectation	28.9k	100%	multitask (MLLM)
Wave UI	44.2k	100%	commands
Wave UI expectation/caption/purpose	3x44.2k	100%	multitask (MLLM)
GUI Course web-single	102.8k	100%	commands
GUI Course caption/expectation	2x51.4k	100%	multitask (MLLM)
RICO ScreenQA	56.6k	100%	visual question answering
Android Control	51.9k	100%	commands

Table 5: Trainset composition for best training configuration (Table 1).

```
            max_height=8,
            max_width=8,
            min_holes=20,
            max_holes=40,
            min_height=8,
            min_width=8,
            fill_value=0,
            p=0.25,
        ),
        A.PixelDropout(dropout_prob
            =0.03, p=0.2),
]
```

C Data annotation prompts

Below we show example prompt for InternVL2, used to annotate GUI Course examples with expected outcomes. For GUI Course there are two commands for every example, one describes purpose, the other ("thought") describes specific action. To denote specific UI element, we mark red frame around it (which is referenced in the prompt). Similar prompts were also used for other datasets and task types.

```
<image>
You are given a UI screenshot. In
     the red box you can see UI
    element. The command, showing
    purpose of this UI element is
    described in 'command' field.
    Your task is to generate an
    expectation - what will happen
     after interaction with UI
    element in the red box. You
    are not telling about red box
    in expectation output.

## EXAMPLE
Lets suppose the screenshot show
    UI with a lot of icons. The
    red box is around Google
    Chrome.
example input:
{"command": "open web browser", "
    action": "click round
    multicolored Chrome icon"}
example output:
{"expectation": "the google
    chrome starting page will be
    opened"}

## TASK
input:
{"command": "<command>", "action
    ": "<thought>"}
output:'''
```