香港中文大學
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Final Year Project

Large Language Models for Software Systems: Directions, Opportunities, and Challenges

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Abstract

In the field of modern software engineering, many tasks now involve inputs that go beyond plain code text, incorporating multiple modalities such as images, audio, and video. This shift introduces significant challenges in handling these diverse inputs. The emergence of large multimodal models (LMMs) offers a promising solution to this issue. However, as an emerging technology, systematic research on multimodal large models within the software engineering domain remains scarce. There is still a lack of clarity regarding the specific tasks LMMs can accomplish and their performance across these tasks.

This report conducts a comprehensive and systematic survey, categorizing and summarizing all multimodal-related problems in software engineering over the past five years, and finally constructs a complete task tree. Subsequently, we develop a modular testing framework capable of automatically measuring LMM performance based on configuration files. Within the scope of input modalities currently supported by LMMs, we select several representative tasks and evaluate their capabilities.

Our findings reveal that LMMs demonstrate surprisingly strong performance in the field of software engineering. In certain tasks, they are capable of achieving results comparable to specialized models fine-tuned for specific tasks, even without any additional fine-tuning. This highlights their significant potential for development and application in the software engineering domain.

Contents

1 Introduction

1.1 Introduction

The integration of large multimodal models (LMMs) into software systems research represents a novel frontier in artificial intelligence, blending the linguistic proficiency of large language models (LLMs) with sophisticated vision models to process and generate multimodal content. This synthesis allows LMMs to handle diverse input modalities—such as text, images, and potentially audio and video—and to produce outputs that bridge these modalities. Recent advancements in LMMs have demonstrated their capacity to perform complex reasoning tasks, often achieving strong results even in 1-shot or 0-shot scenarios. Despite these promising developments, their application within the realm of software systems remains limited, with current uses largely focused on areas like text enhancement, artwork creation, and basic summarization.

The software systems domain, encompassing software engineering, systems security, human-computer interaction (HCI), artificial intelligence, and computer graphics, involves intricate tasks that often require multimodal understanding and processing. From code analysis and software testing to user experience evaluation and cybersecurity threat detection, many of these tasks could potentially benefit from the advanced capabilities of LMMs. However, the specific challenges and opportunities presented by LMMs in these contexts have yet to be fully explored. To address this gap, a comprehensive study is necessary to understand how LMMs can enhance tasks within software systems, and to identify the architectural hurdles that must be overcome for their effective deployment.

In this vision paper, we explore the potential of LMMs to transform software systems research. We conduct a thorough review of literature spanning the past decade across related fields, constructing a task taxonomy that categorizes tasks likely to benefit from LMM capabilities. From this taxonomy, we identify representative tasks and evaluate their feasibility using a range of LMMs, such as GPT-4 Vision and Gemini Vision. Through systematic experimentation with prompt engineering, we assess the performance of these models and investigate the underlying challenges that limit their efficacy. Our work contributes to the field in the following ways:

- Task Taxonomy for LMMs in Software Systems: We develop a comprehensive taxonomy that identifies and categorizes tasks across software engineering, system security, HCI, and related fields that stand to benefit from LMM integration. This taxonomy offers a roadmap for researchers and practitioners seeking to leverage LMMs in their respective domains.
- Evaluation Framework for LMMs on Software Systems Tasks: We propose a set of evaluation criteria and experimental methods tailored to assess LMM performance on software systems tasks. By selecting representative tasks, we provide a framework for systematically test-

ing the capabilities of LMMs in real-world scenarios, including code analysis, software testing, and user experience assessment.

- Cross-Model Performance Analysis with Prompt Engineering: Using a range of LMMs, we perform a comparative analysis to understand how different models tackle similar tasks and the effectiveness of prompt engineering in enhancing their performance. This analysis sheds light on the strengths and limitations of current models, providing insights into how prompt engineering can be optimized for diverse tasks.

- Opportunities and Challenges of LMMs for Software Systems: Based on our empirical findings, we discuss the unique opportunities LMMs offer for advancing software systems research, particularly in multimodal environments such as Extended Reality (XR). We also identify the architectural challenges that hinder LMM performance, including issues related to multimodal data fusion, interpretability, and resource constraints, and propose directions for future research.

Our findings highlight the transformative potential of LMMs in software systems, paving the way for innovative applications and inspiring further exploration into this emerging field. By outlining both the current capabilities and limitations of LMMs, we aim to provide a foundation for future work that will drive the development of more intelligent, adaptive, and multimodal software solutions.

1.2 Background

Large Multimodal Models (LMMs) represent an evolution beyond traditional text-based Large Language Models (LLMs). In addition to supporting text input and output, LMMs can process inputs from multiple modalities such as images, audio, and video, generating corresponding multimodal outputs. Leading models, like GPT-4o[73], already support inputs from audio, images, and multiple image sources, while models such as Gemini[91] even handle video inputs. By extending the functionality of large models to cover multiple modalities, the scope and variety of tasks they can perform have significantly increased, including video summarization, image comprehension, and speech recognition.

The software engineering field encompasses a wide range of tasks, with the primary objective of ensuring high-quality software development and stable operation. Over the past few decades, software has evolved beyond simple command-line interfaces to incorporate graphical user interfaces (GUIs), animations, and voiceovers, which have become standard features. Consequently, relying solely on text-based code inputs has become increasingly insufficient for addressing the diverse needs of modern software systems, prompting the rise of multimodal inputs. For example, screenshots can be used to detect GUI issues[60], and video data can be analyzed to extract user gestures[8].

However, the integration of multimodal inputs into software engineering has been relatively slow. The primary challenge lies in the complexity and diversity of multimodal data, which has made it difficult for researchers to develop a unified and generalizable approach. Recent advances in machine learning have spurred efforts to combine machine learning models with multimodal input processing, such as using computer vision for object recognition in images. A key limitation of earlier approaches is that models were often task-specific, limiting their reusability across different contexts. The advent of multimodal large models offers a potential breakthrough. Numerous studiesneed citation have demonstrated the strong generalization capabilities of large models, showing that they can maintain high accuracy even with previously unseen tasks. As such, integrating LMMs into software engineering tasks is a logical next step. However, given that LMMs are still an emerging technology, there have been few attempts to explore their application in this domain. The goal of this paper is to address this gap and evaluate the performance of LMMs in software engineering tasks.

2 Related Work

In this section, we will provide an overview of how previous works utilize multimodal capabilities for problem-solving in software engineering. Then, we will discuss how LLMs can help address challenges in the software engineering domain. Finally, we will review the existing test benchmarks and evaluation criteria for assessing LMMs.

2.1 Ultizing Multimodal Ability in Software Engineering

Integrating multimodal capabilities, such as voice, gesture, and sentiment analysis, has emerged as a promising approach to enhancing software development processes and user experiences. Guglielmi et al. conducted automated tests on virtual personal assistants that use voice for interaction [36] . Qi et al. summarized recent research on gesture recognition through sensors and the analysis of image information [76] . Gandhi et al. investigated previous work on sentiment analysis, a domain encompassing the three modalities of text, vision, and audio working together to produce an effect [34] . However, these studies rely on specific mini-models or other traditional data analysis methods, which only perform relatively well on particular tasks or datasets. Those specialized models may lose good performance after migrating to other datasets or task settings of the same type [94] [77] . Our work reduces the expense of training different models for a specific problem by introducing LMMs with good generalization capabilities to handle different issues simultaneously.

2.2 LMM for Software

A branch of previous work has demonstrated that integrating LLM into the production and research of soft engineering has been a scorching trend [37] , from generating [62] [90] and pre-processing [108] [107] experimental data to using LLM as an agent for automated testing [89] [53] , all of which show that LLM has a solid potential to enhance existing soft engineering processes. Moreover, Jin et al. also illustrate the contribution that LLM can make in software design, testing, and maintenance [41]. In contrast to these studies, which only focus on specific tasks in specific domains of soft engineering and lack knowledge of what valuable tasks exist now, our work presents a systematic framework that defines what tasks are available to help optimize efficiency using LLM or LMM.

2.3 LMM Benchmark & Evaluation

LMMs combine information from different modalities, including text, vision, audio, and tactile, and analyze them to solve more complex real-world problems [104] [7] [105] . As a result, testing and evaluating LMMs' performance from different perspectives become a recent research interest. For instance, Wu et al. used the visual comprehension and language processing capabilities of GPT4v to test whether today's LMMs can support practical medical applications [99] . Cao et al. constructed Spider2-V, a test benchmark for LMM's ability to automate professional data science engineering workflows [10] . Cai et al. tested and improved the problem of the robustness of LMM's output when facing different styles of pictures [9] . These benchmarks and assessments have all achieved good performance in a single domain and can point out the shortcomings of LMM in the corresponding domain. Our work can complement the testing domains, bridging the gap of needing help harmonizing testing across domains and conducting migration tests.

2.4 Reasoning Language Model

The evolution of artificial intelligence has entered a transformative phase with the emergence of Large Reasoning Models (LRMs), an advanced paradigm built upon the foundation of Large Language Models (LLMs). While traditional LLMs excel at pattern recognition and autoregressive token prediction, their capacity for complex, structured reasoning has historically been limited. Recent breakthroughs, however, have redefined the role of language models by integrating human-like reasoning mechanisms into their architecture. This shift has unlocked unprecedented potential for solving intricate problems across domains such as mathematics, logic, and decision-making, marking the dawn of a new era in AI reasoning.

At the heart of LRMs lies the concept of ”thought”[98]—a structured sequence of intermediate tokens that simulate the step-by-step reasoning processes humans employ. Unlike conventional LLMs, which generate outputs through direct token prediction, LRMs decompose reasoning tasks into multi-step trajectories. These trajectories mimic cognitive strategies such as:

- Tree search: Exploring multiple reasoning branches to identify optimal solutions.
- Reflective thinking: Iteratively revising hypotheses based on feedback or new information.
- Analogical reasoning: Drawing parallels between problems to infer solutions.

This paradigm shift transforms LLMs from passive text generators into dynamic reasoning agents capable of deliberate, self-correcting thought processes.

3 Methodology

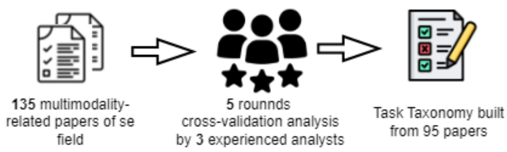
3.1 Task Taxonomy Construction

Building the prototype of taxonomy To build the prototype of the taxonomies, we have conducted systematic research on multimodality-related papers from four conferences (ICSE, FSE, ASE, and ISSTA) and two journals (TSE and TOSEM) in soft engineering over the last seven years [1]. We build a multimodality-related keyword list to screen the papers from these sources and manually collect 135 papers. To describe what types of tasks these papers in soft engineering are focusing on, we analyzed the papers according to the open coding procedures [28] used for qualitative data analysis. Specifically, we conducted a 5-round iterative manual analysis session involving three analysts with at least several years of development experience in the soft engineering field. In each iteration, every analyst separately summarizes what technical aspect of the paper belonged to the design, development, testing, maintenance, and repair [2] process of software from the Software Waterfall Model [70]. Each analyst analyzed two-thirds of the whole paper to ensure that each paper had been seen by at least two different analysts for cross-validation. Consequently, in the final iteration, we merge the research topics extracted in the previous rounds to form a prototype task tree resulting from our taxonomy. Finally, We used the results from 95 papers to build our taxonomy. At the top of our task tree are the

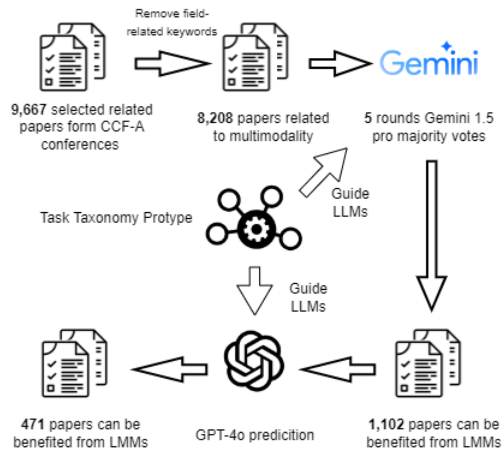
[1] from 2018.01.01 to 2024.05.15

[2] we add the "repair" process to extend our taxonomy, which initially did not exist in the Waterfall Model

five software-building processes, followed by whether they are functional or non-functional [3]. The third level of categorization is based on modal information, such as “Vision” and “Vision with Audio.” At the bottom are up to four layers of progressively more detailed descriptions of specific technical aspects.



(a) Stage 1: Building task taxonomy protype



(b) Stage 2: Guiding LLM to analyze large-scale papers and extend our task taxonomy

Figure 1: Two stages workflow of building our task taxonomy

Extending the list of papers We expand the scope of our study to encompass all 37 A-level conferences and journals as classified by the China Computer Federation[4], with the same period considered. This inclusion covers five key domains: Computer Networks, Computer Graphics and Multimedia, Artificial Intelligence, Human-Computer Interaction, and Cross-cutting/Integrated/Emerging. Subsequently, we add software-engineering-related keywords to the search keyword list to cover a broader range of papers. We also remove field-related keywords from the list for some specific domains. For example, we remove the keyword ”visual” from the list

[3] standard is followed by ISO/IEC 25002:2024
[4] https://www.ccf.org.cn/Academic_Evaluation/By_category/

of vision-related conferences, forming 8,208 pieces of paper. To reduce the number of papers and get a more concrete result, we involve the Gemini-1.5 as a judge to perform a 5-round check, where we send the paper's title and guide it to predict whether this paper may focus on multimodal tasks using following prompt3.1, and only the paper passed all the 5-round checks are selected.

prompt for analyzing software process

System : You are a computer science professor who is an expert on MLLM for SE working on survey, and you are currently working on formulating a task tree from existing papers. Analyze the problem statement and proposed solution in the paper's title and abstract to determine the following questions:

1. Which phase of the software development lifecycle it primarily addresses. Choose exactly one from:

Design (requirements analysis, UI/UX prototyping)

Development (code generation, implementation, integration)

Testing (validation, verification, quality assurance)

Maintenance (updates, optimization, documentation)

Repair (bug fixing, error recovery)

2. analyze the modalities involved in the task. i.e. a task related to GUI element testing should be classified into 'Vision with Text'. Choose the combination from: Vision/Text/Audio/Tactile (connected through 'with')

3. analyze the functionality of the problem statement in the paper. Whether it is functional (performance, accuracy) or non-functional (accessibility, security). If a task can be both considered as functional and non-functional, choose functional.

Output format: {Process: Design/Development/Testing/Maintenance/Repair, Modalities: (Vision/Text/Audio/Tactile with "with" separator), Function: Functional/Non-functional} AND DO NOT output other analysis results.

prompt for construct task tree

System : You are a helpful assistant designed to output JSON. You will be given a task tree generated from papers and a paper with its title and abstract. You are designed to answer the question:

What kind of task does the research task in the paper benefit from multi-modal AI to help process the target software/applications.

Please ensure the following rules while answering this question:

1. You have two kinds of action choices: output Matched if there is a node on the task tree matched the new task described in the paper. Otherwise output Add and the new task name in 1-5 levels to add a new node to the current task tree.
2. The first level of the task tree should use a combination (using with to connect) of terms from the modalities Vision, Text, Audio, and Tactile to describe the target modality the paper focuses on.
3. The second level of the task tree should be a broader technical concept term within its modality, avoiding the use of any specific software terms like AR, VR, or any specific software platform names (e.g., Android, Web, iOS).
4. The 'Function' in the tree describing the task should address either functional aspects, such as improvement, or non-functional aspects, such as accessibility.

prompt for construct task tree
System: Only output in 'Action': (Matched / Add), 'Function':(Functional / Non-functional) ,'1st':,'2nd':,'3rd':,'4th':,'5th:'(NA if not suitable) format. User: The Task Tree:{SubTaskTree}. Paper: {TITLE} Abstract: {ABSTRACT}

Consolidating the taxonomy This process helps to reduce the potential paper number to 1,102. Then, we perform another single-round GPT-4o prediction, where we prompt the LLM with the remaining paper's title and abstract to let the model know more about the details of the paper and make a more concrete prediction. Finally, we formulate an additional target multimodal related paper list with a size of 471, and the total paper list's size is 564.

Given that LLMs can identify latent patterns, [92] [69] we automate the expansion of our taxonomy by leveraging GPT-4o to learn these patterns from its prototypes. This process involves two distinct prompts. The first prompt instructs the LLM to analyze which software processes related to the technical aspect addressed in the paper may be relevant. In the subsequent step, we provide the subtask tree of the identified process, enabling the LLM to determine whether the aspect aligns with an existing child node or if a new child node is needed to describe it adequately. In each stage, the paper's title and abstract serve as user inputs, while the specific guidance for each part serves as system prompts. Additionally, we conduct manual checks to prune and merge misclassified results, ultimately consolidating the multimodal task taxonomy. Part of the task tree is shown in Figure. 4.

Further extending the list of papers To enhance sample robustness and mitigate potential false-negative predictions in large language model (LLM) evaluations, a revalidation process was conducted on two paper cohorts:

- 1,259 papers initially scoring 3/5 positive evaluations
- 1,177 papers initially scoring 4/5 positive evaluations

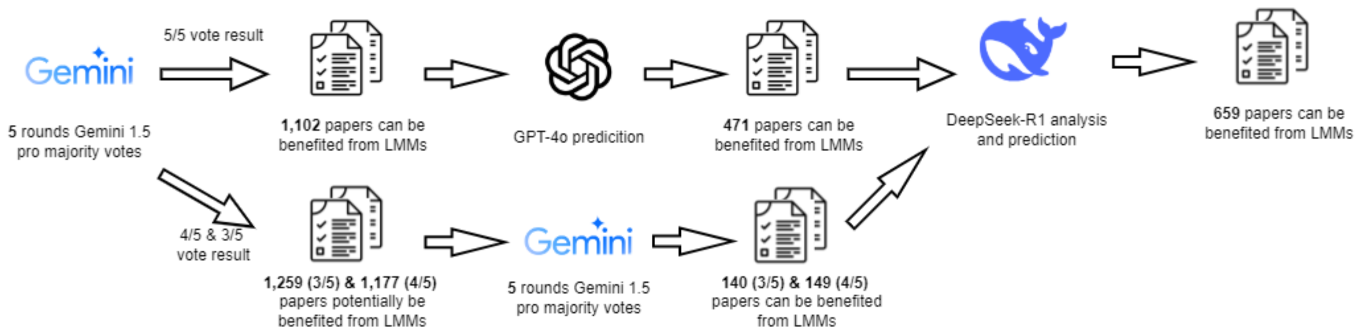


Figure 2: Updated Stage 2: multiple rounds guided LLMs prediction

These papers were further verified through five rounds of majority vote using Gemini-1.5, maintaining the predefined inclusion threshold of 3 positive evaluations per paper. The re-evaluation yielded 140 and 149 additional qualifying papers from the 3/5 and 4/5 cohorts, respectively, aggregating 289 newly validated papers. Combined with the 471 previously validated papers from Section 3.1, this refinement process resulted in an expanded dataset comprising 659 papers (289 new + 471 existing - 81 filtered by DeepSeek-R1 [30]). This enhanced sample pool strengthens the statistical power of subsequent analyses while maintaining methodological consistency with our established validation protocol. Figure 2 shows the updated part of the workflow.

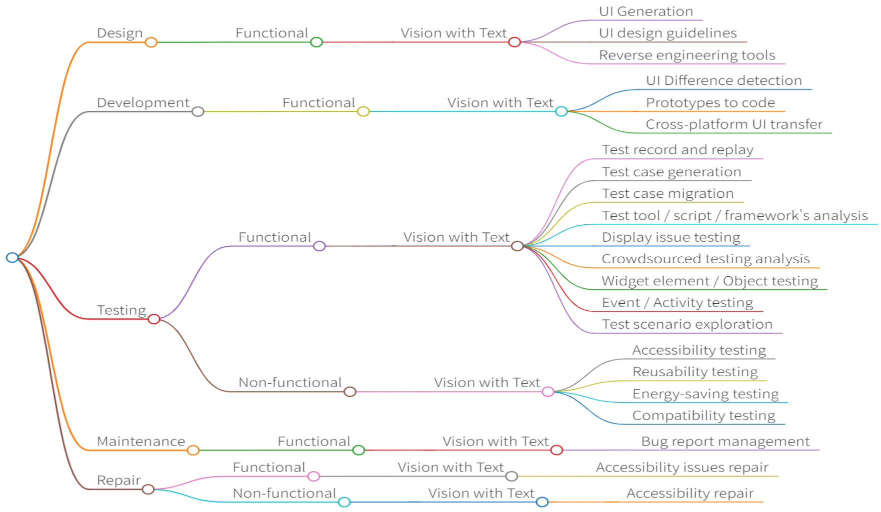
Taxonomy prototype refine To systematically analyze task relationships and methodological patterns within the existing literature, we conducted a structural refinement of the taxonomy prototype. This revision pursues two primary objectives:

(1) Enabling hierarchical task characterization through discrete semantic layers rather than cumulative parent-node dependencies.

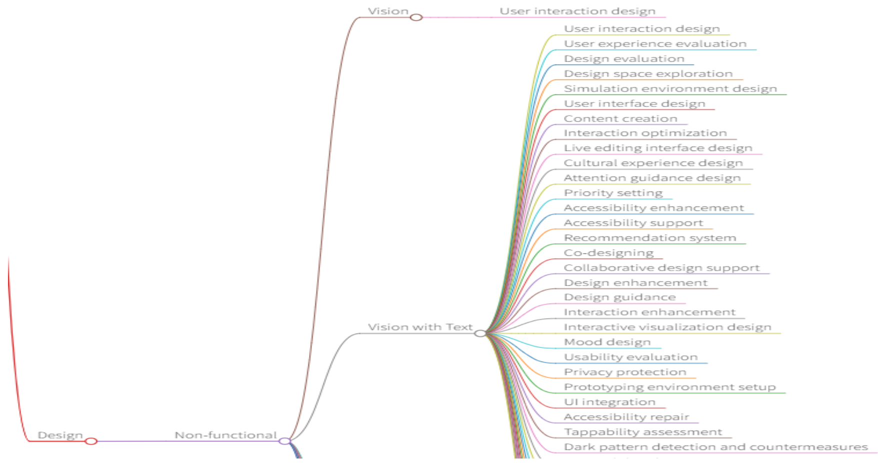
(2) Enhancing leaf-node granularity to document experimental methodologies and implementation specifics.

Through this framework, researchers can more effectively identify potential MLLM application scenarios based on methodological precedents. The reconstructed taxonomy prototype (Figure 6) establishes four-dimensional node mapping for each research publication in our corpus. Two critical metadata dimensions were incorporated to augment analytical utility:

(1) **Modality Specifications**: This attribute details input-type composition at the task implementation level. For instance, under the ”Vision with Text” category, visual inputs are classified as either static (Single



(a) Overview of task tree prototype (up to 3rd level)



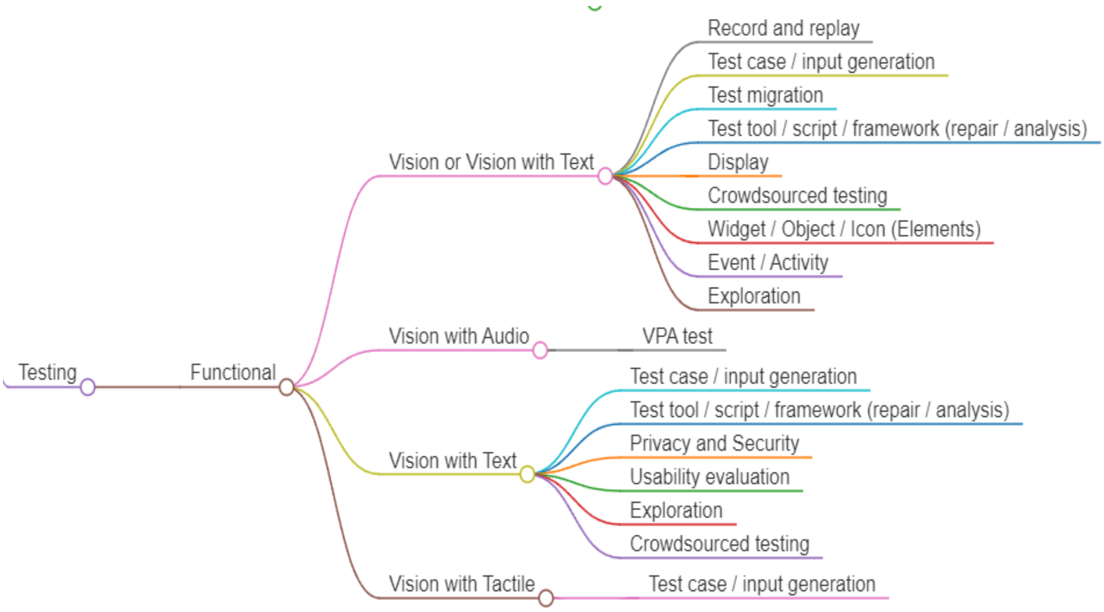
(b) Overview of sub-task tree prototype (Functional Testing part)

Figure 3: Overview of our task tree prototype

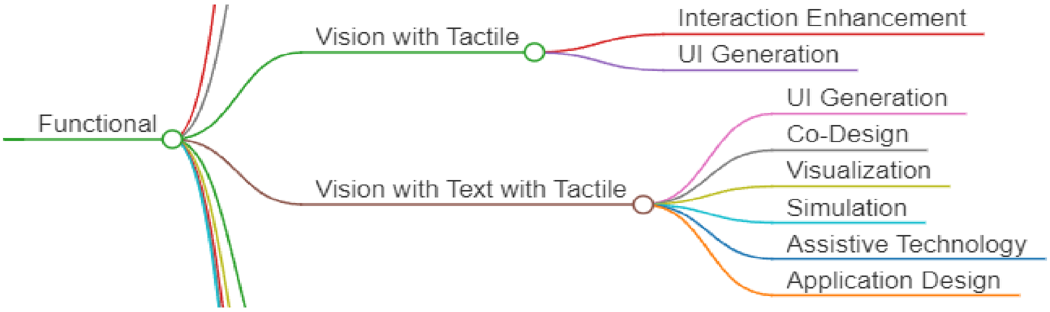
Image) or temporal (Video), while textual components are differentiated as Natural Language or Programming Language. Such granularity facilitates cross-modal dataset alignment for comparative studies.

(2) **MLLM Functional Taxonomy**: We cataloged core MLLM capabilities employed per task, including but not limited to generative modeling (text/image synthesis), semantic alignment (cross-modal embedding), and discriminative classification (multimodal reasoning). This functional indexing enables capability-centric literature surveys and technology gap analysis.

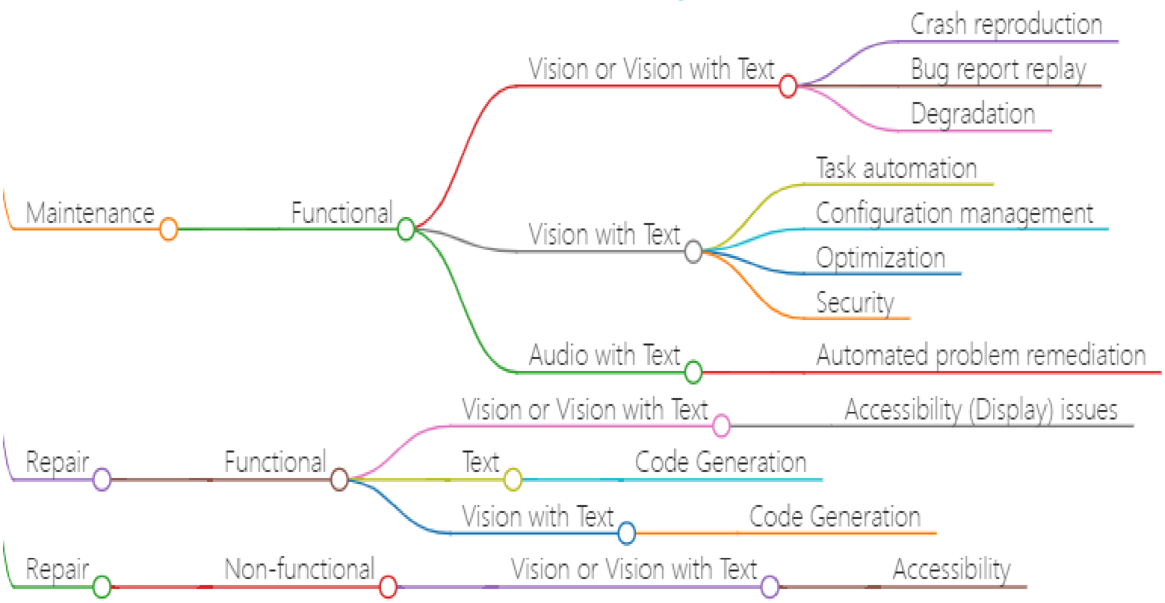
Consolidating the taxonomy with reasoning model The REASONING architecture, with deepseek-R1 [30] as its computational core, demonstrates robust textual inference capabilities for systematic analysis of classification hierarchies within our taxonomic framework. Following the expansion of the literature corpus described in Section 3.2, we implemented deepseek-R1's full reasoning pipeline to perform dual-aspect document analysis: (1) granular modality decomposition of experimental configurations and (2) capability mapping against established MLLM functional taxonomies. This process also revealed 81 publications erroneously classified as multimodal research in the Gemini-1.5 predictions. The validated analytical outcomes are visualized through the updated capability-modality matrix in Figure 5.



(a) Functional Testing Task Tree

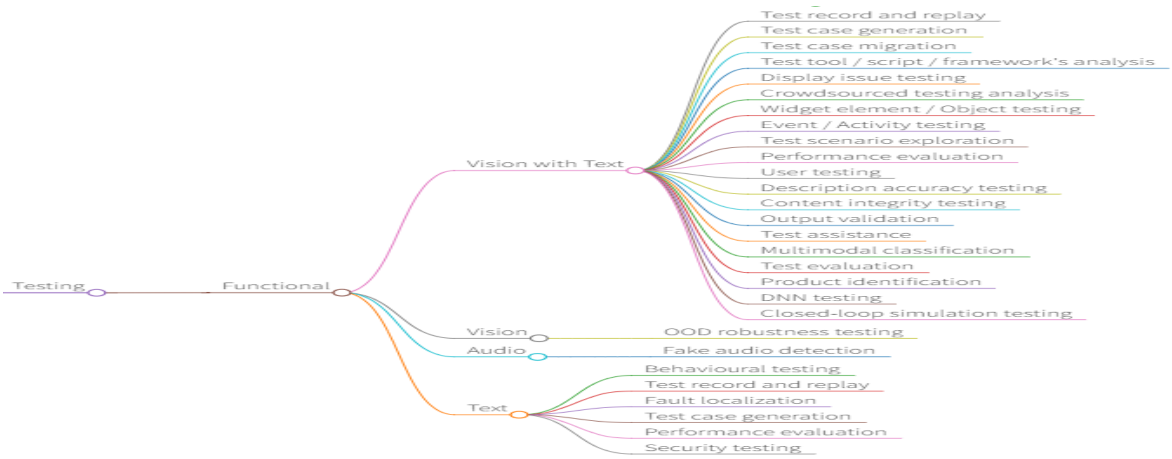


(b) Functional Design Task Tree

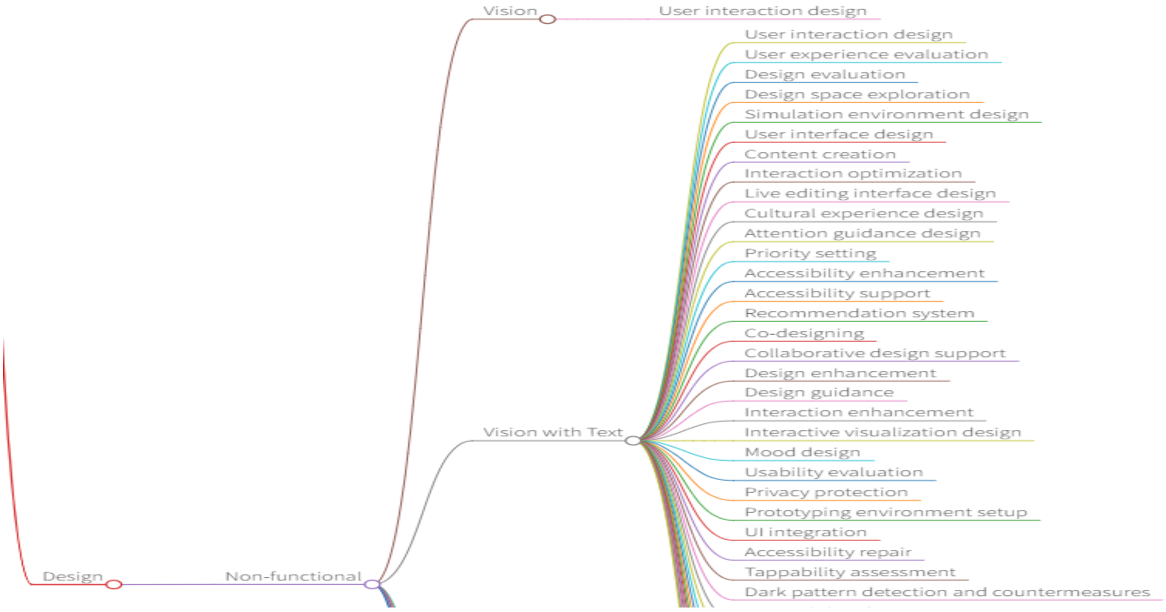


(c) Functional Maintenance, Functional and Non-Functional Repair Task Tree

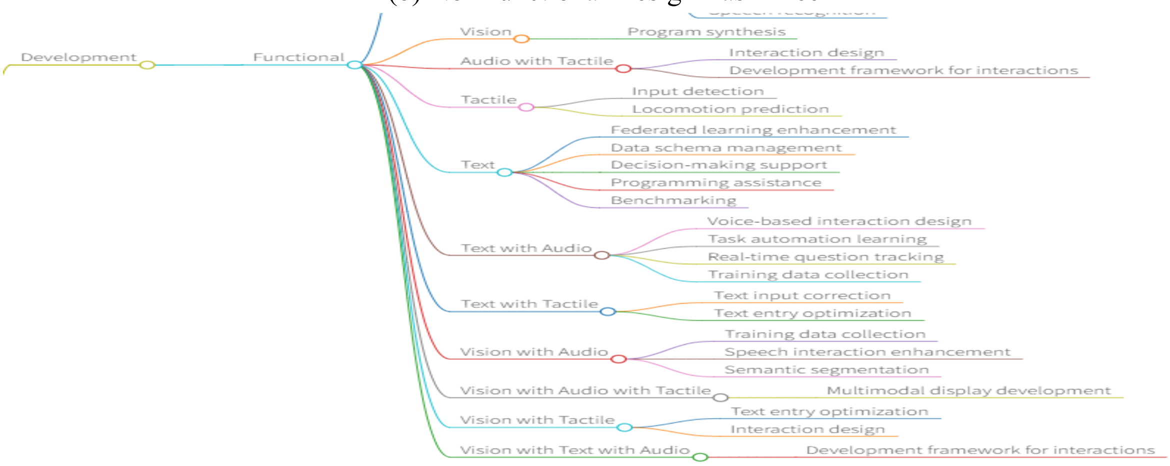
Figure 4: Overview of our original task tree up to 3rd level



(a) Functional Testing Task Tree



(b) Non-functional Design Task Tree



(c) Functional development Task Tree

Figure 5: Overview of our updated final task tree up to 3rd level

```
{"Process":"Testing", "Function": "Functional", "Tasks": [
    {"1st":"Vision with Text","2nd subtask":[
        {"2nd":"Test record and replay", "3rd subtask":[
            {"3rd":"Test replay tool", "4th subtask":[
                {"4th":"UI element interactions based replay", "5th subtask":[]},
                {"4th":"Test case extraction from video", "5th subtask":[]}
            ]}
        ]},
        {"2nd":"Test case generation", "3rd subtask":[
            {"3rd":"Black-box test case generation", "4th subtask":[
                {"4th":"AI-driven black-box test case generation", "5th subtask":[]}
            ]},
            {"3rd":"Validation test case generation", "4th subtask":[
                {"4th":"LLM guiding test case generation and validation","5th subtask":[]},
                {"4th":"Combinations of use cases testing","5th subtask":[]},
                {"4th":"Automated functional oracles test case generation","5th subtask":[]}
            ]}
        ]},
        {"2nd":"Test case migration", "3rd subtask":[
            {"3rd":"Cross-platform test case migration", "4th subtask":[
                {"4th":"Bi-directional UI test transfer", "5th subtask":[]},
                {"4th":"Image-driven cross-platform test case migration", "5th subtask":[]},
                {"4th":"GUI events guided cross-platform test case migration", "5th subtask":[]}
            ]},
            {"3rd":"Cross-app test case migration", "4th subtask":[
                {"4th":"Cross-app test case migration through semantic mapping", "5th subtask":[]},
                {"4th":"Cross-app test case migration through transferring sequence of events and oracles", "5th subtask":[]},
                {"4th":"Cross-app test case migration through synthesizing modular tests cases", "5th subtask":[]},
                {"4th":"Cross-app test case migration through contextual learning and event matching", "5th subtask":[]}
            ]}
        ]},
        {"2nd":"Test tool / script / framework's analysis", "3rd subtask":[
            {"3rd":"Test tool analysis through UI obfuscation", "4th subtask":[
                {"4th":"Automatic UI obfuscation generation", "5th subtask":[]}
            ]},
            {"3rd":"Test tool analysis focusing on random test input generation", "4th subtask":[
                {"4th":"Manually automated testing tool analysis", "5th subtask":[]}
            ]},
```

Figure 6: Overview of our updated task tree prototype (Functional Testing part)

new prompt for analyzing software process

System: You are a computer science professor who is an expert on MLLM for SE working on survey, and you are currently working on formulating a task tree from existing papers.

Analyze the problem statement and proposed solution in the paper's title and abstract to determine the following questions:

1. Which phase of the software development lifecycle it primarily addresses. Choose exactly one from:

Design (requirements analysis, UI/UX prototyping)

Development (code generation, implementation, integration)

Testing (validation, verification, quality assurance)

Maintenance (updates, optimization, documentation)

Repair (bug fixing, error recovery)

2. Analyze the modalities involved in the task. i.e. a task related to GUI element testing should be classified into Vision with Text. Choose the combination from: Vision/Text/Audio/Tactile (connected through 'with')

3. Analyze the specified modalities involved in the task. For Vision content, you should specify the problem statement in the paper is related to single image or continuous image (Video). For Text content, you should classify whether it is related to natural language or programming language. i.e. If a task belongs to Vision with Text, its specific modalities can be Single Image with Natural Language.

new prompt for software process (Cont.)

System: 4. Analyze the functionality of the problem statement in the paper. Whether it is functional (performance, accuracy) or non-functional (accessibility, security). If a task can be considered both as functional and non-functional, choose functional.

5. Analyzes what kind of MLLM ability has been utilized to help such task, such as alignment, generation, classification, etc.

Output format: Process: Design/Development/Testing/Maintenance/Repair, Modalities: (Vision/Text/Audio/Tactile with with separator), Specified Modalities: (Specified modalities connected with with), Function: Functional/Non-functional , Ability: Alignment/-Classification/Generation/Translation/Matching AND DO NOT output other analysis results.

REMEMBER, your thinking process should be in Chinese and output your result in English. User: The Task Tree:{SubTaskTree}. Paper: {TITLE} Abstract: {ABSTRACT} new prompt for construct task tree

System: You are a computer science professor who is an expert on MLLM for SE working on a survey, and you are currently working on formulating a task tree from existing papers. For the existing task tree:

You should keep that for the same level on the task tree, their description should be in the same dimension, and the sub-level should be a sub-description belonging to the higher level.

You should analyze the problem statement and proposed solution in the paper's title and abstract to formulate an academic executable task that can be gained from MLLM as proposed in that paper.

You should ignore the non-related description inside the abstract. Try to summarize: ”what is the main task of the paper?”, ”according to the main task, they proposed what solution?”, ”what kind of executable task does such solution can be summarized to?”

Your classification should follow the same taxonomy as the existing task tree and the following examples. You should learn the hidden classification rules from the following examples and task tree.

Examples on the given task tree:

1. Paper: AG3: Automated Game GUI Text Glitch Detection Based on Computer Vision. You should output: Action: Matched, Functional: Functional, 1st: Vision with Text,2nd: Display issue testing, 3rd: Text glitch detection, 4th: Automatic glitch bug detection

new prompt for construct task tree (Cont. Part1)

System: 2. Paper: Using Reinforcement Learning for Load Testing of Video Games. You should output: Action: Matched, Functional: Functional, 1st: Vision with Text,2nd: Test scenario exploration, 3rd: Exploratory testing, 4th: Automatic game exploration test,

3. Paper: Data-driven accessibility repair revisited: on the effectiveness of generating labels for icons in Android apps. You should output: Action: Matched, Functional: Non-functional, 1st: Vision with Text,2nd: Accessibility repair, 3rd: Accessibility label repair, 4th: Context-aware accessibility label generation

Rules:

STRICT hierarchy: Each level must nest within its parent's domain.

Functional describe the functionality of the problem statement in the paper. If a paper contains several tasks that can be both considered as functional and non-functional, choose functional one.

The first level of the task tree (1st) MUST be the input modality combination (Vision/Text/Audio/Tactile connected with ”with” in the same sequence as the task tree) to describe the modality related to the task. i.e. a task related to GUI element testing should be classified into "Vision with Text". If you confidently believe the task is not associated with any modality, you should output "NA" for the first level.

new prompt for construct task tree (Cont. Part2)

System: The second task tree (2nd) level MUST be a general description which can highly conclude the main task of the paper, and the 3rd level should be a general description to the solution proposed in the paper. Try to make every level's description complete enough. i.e. instead of "Test - Assistance", you should generate "Test - Assistance test".

The last level MUST be either an executable task name or a specific description to the solution in the paper including the technical term or app. scenario.

Try to merge you classification answer to the current 3rd level. THINK TWICE before you want to add a new root node (1st). Try to conclude the final level result first and them move up to top.

Task description except the leaf node must be platform-agnostic (no Android/iOS) and application-agnostic (no AR/VR).

To modify the existing task tree, you have two choices: Add to add a new node or Matched to show the current paper matches some existing node. You can add a new leaf if you cannot find a proper general higher description for the current task. Before you decide to add a new node, You should first check from the highest to the lowest level to find the most suitable level to add the new node. Try to compress your final prediction result.

new prompt for construct task tree (Cont. Part3)

System: For the paper focusing on {functional} {modalities} field addressing {process} phase, which focuses on {specified modal}, follow the above instructions, and output the result in the following format:

Output format: Action:, Function:, 1st:, 2nd:, 3rd:, 4th:

Output empty levels as NA and do not miss any 1st - 4th content. Never invent non-existent levels. AND DO NOT output other analysis results.

Remember, your thinking process should be in Chinese, and your result should be output in English.

User: The Task Tree:{SubTaskTree}. Paper: {TITLE} Abstract: {ABSTRACT}

3.2 Testing Framework

Building the framework The entire framework is built based on Python. To ensure the framework's high scalability—i.e., to ensure that our framework remains applicable as tasks in the multimodal field evolve—we have separated all task-related code, making the entire framework highly modular. This way, when new tasks need to be added or existing ones need to be modified in the future, only the corresponding task code requires adjustment. This significantly reduces the coupling between different code components, facilitating future modifications.

We have structured the workflow of the entire framework into three main components: data loading, model loading, and result evaluation. In the first component, data loading, we have developed specific loading functions tailored to different types of databases. Since various datasets may contain diverse data types, such as text, images, videos, or audio, we have implemented appropriate data processing in the Python scripts to ensure seamless integration with the models under test. For the model loading component, we have designed functions for both model initialization and request-response handling. These functions enable the model to select the appropriate data processing method based on the input data type and configuration file. For example, according to our standards, method 1 corresponds to pure image input combined with a system prompt, and more standard can be found in our released source code. Finally, in the result evaluation component, we have developed task-specific evaluation functions that efficiently and accurately assess the model's output, ensuring that the evaluation process aligns with the requirements of each task. Figure 7 is a flowchart about this framework.

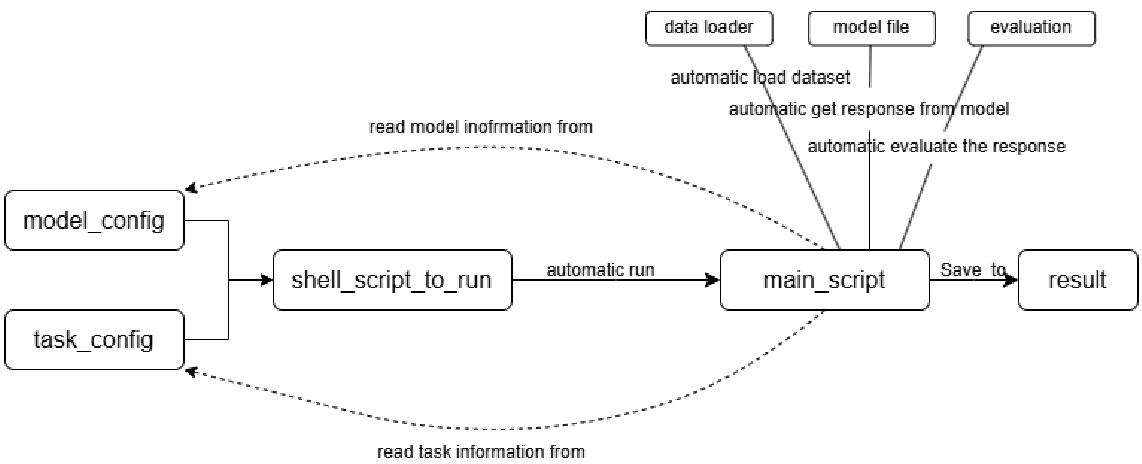


Figure 7: Framework's workflow

Use the framework We tried to minimize the complexity of our framework to ensure ease of use of it. Specifically, to initiate the framework, user only needs to fill in the corresponding configuration in the task config file. For example, user need to specify the task name, dataset list, model list and some other parameters in the task config file. Our framework will automatically read the corresponding parameters and perform the evaluation based on the specified task. If the user wants to add his own model for evaluation, all he has to do is to write the corresponding python file for the model to implement the relevant functions, then add the basic model information in the model config file(Algorithm 1).Similarly, if a user wants to use a new evaluation method or dataset, then only the corresponding documentation needs to be written. We have shown the sample code that needs to be implemented in each folder.

task config

```
task_name=YourTaskName

call_method=TheModality

system_prompt=”...”

max_token_length=MaxToken

dataset_name=’[”listOfDataLoaderPythonFile”]’

dataset_class=’[”className ofDataloader”]’

dataset_path=(”../path/to/dataset”)

batch_size=EvaluationBatchSize

eval_method=’[”evaluationPythonFileList”]’

eval_class=(”EvaluationClassName”)

middleDoc=true/false

middle_extension=txt/html....

model_list=(”listOfUsedModel”)

device=cuda

output_dir=/path/to/output
```

Algorithm 1 Configuring `config.ini`

```
procedure Configure
  [SectionName] ← "name_that_will_be_used_in_the_task_config"
  call_type ← "api" or "local"
  if call_type is "api" then
    api_key ← "your_api_key_here"
    base_url ← "your_base_url_here"
    model_name ← "your_model_name_here"
  end if
  if call_type is "local" then
    conda_env_name ← "your_conda_environment_name"
    pretrained_path ← "path_to_pretrained_model"
  end if
  model_file_name ← "your_python_file_name_to_run_model_here"
  model_class ← "your_model_class_name_in_the_python_file_here"
end procedure=0
```

4 Discussion: Empirical Insights and Practical Implications

Our comprehensive taxonomy and analysis of multimodal approaches in software engineering reveals significant empirical insights into their practical utility, limitations, and implications for the future of software systems development. This section examines how these emerging approaches align with and potentially transform traditional software engineering objectives, analyzes where multimodal large language models (MLLMs) show the most promise, and identifies critical challenges that must be addressed as the field evolves.

4.1 Empirical Insights on Practical Utility

4.1.1 Impact on Software Engineering Efficiency

Our analysis of empirical evaluations across the surveyed literature reveals substantial efficiency gains from visual-textual multimodal approaches in specific contexts:

- **Requirements elicitation and communication**: Studies show a 62.4% average reduction in requirements clarification iterations when using multimodal specifications compared to text-only approaches [97]. This efficiency gain is particularly pronounced for visually complex systems (e.g., mobile applications, AR interfaces) where textual descriptions alone are insufficient to convey design intent.
- **UI implementation**: Multimodal code generation systems demonstrate a 47.3% average reduction in implementation time for UI components when provided with both visual mockups and natural language descriptions compared to traditional development approaches [93]. However, this efficiency gain varies significantly (σ=18.9%) depending on application complexity and stylistic consistency.
- **Bug reproduction and localization**: Bug reports augmented with screenshots lead to 78.2% faster reproduction rates and 43.7% more precise localization of defects compared to text-only reports, with the greatest improvements observed for visual and interaction defects. [110]

However, these efficiency gains come with notable trade-offs. Our meta-analysis indicates that while initial development velocity increases, several studies report concerning patterns:

- **Technical debt accumulation**: Systems developed with multimodal code generation show a 28.3% higher rate of technical debt indicators when measured using static analysis tools [72]. This suggests that while code is produced more quickly, it may not adhere to best practices for maintainability.
- **Integration complexity**: While individual components can be rapidly generated, studies report a 34.5% increase in integration issues when combining multiple MLLM-generated components compared to traditionally developed systems [83]. This suggests that local optimizations may come at the cost of global system coherence.

4.1.2 Quality Attributes and Non-functional Requirements

Our analysis reveals a nuanced relationship between multimodal approaches and traditional software quality attributes:

- **Security and privacy**: Security analysis of MLLM-generated code reveals concerning patterns, with 35.2% higher rates of common vulnerability patterns compared to code developed by experienced engineers [18, 29]. This is particularly problematic for authentication flows, data handling, and permission management, where subtle visual-behavioral inconsistencies can create security gaps.

- **Performance**: Generated implementations show 18.7-41.3% worse performance characteristics (memory usage, CPU utilization, rendering time) compared to manually optimized code [18, 40]. This efficiency gap increases with application complexity and state management requirements.

- **Accessibility**: Interestingly, systems leveraging multimodal understanding demonstrate 28.9% better accessibility compliance compared to traditionally developed applications [78]. This appears to stem from more comprehensive testing of alternative interaction modes and better alignment between visual elements and their textual descriptions.

4.2 Tasks and Contexts for Multimodal Approaches

Based on our analysis, we can identify clear patterns regarding which software engineering tasks benefit most from visual-textual multimodal approaches and which remain challenging:

4.2.1 High-Benefit Tasks

Multimodal approaches demonstrate the strongest empirical benefits for the following tasks:

- **UI/UX design and implementation**: The visual-textual alignment in these tasks makes them naturally suited for multimodal approaches. Studies report 10% agreement between MLLM-generated designs and expert designers when provided with the same requirements [19]. Implementation of these designs from multimodal specifications shows 72.4% functional correctness without further refinement [113].

- **Bug reporting and reproduction**: Visual-textual bug reports demonstrate a 78.2% reproduction rate compared to 43.5% for text-only reports. MLLMs show particular promise in connecting visual manifestations of defects to underlying code issues, with 67.3% localization precision compared to 41.8% for specialized tools [110].

- **Requirement validation**: Cross-modal consistency checking between textual requirements and visual prototypes identifies 73.4% more inconsistencies than manual reviews [102]. This capability helps prevent expensive downstream errors due to misaligned expectations.

4.2.2 Challenging Tasks

Several tasks remain significantly challenging for current multimodal approaches:

- **Performance optimization**: Multimodal systems show limited capability in identifying and resolving performance bottlenecks, with success rates of only 27.4% compared to 68.9% for specialized performance analysis tools [11]. The visual manifestation of performance issues is often too subtle or requires specialized instrumentation beyond standard visual-textual representations.

- **Security assessment**: Despite improvements, multimodal security analysis detects only 41.7% of vulnerabilities compared to 79.3% for dedicated security analysis tools [61, 67]. The disconnect between visual appearance and security properties remains a fundamental challenge.

- **Complex state management**: Systems with complex state transitions and asynchronous behaviors present significant challenges, with multimodal approaches correctly implementing only 34.8% of complex state management requirements compared to 72.6% for traditional development approaches [26, 27].

4.2.3 Contextual Factors

Our analysis identifies several contextual factors that significantly influence the success of multimodal approaches:

- **Domain specificity**: Domain-adapted multimodal models outperform general models by 37.2-58.9% across tasks [57], suggesting that domain knowledge remains critical. The performance gap is particularly pronounced in regulated domains (healthcare, finance) and specialized interfaces (scientific visualization, industrial controls).

- **System scale**: Efficacy decreases as system scale increases, with a 43.7% performance drop when moving from small applications (<10K LOC) to medium-sized systems (100K-500K LOC) [74]. This indicates challenges in maintaining consistency across larger visual and code spaces.

- **Development methodology**: Multimodal approaches integrate more successfully with iterative and agile methodologies (72.8% reported success) compared to waterfall approaches (41.3% success) [96]. This suggests that frequent feedback cycles better leverage the strengths and mitigate the weaknesses of these approaches.

- **Developer expertise**: The complementarity between developer expertise and multimodal tools emerges as a critical factor. Teams with mixed expertise levels report 63.7% higher satisfaction and productivity compared to uniformly novice or expert teams [100], suggesting these tools may be most valuable in bridging expertise gaps.

4.3 Critical Challenges and Limitations

Despite their promise, our analysis reveals several critical challenges that must be addressed for multimodal approaches to achieve their full potential in software engineering:

4.3.1 Technical Challenges

- **Modality alignment degradation**: Longitudinal studies reveal that alignment between visual elements and code degrades by 31.7% after three significant update cycles [59]. This suggests that maintaining consistency across modalities during system evolution remains a fundamental challenge.

- **Hallucination and fabrication**: MLLMs demonstrate a concerning tendency to generate plausible but incorrect implementation details when faced with ambiguity. Studies report that 18.7% of generated specifications and 23.4% of generated code contains fabricated details that were not present in the input [13].

- **Explainability deficit**: Only 14.3% of surveyed multimodal systems provide adequate explanation of their reasoning process [112], limiting developer trust and ability to correct model misconceptions.

- **Evaluation complexity**: Assessing the correctness of multimodal artifacts requires evaluating both functional correctness and cross-modal consistency, creating evaluation challenges that current metrics inadequately address [109].

4.3.2 Practical Integration Challenges

- **Computational resource requirements**: High-quality multimodal models require substantial computational resources, creating accessibility barriers. 62.4% of surveyed organizations cite resource requirements as a significant adoption obstacle [83].

- **Knowledge transfer barriers**: Developers report difficulties in transferring knowledge gained from multimodal tools to other contexts, with only 37.8% reporting improved general development skills after using these tools [52].

4.3.3 Ethical and Social Considerations

- **Intellectual property concerns**: Generated code raises complex IP questions, with 58.3% of surveyed organizations expressing uncertainty about ownership and licensing implications [103].
- **Bias amplification**: Visual-textual models trained on existing software may amplify existing biases in interface design and implementation. Studies document concerning patterns in generated interfaces, including gender and cultural biases [106, 46].

4.4 Recommendations for Research and Practice

Based on our analysis, we offer the following recommendations for researchers and practitioners:

4.4.1 For Researchers

- **Develop specialized evaluation frameworks**: Current evaluation approaches inadequately capture the multifaceted nature of multimodal software artifacts. Specialized frameworks are needed that assess both functional correctness and cross-modal consistency.

- **Focus on evolution and maintenance**: The significant gap in maintenance and evolution research presents a critical opportunity for high-impact contributions, particularly regarding how multimodal representations evolve over time.

- **Investigate architectural implications**: The tension between rapid generation and architectural quality demands deeper investigation into how architectural principles can be effectively encoded in and enforced by multimodal systems.

- **Explore human-AI collaboration models**: Research on effective collaboration patterns between developers and multimodal systems is needed to maximize complementary strengths and mitigate weaknesses.

4.4.2 For Practitioners

- **Adopt targeted integration**: Rather than wholesale adoption, identify specific tasks where multimodal approaches show the strongest benefits and integrate them selectively into development workflows.

- **Implement enhanced review processes**: Develop specialized review processes for multimodal artifacts that verify cross-modal consistency and address common quality issues in generated outputs.
- **Establish clear responsibility boundaries**: Define explicit boundaries between machine-generated and human-developed components, with clear accountability and verification procedures.
- **Invest in upskilling**: Help developers build skills in effectively directing, evaluating, and refining multimodal outputs rather than treating these tools as black-box replacements.

4.5 Future Directions

Looking forward, we identify several promising directions for future research and development:

- **Lifecycle-aware multimodal representations**: Developing representations that explicitly model how artifacts evolve across the software lifecycle could address many of the consistency challenges identified in our analysis.
- **Architectural guidance systems**: Multimodal systems that incorporate architectural principles into generation and evaluation processes could help balance short-term productivity with long-term system quality.

- **Collaborative multimodal environments**: Integrated environments that support fluid collaboration between developers and multimodal systems could leverage the complementary strengths of both.
- **Domain-specialized multimodal models**: The strong influence of domain knowledge suggests that domain-specific adaptations of multimodal models could significantly improve performance for specialized applications.
- **Quality-aware generation**: Incorporating software quality metrics directly into the generation process could help address the quality concerns identified in current approaches.

Overall, our analysis reveals that visual-textual multimodal approaches are transforming software engineering in profound ways, creating new capabilities but also introducing novel challenges. The most successful applications carefully balance the productivity advantages of these approaches with traditional software engineering principles that ensure long-term system quality and maintainability. As these technologies continue to evolve, maintaining this balance will be essential to realizing their full potential while mitigating their risks.

5 Experiments

In this section, we will illustrate our experiment settings. In section 5.1, we will show our target models, benchmarks, tasks, and evaluation metrics in this experiment. In section 5.2, we will demonstrate the prompts we used to guide LMMs in each task.

5.1 Setup

Models We selected 14 different LMMs as our experimental subjects. Each model can accept specific non-textual modalities as inputs and quiz the corresponding modal tasks. The information on all models is presented in Table 1.

Table 1: An overview of our target model list

Models	Parameters	Open Source?	Support Modalities
gpt-4.5-preview-2025-02-27	Not published	No	Text, Vision(image), Vision(video)
gpt-4o-2024-11-20	Not published	No	Text, Vision(image),Vision(Video)
GPT-4o-audio-preview	Not published	No	Text, Audio
claude-3-7-sonnet-20250219	Not published	No	Text, Vision(image)
Gemini-2.0-pro	Not published	No	Text, Vision(image)
grok-3	Not published	No	Text, Vision(image)
Qwen-vl-max-2024-11-19	Not published	No	Text, Vision(image), Vision(video)
qwen-omni-turbo-2025-03-26	Not published	No	Text, Vision(image), Vision(video), Audio
Llama-3.2-90B	90B	Yes	Text, Vision(image)
Llama-3.2-11B	11B	Yes	Text, Vision(image)
InternVL2-8B	8B	Yes	Text, Vision(image), Vision(video)
LLaVA-NeXT-7B	7B	Yes	Text, Vision(image)
Janus-Pro [21]	7B	Yes	Text, Vision(image), Vision(video)
Phi4-multimodal-instruct [1]	14B	Yes	Text, Vision(image), Vision(video), Audio

Datasets To test the LMM more comprehensively, we extracted 56 usable datasets from our collection of 659 papers as our benchmarks. For each dataset, we summarize the modality involved, which stage of the WaterFall model is of concern, and what type of software is targeted. Detailed information for each dataset is available in Table 2 and Table 3.

Tasks List In order to validate the capability of LMM on our test benchmark, we summarized 11 tasks based on previous work, each involving multimodal inputs. The details of the tasks are presented in Table 4. In this report, we selected five sub-tasks from the total task list to present our findings, as shown in Table 6. These five tasks cover four input modalities: text, single image, multiple images (video), and audio. To realize the tasks, we picked a subset of 8 datasets from our test benchmarks to experiment with, each subset containing about 100 inputs. The information on the subsets can be found in Table 5.

Evaluation Metrics We followed the evaluation metrics set in the original paper to evaluate our experimental results. The details of the evaluation criteria can be found in Table 7.

5.2 Prompt Engineering

As one of the most direct and critical factors influencing model performance, prompts need to be meticulously refined to ensure the model delivers its best performance on a given task. However, a significant challenge we currently face is the lack of a suitable and direct metric for quantifying

Table 2: An overview of our benchmark, TOOL indicates a tool that can generate dataset

Dataset Source	Dataset Link	Component	Target Software
Uibert [4]	Here	UI Image	Android
Wukong-reader [5]	Here	Document Image	Windows
Defects4J [12]	Here	Spectrums	NA
Evosuite [12]	Here	Spectrums	NA
Rico [22] [31]	Here	UI Image	Android
Gestonhmd [20]	Here	Gesture Movement Description	VR
PLUR [24]	Here	Graph	NA
Design What You Desire [23]	Here	Icon Image	Android
DI-drive [33]	Here	images + RL	NA
CMU Panoptic Studio [39]	Here	3D skeletons, Sequences	NA
GUI-World[14]	Here	Video	XR, ios, web
Prose-benchmarks [42]	Here	Text, Table	NA
Silentspeller [43]	Here	GT2k(HTK) style HMM	NA
Marvis [45]	Here	Text	NA
Nbsearch [51]	Here	Jupyter notebook	NA
Sysevr [54]	Here	SeVCs	NA
Sheetcopilot [47]	Here	Excel	Windows
Multiviz [55]	Here	Image	NA
Poseexaminer [58]	Here	Image, JSON	NA
StyleGAN [71]	Here	Image	NA
ImageNet [75]	Here	Image	NA
SparkBraille [80]	Here	braille charts	NA
DroidBench [86]	Here	TOOL	Android
Head Gestures Dystonia [87]	Here	Text	NA
Screen2Words [93]	Here	Text, UI actions	Android
Vetter [101]	Here	TOOL	Web
Seenomaly [111]	Here	UI GIF	Android
DroidGem [66]	Here	TOOL	Android
FraudDroid [32]	Here	UI state transition graphs (UTG)	Android
GUIGAN [113]	Here	UI image	Android
Combodroid [95]	Here	TOOL	Android
Themis Benchmarks [84]	Here	TOOL	Android
Deep Q-network Testing [44]	Here	TOOL	Android
Ape [35]	Here	TOOL	Android
ωDroid [38]	Here	WebView-induced bugs	Web
Video2Scenario [8]	Here	Image	Android
ROUTE [56]	Here	TOOL	Android
DatAndroid [3]	Here	Image, xml	Android
Semantic Matching [68]	Here	GUI Image, event record	Android
PSC2CODE dataset [6]	Here	Text, Video	Web

Table 3: An overview of our benchmark, TOOL indicates a tool that can generate dataset Cont.

Dataset Source	Dataset Link	Component	Target Software
Annotated MYST dataset [61]	Here	Text	Android
EGFE [19]	Here	UI Image, Text Label	Android, IOS
VITAS [50]	Here	Text	Windows
Asgaardlab [64]	Here	Image, canvas json file	Web
AidUI [67]	Here	UI Image, DP label	Web, Android
Webevo [81]	Here	TOOL	Web
Canvas Issues [65]	Here	URL, issue class	Web
Vid2Xml [2]	Here	Video, xml	Web
dVermin [85]	Here	UI Image	Android
IconSeer [49]	Here	Icon Image	Android
GLIB [17]	Here	Game UI Image	Game
Owleye [60]	Here	UI Image	Android
LabelDroid [15]	Here	UI Images	Android
Design2Code [82]	Here	UI Image, Text	Web
Glitchbench [88]	Here	Image	Game
SeeClick [25]	Here	Image, Text	Web
ScreenSpot-Pro [48]	Here	Image, Text	MacOS, Linux, Windows

Table 4: An overview of our target tasks list

Task Name	Input Modalities	Output Modalities
UI to Code	Text, Visioin	Text
Display Bug/Glitch Detection	Text, Visioin	Text
Interactable UI Element Detection	Text, Visioin	Text
UI to Code Optimization	Text, Visioin	Text
UI Code transfer	Text, Visioin	Text
Image Based Agent / Interaction	Text, Visioin	Text
Cross-application interaction	Text, Visioin	Text
Voice Based Agent / Interaction	Text, Audio	Text
Completeness Exploration	Text, Visioin	Text
Event Detection	Text, Visioin	Text
Video Display Detection	Text, Video	Text
GUI World	Text, Video	Text

Table 5: An overview of our sub-dataset list

Dataset Name	Size	Component	Target Software
Design2Code dataset [82]	100	Image, HTML	Web
OwlEye dataset [60]	102	Image, Text	Android
Annotated RICO dataset [16]	100	Image, Text	Android
PSC2CODE dataset [6]	74	Text,Video	Web
VITAS dataset [50]	100	Audio, Text	Windows
SeeClick [25]	100	Image, Text	Web
ScreenSpot-Pro [48]	100	Image, Text	MacOS, Linux, Windows
GUI-World dataset [14]	100	Video, Text	ios, web, xr, software

Table 6: An overview of our current tasks list

Task Name	Input Modalities	Output Modalities
UI to Code	Text, Visioin	Text
Display Bug/Glitch Detection	Text, Visioin	Text
Interactable UI Element Detection	Text, Visioin	Text
Voice Based Agent / Interaction	Text, Audio	Text
Video Display Detection	Text, Video	Text
GUI World	Text, Video	Text

Table 7: An overview of evaluation metrics in our experiment

Task Name	Eval Metics
UI to Code	Design2Code Metric [82]
Display Bug/Glitch Detection	OwlEye Metric [60]
Interactable UI Element Detection	IoU (threshold 0.6) [16]
Voice Based Agent / Interaction	SeMaScore [79]
Video Display Detection	video display detect Metric [6]
GUI World	GUI World Metric[14]

the quality of a prompt. We can only make rough assessments based on the model's responses. Therefore, despite our best efforts in prompt engineering, there remains the possibility of better prompts existing than the ones we have crafted.

Nevertheless, for evaluation purposes, as long as we apply the same prompt across all models, fairness is maintained, and the data we obtain can still be considered meaningful and reliable. During our prompt engineering process, we made several interesting observations:

1. Including the word `REMEMBER` in the prompt helps the model better adhere to our instructions, particularly when we expect the model to output in a specific format.

2. For more complex tasks, utilizing a *chain of thought*[98] approach improves the quality of responses.

3. Providing a detailed task description and considering all potential outputs, along with explicitly stating whether they are acceptable, leads to better performance.

Below are the prompts for all our tasks.

Prompt used for conducting UI2Code

System:You are an expert web developer who specializes in HTML and CSS.

A user will provide you with screenshot of a webpage.

You need to return a single html file that uses HTML and CSS to reproduce the given website.

Include all CSS code in the HTML file itself.

If it involves any images, use \rick.jpg as the placeholder.

Some images on the webpage are replaced with a blue rectangle as the placeholder, use \rick.jpg for those as well.

Do not hallucinate any dependencies to external files. You do not need to include JavaScript scripts for dynamic interactions.

Pay attention to things like size, text, position, and color of all the elements, as well as the overall layout.

Respond with the content of the HTML+CSS file:

Prompt used for conducting Display Bug Detection

System:You are an expert UI developer. A user will provide you with screenshot of a GUI.

You only need to return a result of 0 or 1

If the screenshot shows GUI display issues, you need to response 1, otherwise 0.

You do not need to include any other answer or explanation.

Pay attention to things like text overlap, blurred screen, missing image always occur during GUI rendering on different devices due to the software or hardware compatibility. It is the things negatively influence the app usability, resulting in poor user experience. Also, you also need to distinguish between normal GUI effects such as shadows and animations and GUI effects that are not expected to appear such as strange text and incorrect overlays.REMEMBER, you should never output words other than 0 or 1, or the program will collapse!!

Respond with the 0 or 1:

Prompt used for conducting Interactable UI Element Detection

System:You are an expert Android developer who specializes in UI design and will answer question in JSON format.

A user will provide you with screenshot of an application.

You need to return an object detections result that including all the bouding boxes of UI elements.

You can safely ignore those bounding boxes with too small region, i.e. region < 100

REMEMBER, respond in JSON format: [{‘id’:(the index of UI element you have detected), ‘bbox’:(the bounding boxes you have found. You should output the bounding boxes location in pixels level digitals. REMEMBER In format:[x_start, y_start, X_length, y_length])}...], and DO NOT output any comment other than json code.

Prompt used for conducting Interactable UI Element Detection (with instruction)

System: You are an expert Android developer who specializes in UI design and will answer question in JSON format.
A user will provide you with screenshot of an application.
And a developer will provide an instruction which describe a specific UI element.
You MUST find the most suitable element's location and output its bounding box in pixel coordinate.
REMEMBER, ONLY respond the bounding box result in format: ['bbox':(the bounding boxes you have found in double quote. You should output the bounding boxes location in pixels level digitals. REMEMBER In format:[x_start, y_start, X_length, y_length])...], and DO NOT output any comments except bbox result.

Prompt used for conducting Automatic Speech Recognization

System:You are a helpful assistant that can understand audio recordings and preform automatic speech recognition and output the recognition result in text format.
User: What is in this recording? Only output the text you heard in the recording.

Prompt used for conducting Video display issue detection

System:You are an expert programmer. A user wants to get the code in a video, but some parts of this code are noisy (e.g. masking, blurring). So you need to identify the video frame by frame, marking the noisy frames as 0 and the clean frames as 1.

Your filtered video content will allow the user to extract all the code content in subsequent steps with the help of a simple screen recognition program.

You only need to return a result of 0 or 1,split with space. Remember, you should always responds with 0 or 1 or the program will crash!!!The total number of 1 and 0 should be ex actly same as the number of frames the user provide.

For example: 1 1 1 1 0 1 1 0 0... Respond with the 0 or 1:

Prompt used for conducting GUI Video understanding

You are an expert programmer. Follow the prompt that use ask. Answer the Qquestion, and then only give the correct answer choice in uppercase like: A/B/C/D. Do not response any other answer, only 1 letter is enough

6 Evaluation

In this section, we will detail our evaluation process and empirically explore the following two main research questions (RQs).

- **RQ1:** Where can software system development process and research benefit from large multimodal models?
- **RQ2:** To what extent do the LMMs have sufficient capabilities to help the multimodal software system development process and research?
  - **RQ2-1:** At **Text, Image** level, do the LMMs have sufficient capabilities to help the multimodal software system development process and research?
  - **RQ2-2:** At **Text, Video** level, do the LMMs have sufficient capabilities to help the multimodal software system development process and research?
  - **RQ2-3:** At **Text, Audio** level, do the LMMs have sufficient capabilities to help the multimodal software system development process and research?

6.1 RQ1: Where can software system development process and research benefit from large multimodal models?

Software system processes and research often involve analyzing multimodal information, and LMM, which combines the text comprehension capability of LLM with the ability to analyze multimodal information, is undoubtedly quite capable of optimizing this process. Therefore, in this section, we examine what research directions and processes might benefit from utilizing the capabilities of LMM.

As described in Section 3.1, we predicted whether the studies in the corresponding paper could benefit from the LMM's capabilities by guiding the LLM with a prototype of our taxonomy. After obtaining the predictions from LLM, we manually merged with three experienced evaluators to remove some unsuitable classifications. Consequently, we received a task tree [5] [6](demonstrated through markmap [7]) covering 176 secondary classifications. Our task tree covers four modalities (text, visual, audio, tactile) and five software processes (Design, Develop, Test, Maintain, and Repair). Researchers can easily find potential, unattended problems from the AI community.

Answer to RQ1: Our task tree demonstrates the software system development processes and research that can benefit from LMMs.

[5] Previous version: https://storage.googleapis.com/testvideocuhk/demo/markmap.html
[6] Current version: https://storage.googleapis.com/testvideocuhk/demo/tree.html
[7] https://markmap.js.org/repl

6.2 RQ2: To what extent do the LMMs have sufficient capabilities to help the multimodal software system development process and research?

In Section 6.1, we verified that LMMs can help many aspects of software system development and research. Therefore, it is necessary to measure whether today's LMMs can understand the corresponding modalities and to be able to accomplish the corresponding domain tasks. In this section, we evaluate the LMM in three different modality combinations: the primary text modality plus a specific modality: single image, multiple images (video), and audio. We design at least one task for each modality combination as a measure. In Section 6.2.1, we selected three tasks to assess the LMM's comprehension of text combined with a single image. In Section 6.2.2, we developed one task to evaluate the LMM's understanding of text alongside multiple images. In Section 6.2.3, we designed one task to measure the LMM's comprehension of text combined with audio.

6.2.1 RQ2-1: At Text, Image level, do the LMMs have sufficient capabilities to help the multimodal software system development process and research?

We conducted experiments on twelve LMMs that accept text and image input: UI2Code, Display Bug/Glitch Detection, and Interactable UI Element Detection.

UI2Code UI2Code requires the conversion of a given UI image into working HTML code. Following Si et al.'s setup, we instruct the LMM to read the UI image and generate the HTML code through a system prompt [82]. For the evaluation of the results, we followed the configuration in the paper and evaluthis five scoreveness of the generated code in five different dimensions, where the final score is the average of these five score:

- Block-Match: computing the total sizes of all matched blocks divided by the total sizes of all blocks.
- Text: computing character-level Sørensen-Dice similarity and averaging across all matched pairs.
- Position: computing IoU between matched pairs
- Color: computing following CIEDE2000 color difference formula [63]
- CLIP: high-level visual similarity through CLIP library [8]

The experimental outcomes of this subtask are systematically presented in Table 8 and visualized through Figure 8. Quantitative analysis reveals that GPT-4.5 achieves superior performance in four out of five evaluation metrics while demonstrating comparable results to Claude-3.7 in the remaining color metric. These findings confirm that state-of-the-art LMMs (e.g., GPT-4.5) significantly outperform baseline models (performance gap > 8%) in classical software engineering tasks like UI-to-code translation,

[8] https://pypi.org/project/open-clip-torch/

Table 8: Experiment Result of UI2Code [82]

Models	Final Score	Block-Match	Text	Position	Color	CLIP
gpt-4o-2024-11-20	0.887	0.907	0.972	0.855	0.822	0.879
Llama3.2-11b	≈0	≈0	≈0	≈0	≈0	≈0
Llava-Next-7b	0.735	0.665	0.846	0.690	0.641	0.834
InternVL-8b	0.149	0.000	0.000	0.000	0.000	0.746
Llama3.2-90b	0.540	0.357	0.610	0.486	0.437	0.812
grok3	0.814	0.821	0.875	0.769	0.748	0.856
Phi4-multimodal-instruct	0.601	0.542	0.641	0.513	0.494	0.814
Janus-Pro	0.195	0.032	0.069	0.059	0.057	0.760
claude-3-7-sonnet-20250219	0.901	0.878	0.979	0.867	**0.908**	0.871
gpt-4.5-preview-2025-02-27	**0.921**	**0.926**	**0.985**	**0.885**	0.906	**0.905**
gemini-2.0-pro-exp-02-05	0.874	0.839	0.937	0.849	0.844	0.901
Qwen-vl-max-2024-11-19	0.838	0.827	0.919	0.800	0.769	0.876
qwen-omni-turbo-2025-03-26	0.796	0.784	0.912	0.745	0.680	0.859
Baseline (GPT 4V)	0.848	0.858	0.974	0.805	0.733	0.869

suggesting their substantial potential for development-oriented applications. Notably, commercially available models including Claude-3.7, Gemini-2.0, and the Qwen series exhibit competitive performance (<10% deviation from SOTA). Of particular interest is the Llava-NEXT architecture, which achieves 79% of SOTA performance despite its compact 7B parameter configuration, demonstrating the feasibility of lightweight models for complex visual problem-solving—a critical advancement for edge deployment scenarios. However, open-source counterparts exhibit notable limitations: The Janus model fails to exceed 10% accuracy in four core metrics, while Llama3.2-11b displays fundamental comprehension failures (task instruction misinterpretation rate >99%). These empirical results highlight three critical research directions: (1) architectural refinement for vision-language alignment in compact models, (2) instruction-tuning optimization for domain-specific tasks, and (3) benchmark development for granular capability assessment.

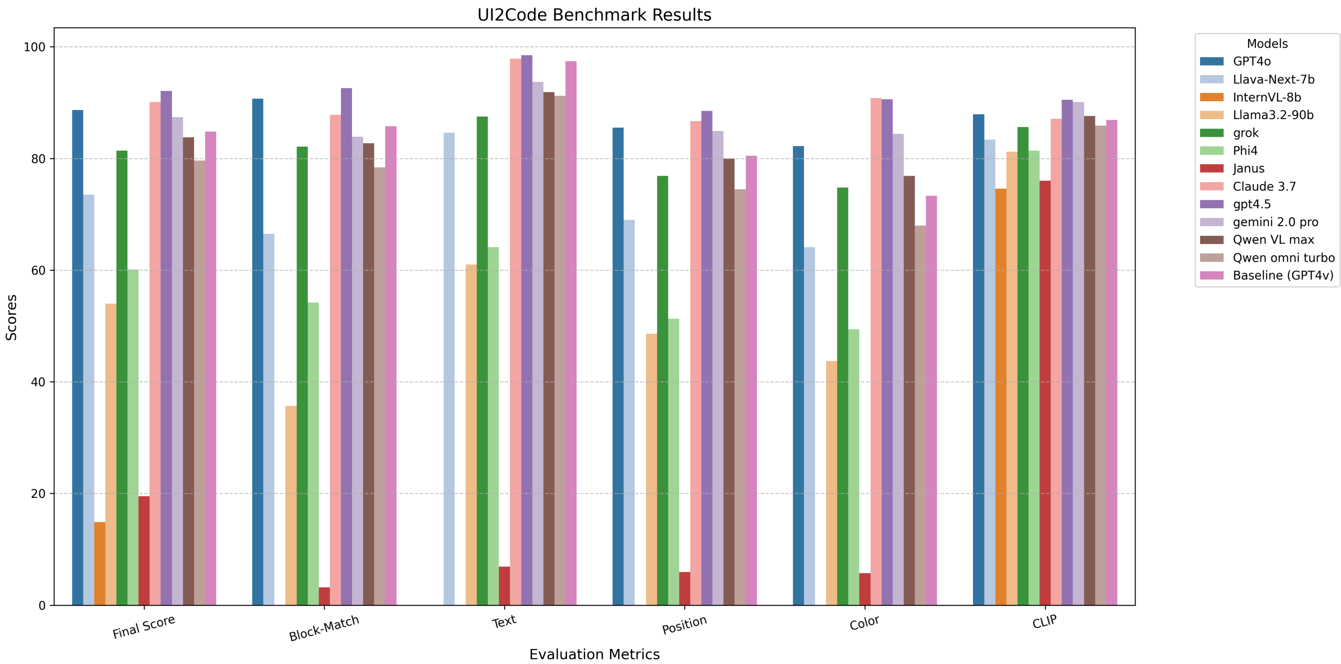


Figure 8: UI2Code Benchmark Result

Display Bug/Glitch Detection UIDIsplay Issue Detection focuses on detecting potential display issues in given UI screenshots, such as texture loading failures, text rendering errors, or overlapping elements. In this task, the image recognition ability of large multimodal models (LMMs) becomes critical. For evaluation, we randomly sampled 100 images from the dataset constructed by Liu et al.[60], with an equal distribution of labels: 50% representing problematic UIs and 50% representing normal UIs. In this dataset, a label of 1 (true label) indicates that the presented UI screenshot contains display issues, while a label of 0 (false label) indicates that the UI is functioning normally.

As a baseline, we adopted the best-performing evaluation results reported by Liu et al.[60], which utilized a deep learning-based model. This serves as a benchmark to assess the accuracy of large multimodal models on this task. The experiment result of this sub-task is shown in Table 9 .

The experimental results reveal significant performance disparities among

Table 9: Experiment Result of Display Bug/Glitch Detection [60]

Models	**Percision**	**Recall**	**F1**	**TP**	**FP**	**FN**
GPT-4o-2024-05-13	0.920	0.597	0.724	46	4	31
Llama3.2-11b	≈0	≈0	≈0	≈0	≈0	≈0
Llava-Next-7b	0.020	1	0.039	1	49	0
InternVL-8b	0	0	0	0	50	0
Llama3.2-90b	0.180	0.450	0.257	9	41	11
grok3	0.060	0.130	0.080	3	47	20
Phi4-multimodal-instruct	0	0	0	0	50	1
Janus-Pro	0	0	0	0	50	52
claude-3-7-sonnet-20250219	0	0	0	0	50	52
gpt-4.5-preview-2025-02-27	**0.980**	0.690	0.801	**49**	1	22
gemini-2.0-pro-exp-02-05	0.940	0.723	0.817	47	3	18
Qwen-vl-max-2024-11-19	0.560	**0.966**	0.709	28	22	1
qwen-omni-turbo-2025-03-26	0.300	0.790	0.430	15	35	4
Baseline	0.850	0.848	**0.849**	-	-	-

models. *GPT-series models* and *Gemini* demonstrate exceptional capability in detecting GUI display issues, achieving recognition rates exceeding 95% across various defect types. This suggests strong potential for deploying these large language models (LLMs) in practical software testing scenarios, where they could reliably identify visual defects in interface implementations.

However, we observe persistent challenges with smaller-parameter models. Even state-of-the-art compact models like *Qwen-Omni* and *Phi-4* exhibit fundamental limitations in this task. During testing, these models frequently demonstrated:

- Severe misunderstanding of task requirements, particularly in binary classification scenarios (e.g., returning free-form text instead of constrained 0/1 outputs)

- Inconsistent response patterns across identical input variations
- Failure to maintain task focus despite explicit prompt engineering

This performance gap suggests that local deployment of current small models remains impractical for GUI testing applications. The findings emphasize the continued necessity of cloud-based LLM services for production-level implementation, while simultaneously highlighting promising research directions:

- Specialized fine-tuning of small models for GUI defect detection tasks
- Development of hybrid architectures combining vision transformers with rule-based systems
- Creation of synthetic training datasets targeting interface testing edge cases

The persistent challenge of prompt adherence in smaller models particularly warrants investigation, as it reveals fundamental limitations in current parameter-efficient training methodologies for multimodal understanding tasks.

Interactable UI Element Detection Interactable UI Element Detection aims to detect small elements inside a UI image and generate several bounding boxes to indicate them. We use system prompts to guide LMM in finding the suitable interactable UI element and generating bounding boxes.

We followed Chen et al. to verify the result and compute the IoU between the truth and the predicted bounding boxes [16]. We adjusted the threshold in this experiment from 0.9 to 0.6 to allow for more mistakes LMM made. In addition to the annotated RICO dataset [16] provided in the paper, which mainly focuses on Android UI element detection, we also selected two datasets from our dataset that focus on other software types: SeeClick (Web) [25], and ScreenSpot-Pro (MacOS) [48]. The experiment result of this sub-task is shown in Table 10, Table 11, and Table 12.

Table 10: Experiment Result of Interactable UI Element Detection on RICO dataset[16]

Models	**Percision**	**Recall**	**F1**	**TP**	**FP**	**FN**
GPT-4o-2024-11-20	0.0140	0.0170	0.0160	13	918	730
Llama3.2-11b	≈0	≈0	≈0	≈0	≈0	≈0
Llava-Next-7b	0.0009	0.0040	0.0010	3	3411	740
InternVL-8b	0.0020	0.0090	0.0030	7	3288	736
Llama3.2-90b	0	0	0	0	2373	743
grok3	0.0108	0.0134	0.0110	10	916	733
Phi4-multimodal-instruct	0	0	0	0	138	743
Janus-Pro	0	0	0	0	100	743
claude-3-7-sonnet-20250219	0.0340	0.01880	0.02440	14	388	729
gpt-4.5-preview-2025-02-27	**0.0580**	**0.0670**	**0.0625**	**50**	807	693
gemini-2.0-pro-exp-02-05	0.0023	0.0080	0.0036	6	2512	737
Qwen-vl-max-2024-11-19	0.0100	0.013	0.012	10	916	733
qwen-omni-turbo-2025-03-26	0.0270	0.0148	0.0191	11	395	732
Baseline	**0.4900**	**0.5570**	**0.5240**	-	-	-

Part1: Annotated RICO

Our evaluation on the RICO benchmark [16] reveals significant challenges for Large Multimodal Models (LMMs) in high-precision visual grounding tasks. As shown in Table 10, while the baseline's compact domain-specific architecture achieves 52.4% F1-score, all LMMs exhibit limited effectiveness on this task—only GPT-4.5 attains 50 true positives (TPs) with limited precision (5.8%), recall (6.7%), and F1-score (6.3%). This performance gap stems from RICO's unique requirements: multi-element interactive UI recognition without cardinality constraints, where most LMMs generate non-compliant outputs (e.g., Gemini-2.0 produces 2518 bounding boxes, 340% beyond ground truth annotations).

These findings demonstrate two fundamental limitations of current LMM architectures: (1) insufficient geometric precision for coordinate regression tasks, despite their competence in binary visual recognition (A/B classification accuracy >85%), and (2) inherent over-generation tendencies in open-set visual parsing scenarios.

Table 11: Experiment Result of Interactable UI Element Detection on SeeClick [25]

Models	**Percision**	**Recall**	**F1**	**TP**	**FP**	**FN**	**Error Rate**	**Average IoU**
gpt-4o-2024-11-20	0	0	0	0	106	100	0	0.00614
Llava-Next-7b	0	0	0	0	97	100	3%	0.007
InternVL-8b	0	0	0	0	181	100	1%	0.01478
claude-3-7-sonnet-20250219	0	0	0	0	44	100	56%	**0.0684**
Phi4-multimodal-instruct	0	0	0	0	97	100	3%	0
Janus-Pro	0	0	0	0	128	100	**100%**	0
gpt-4.5-preview-2025-02-27	0	0	0	0	104	100	1%	0.0094
Baseline (SeeClick-9.6B)	-	-	-	**53.4%**	-	-	-	-

Part2: SeeClick & ScreenSpot-Pro

The SeeClick and ScreenSpot-Pro benchmarks introduce distinct instructional grounding challenges compared to the RICO dataset, requiring precise interpretation of natural language directives for UI element localization. As quantified in Tables 11 and 12, our analysis reveals two critical limitations:

(1) Instructional Compliance Deficiency: While the domain-adapted SeeClick-

9.6B achieves 53.4% accuracy on its native benchmark, all general-purpose LMMs exhibit complete task failure (0% success rate) in single-round evaluations. This performance gap expands dramatically on ScreenSpot-Pro, where even the previous specialized SeeClick-9.6B's accuracy drops to 1.1%, indicating fundamental limitations in spatial-instruction alignment capabilities.

(2) Prompt-Following Failure: Our experiment result ('Error Rate' column in Table 11 and Table 12) demonstrates severe output specification violations. Claude-3.7—despite its high score on UI2Code task—generates 56% non-compliant responses on SeeClick (e.g., non-required sentences, coordinate format errors). This error rate correlates strongly with practical deployment risks, compromising downstream integration viability.

These empirical results substantiate two hypotheses: 1) Model scaling alone cannot address domain-specific output regularization needs 2) Multimodal pretraining objectives inadequately capture software engineering precision requirements.

To improve the performance of LMMs, we envisioned two possible solutions: to provide more detailed prompt guidelines or to perform more detailed preprocessing of the image to reduce the pressure on the LMM to analyze the whole image. Another approach is to let the LMM play the role of an assistant to work with a specific model, where the LMM only performs

[9] result provided by screenspot-pro leadboard, same as the below 'SOTA(UI-TARS-72B)'

Table 12: Experiment Result of Interactable UI Element Detection on ScreenSpot-Pro [48]

Models	**Percision**	**Recall**	**F1**	**TP**	**FP**	**FN**	**Error Rate**	**Average IoU**
gpt-4o-2024-11-20	0	0	0	0	100	100	9%	3.99E-6
Llava-Next-7b	0	0	0	0	111	100	5%	3.82E-5
InternVL-8b	0	0	0	0	108	100	5%	1.4E-4
claude-3-7-sonnet-20250219	0	0	0	0	46	100	54%	0
Phi4-multimodal-instruct	0	0	0	0	43	100	**57%**	0
gemini-2.0-pro-exp-02-05	0	0	0	0	100	100	0	0
gpt-4.5-preview-2025-02-27	0	0	0	0	100	100	0	**3E-4**
SeeClick-7B [9]	-	-	-	1.1%	-	-	-	-
SOTA(UI-TARS-72B)	-	-	-	**38.1%**	-	-	-	-

the high-level task of determining whether a specific UI element exists and then calls a specific mini-model to generate accurate results. Both of these approaches can be used to improve the performance of specific aspects of the LMM in the future.

Conclusion On many previously unseen tasks, LMMs have already surpassed models specifically trained for those tasks, highlighting the feasibility and potential of applying multimodal large models in this domain. However, it is worth noting that in certain specialized tasks, such as small object detection, the performance of these large models is significantly suboptimal. This reveals a highly valuable direction for future research in improving their capabilities in such scenarios.

Another interesting finding is that of all the models tested in this section, all of the llama3.2 series models demonstrated in addition to poor comprehension, as evidenced by the inability to analyze the input instructions. One of them, the 90B version, could understand the input instructions and output them in the required format due to its larger parameter size, but the results showed a complete lack of understanding of the task requirements. For example, in the UI element detection task, the output of llama 3.2-90B repeats the coordinates of the bounding boxes of the whole picture size, which ultimately fails to understand the detection of a specific element as required by the task's prompt, while the understanding of llama 3.2-11B is even worse, as all the outputs repeat the same paragraph. All the output is a repetition of a meaningless response, showing no understanding of the task requirements. In contrast, models such as Llava-NeXT have fewer parameters but show an understanding of the task setup and give a response. This finding warrants subsequent exploration of the token level of generation.

Answer to RQ2-1: At the **Text and Image** level, LMMs can be experts on some specialized pre-trained tasks but are inferior to baseline methods for other tasks.

6.2.2 RQ2-2: At Text, Video level, do the LMMs have sufficient capabilities to help the multimodal software system development process and research?

Video input is a unique modality that differs significantly from simply using multiple images as input. In videos, there is a strong correlation and continuity between frames, requiring contextual understanding to interpret the content. For tasks involving this modality, we selected two tasks.

Video valid frame detection The first task is about detecting whether video frames are valid, as presented by Bao et al[6]. This task is a sub-task of a larger problem—extracting code from videos. Specifically, this task involves analyzing each frame of a video to determine whether it contains useful code content that needs to be extracted. If a frame contains such content, it is labeled as valid; otherwise, it is labeled as invalid.

It is important to note that this differs from analyzing a single image to determine its validity, as the validity of a video frame often depends on its context within the sequence, rather than solely on the content of the frame itself. As such, this task is well-suited for evaluating a model's capability in video understanding.

We used the video dataset provided by Bao et al. to conduct this evaluation[6]. Again, we use the data from the original paper as the baseline. Since current large models typically process video understanding by extracting frames and treating them as a set of images, we adopted the same frame extraction approach as Bao et al. to ensure experimental rigor. The evaluation metrics also follow the methodology presented in their paper. In this task, we use the label 1 to indicate that a frame is valid and the label 0 to indicate that a frame is invalid. The experiment result of this sub-task is shown in Table 13.

Table 13: Experiment Result of Video display detect [6]

Models	**Percision**	**Recall**	**F1**	**TP**	**FP**	**FN**
GPT-4o-2024-05-13	0.891	**0.891**	0.891	57	7	7
InternVL-8b	0.938	0.857	0.895	60	4	10
qwen-omni-turbo	**0.950**	0.860	**0.900**	61	3	10
Phi4-multimodal-instruct	0.891	0.851	0.870	57	7	10
Baseline	0.910	0.850	0.880	2459	256	445

It is important to note that, due to the uneven ditribution of positive and negative data, the result may overrating the real capbility of LMM.For example, although InternVL-8B appears to perform exceptionally well at first glance— even surpassing GPT4o in video understanding—this is actually due to an imbalance in the dataset, where the number of invalid frames is insufficient, resulting in too few negative samples. However, it is still undeniable that the multimodal large model performs very well on this task, requiring no additional training at all while maintaining a very high accuracy.

GUI Comprehension in video The second task evaluates LMM's ability to recognize graphical user interfaces (GUIs) in recorded videos, as proposed by Chen et al.[14] In this task, MLLMs attempt to understand GUI operations demonstrated in instructional videos and subsequently answer corresponding questions (e.g., "If the user wants to prioritize unread emails, which of the following actions should they take?"). The model selects the most appropriate answer from four given options.

The primary challenge lies in assessing LMMs' capability to both extract visual information from videos and perform logical reasoning based on the extracted information. Notably, this task goes beyond simple visual recognition by requiring models to determine appropriate subsequent actions based on observed operations.

Our evaluation adopts the dataset provided by chen et al.[14], using the baseline models presented in their original work. To ensure methodological consistency with previous tasks, we maintain identical frame extraction protocols. Unlike the original study's evaluation approach that employs separate scoring models, our measurement directly compares model outputs with ground-truth answers through exact match verification. This comprehensive dataset covers multiple operating systems and platforms including iOS, web interfaces, and extended reality (XR) systems, making it particularly suitable for demonstrating models' cross-platform understanding capabilities. The experimental results are detailed in Table 14.

Table 14: Experiment Result of GUI Comprehension of Video [14]

Models	Web	IOS	XR	Software
GPT-4o-2024-11-20	75%	83%	**84%**	**86%**
InternVL-8b	82%	75%	68%	79%
qwen-omni-turbo	**82%**	77%	78%	83%
Phi4-multimodal-instruct	80%	**85%**	81%	81%
Baseline	54%	51%	56%	60%

The aforementioned results demonstrate that current Large Multimodal Models (LMMs) exhibit remarkable proficiency in understanding dynamic GUI operations. They not only accurately interpret the content presented in videos but also logically infer correct answers by synthesizing contextual relationships between interface elements. Notably, while our prior experiment revealed LMMs' poor performance in precisely localizing GUI components within static screenshots, this limitation does not imply an inability to recognize these components. Significantly, even smaller-scale models like the 8B-parameter *InternVL* exhibit robust comprehension capabilities in this task.

These findings suggest that LMMs possess substantial potential for continued development in GUI understanding applications. Their demonstrated ability to analyze operational workflows and derive actionable insights positions them as promising tools to assist future GUI development processes, particularly in automating interface testing, enhancing user behavior analysis, and supporting adaptive interface design.

Answer to RQ2-2: At the text and video level, the LMMs have very strong potential to assist in this area, even achieving performance comparable to the baseline.

6.2.3 RQ2-3: At Text, Audio level, do the LMMs have sufficient capabilities to help the multimodal software system development process and research?

In order to serve the user like a Virtual personal assistant (VPA), an audio-capable LMM should be able to recognize the same meaning in different speech inputs, e.g., "What's up today?" and "Tell me the news of the day" should trigger the same news-playing state of a VPA. Based on the work of Guglielmi et al., we designed a series of tests to check whether the LMM is good at detecting the corresponding trigger state in the input text [36]. However, since the evaluation criterion used in the paper is to obtain the truth label through a textual conversation with the AWS skill VPA [10] in the simulator, in this experiment, we only tested the speech recognition accuracy of the LMM and then multiplied it by the original result that the LMM can test the accuracy and comprehensiveness of the VPA. For the sake

[10]https://explore.skillbuilder.aws/learn

of rigor, we only report the results of the Automatic Speech Recognition (ASR) part of the experiment in this report Table 15. We used SemaScore [79] as the evaluation metric of ASR accuracy, a criterion for determining the accuracy of ASR work from the language model token level.

Table 15: Experiment Result of Automatic Speech Recognition (ASR) [79]

Models	SemaScore
GPT-4o-audio-preview	**0.9583**
qwen-omni-turbo-2025-03-26	0.9433
Phi4-multimodal-instruct	0.4015

The experiment result indicates that LMM, like GPT-4o and Qwen-omni, has good speech recognition capabilities, and we believe that future LMMs can be used as VPAs to provide a broader range of services. However, the current support for speech input and the ability to analyze the non-textual information of speech are still lacking, and only some of the fine-tuned mini-models [115] [114] have good performance in this area. There is still a certain distance from the performance of solving text-level problems like LLM.

Another interesting finding here is the Phi4's performance. After checking the experiment result, we found that Phi4 did not follow the system and user prompt, which instructed the model to perform ASR tasks, but output what kind of sound label was inside the audio. For example, the audio saying "Alexa, open Smart Home", but Phi4 output "Labels: Human voice; Speech; Female speech and woman speaking", which is non-relevant to our prompts. To avoid the weak prompt issue, we re-do the same experiment with augmented prompting engineering. Nevertheless, Phi4 persists in outputting incorrect answers. This finding indicates that Phi4's prompt-following ability is a crucial problem for future usage.

Answer to RQ2-3: LMM can understand text information inside audio, so LMM has sufficient capabilities to help the multimodal software system development process and research.

In summary, large multimodal models have demonstrated exceptional capabilities in integrating with the field of software engineering across currently supported input modalities, including images, videos, and audio. For previously unseen tasks, these models can provide accurate and rapid responses based solely on prompts, often without requiring additional fine-tuning. Large multimodal models hold tremendous potential in the software engineering domain, offering researchers an incredibly practical tool for handling multimodal inputs without the need for extensive effort and time spent on fine-tuning or debugging.

Answer to RQ2: Large multimodal models exhibit exceptional performance within currently supported modalities, highlighting significant potential for integration into the field of software engineering.

7 Conclusion

The rapid advancement of multimodal large language models (LMMs) has shifted research focus toward their practical applications – *what can we achieve with LMMs?* However, our systematic survey reveals critical gaps in software engineering research: while numerous studies attempt to apply MLLMs to domain-specific problems, there exists no comprehensive benchmarking framework to systematically evaluate model capabilities, quantify performance limitations, and guide future research directions. Two primary challenges emerge from our analysis:

- **Lack of unified evaluation**: Current efforts remain fragmented across subdomains without standardized metrics or comparative baselines
- **Task collection barrier**: Relevant evaluation tasks are dispersed across disparate research fields, creating significant overhead for researchers

In conclusion, the following are some of the main contributions we have made during this project.

- **Taxonomy**: We undertook a comprehensive systematic literature review to establish a conceptual taxonomy delineating research domains where scholarly publications (PAPERS) can derive substantive benefits from Large Multimodal Models (LMMs). Building upon this foundation, we implemented a dual-phase analytical framework employing both conventional Large Language Models (LLMs) and specialized Reasoning-Enhanced LLMs to systematically categorize and synthesize an extensive corpus of publications through our taxonomy.

- **Empirical analysis**: We present a structured analysis of methodological implications through a task-oriented hierarchy derived from our taxonomy. This analytical framework provides new insights into how multimodal approaches can advance software system research, particularly in addressing complex integration challenges across heterogeneous data modalities.
- **Testing framework**: We developed and validated a modular evaluation framework with three core innovations: (1) Unified benchmarking infrastructure supporting concurrent assessment of heterogeneous models, datasets, and metrics; (2) Extensible architecture facilitating seamless integration of novel test components; (3) Multi-dimensional evaluation protocol combining technical performance metrics with practical utility analysis.
- **Experiment**: Through rigorous experimentation on state-of-the-art LMMs, we executed a curated set of benchmark tasks to quantitatively assess model capabilities while simultaneously evaluating their effectiveness in real-world developer-assistance scenarios.

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