# DYNAMIC API DOCUMENTATION GENERATOR

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## Abstract

API documentation is a critical component of software development, serving as a bridge between developers and the functionality offered by APIs. However, maintaining accurate and up-to-date documentation remains a significant challenge due to its manual and time-consuming nature. Neglected documentation often leads to outdated references, increased technical debt, and slower integration processes, hindering overall developer productivity. To address this issue, we propose a Dynamic Documentation Generator powered by Large Language Models (LLMs). Our system automates the generation of clear, structured, and comprehensive API documentation by analyzing API source code and endpoint definitions, outputting results in Markdown format.

The solution adopts two approaches: Full File Mode, which processes the entire API file at once, and API-by-API Mode, which generates documentation at the endpoint level for improved scalability with large codebases. We compare the performance of two models, GPT-4o and GPT-4o-mini, to determine their suitability for different scenarios. GPT-4o handles larger context windows and is ideal for bulk documentation, while GPT-4o-mini provides faster and more cost-efficient results for endpoint-specific tasks. To ensure high-quality documentation, we incorporated a prompt evaluation pipeline, which evaluates outputs based on key metrics like completeness, clarity, accuracy, and relevance. Multiple prompt versions were tested and refined to optimize the performance of the system.

The final implementation includes an interactive web-based application built using frameworks like Streamlit or Gradio, enabling developers to input their API files and generate documentation dynamically. This solution significantly reduces manual effort, ensures consistency, and improves the overall quality of API documentation. By integrating advanced techniques like prompt optimization and LLM evaluations, our approach sets a new standard for automated API documentation, addressing key pain points in the modern development lifecycle.

# Introduction

In modern software development, APIs (Application Programming Interfaces) play a crucial role in enabling communication between applications, systems, and services. Whether for public APIs exposed to external developers or internal APIs used within an organization, having clear, accurate, and up-to-date documentation is essential. Good documentation accelerates onboarding, improves integration, and reduces errors by providing developers with an understanding of API functionality, parameters, and usage examples.

However, maintaining high-quality API documentation is a significant challenge. The traditional documentation process is manual, time-consuming, and often deprioritized due to tight development schedules. As APIs evolve, changes to endpoints, parameters, and behaviors are often not reflected in the documentation, resulting in outdated or incomplete references. This creates technical debt, slows down development workflows, and increases confusion among developers, especially those unfamiliar with the codebase.

To solve this problem, we propose a Dynamic Documentation Generator that leverages Large Language Models (LLMs) to automate API documentation generation. By analyzing API source code and endpoint definitions, our tool generates structured documentation in Markdown format, including key details like descriptions, parameters, and example requests/responses.

Our solution incorporates two primary approaches:

1. Full File Mode: Processes the entire API file in one step, ideal for small and concise APIs.
2. API-by-API Mode: Generates documentation at the endpoint level, allowing better handling of complex and large-scale APIs.

To further optimize quality, we implemented a prompt versioning and evaluation mechanism. Multiple versions of prompts were tested and evaluated based on criteria like completeness, clarity, accuracy, and relevance to identify the best-performing templates. Additionally, we compared the performance of GPT-4o and GPT-4o-mini, selecting models based on specific requirements such as context size, processing speed, and cost efficiency.

The resulting system ensures up-to-date, high-quality documentation while reducing the manual effort required from developers. An interactive web-based application provides a simple interface to input API files and generate documentation dynamically, making this solution accessible and user-friendly.

## Related Work

The importance of API documentation as a critical resource for software developers has led to the development of various tools and methodologies over the years. Traditional solutions like Swagger (OpenAPI), Postman, and Sphinx have been widely adopted for generating and maintaining API documentation. While these tools have simplified parts of the documentation process, they still require significant manual intervention and are often rule-based, limiting their adaptability to evolving and complex APIs.

Swagger (OpenAPI) generates static documentation by parsing code annotations or metadata provided by developers. It offers a structured approach to documentation but relies heavily on developers to manually maintain annotations in the codebase. As APIs grow and evolve, these annotations often become outdated or incomplete, requiring continuous effort to ensure accuracy. Postman, on the other hand, provides a more interactive approach by allowing developers to create request collections for APIs, but its documentation feature is tightly coupled with testing workflows. Similarly, tools like Sphinx are commonly used in Python ecosystems, extracting inline docstrings from the code to produce documentation. However, this approach still requires developers to explicitly write detailed and well-structured descriptions within their code, making it labor-intensive and error-prone.

Rule-based tools like these cannot interpret code behavior or context dynamically, which limits their ability to handle complex or undocumented APIs. Additionally, they fall short when it comes to automatically generating human-like, well-structured documentation. This has led to a growing demand for intelligent documentation systems that leverage recent advancements in Natural Language Processing (NLP) and Large Language Models (LLMs) to automate the process.

The rise of LLMs, particularly GPT-3.5 and GPT-4, has demonstrated the potential to transform tasks traditionally requiring human cognition. LLMs have shown significant capabilities in generating natural language text that is clear, coherent, and contextually relevant. Tools like GitHub Copilot and Tabnine have already applied LLMs for auto-completing code and generating inline comments. GitHub Copilot, for example, helps developers write code faster by suggesting code snippets based on context, but its focus remains limited to inline assistance rather than end-to-end documentation. These tools lack the ability to generate comprehensive API documentation with sections like overview, parameters, methods, and examples, which are critical for developers seeking to understand and integrate APIs.

In recent years, there has been growing interest in leveraging LLMs for automated documentation. Several studies have explored the use of LLMs for text generation tasks, demonstrating their effectiveness in producing human-like outputs with high clarity and accuracy. For instance, the use of GPT-based models has been tested for summarization, knowledge extraction, and text generation in software engineering tasks. However, generating API documentation presents unique challenges, such as handling large codebases, ensuring accuracy in technical details, and maintaining consistency across endpoints.

The problem of context size is particularly notable when dealing with large API files. Models like GPT-3.5 face limitations due to smaller context windows, which restrict the amount of information they can process at once. This limitation has been addressed with GPT-4 and its variants, such as GPT-4o, which offer extended context capabilities, making them suitable for handling bulk documentation tasks. Additionally, lightweight models like GPT-4o-mini provide faster inference and cost-effective solutions, making them ideal for scenarios where endpoints are processed individually.

Our work builds on these advancements by creating a system that automates API documentation while addressing the shortcomings of existing tools. Unlike traditional tools, our approach leverages LLMs to analyze API source code and generate comprehensive, well-structured documentation in Markdown format. We incorporate two approaches—Full File Mode for smaller APIs and API-by-API Mode for handling large and complex codebases. By implementing a prompt evaluation pipeline, we ensure that the generated documentation meets key quality metrics, including completeness, clarity, accuracy, and relevance.

We also contribute to the field by exploring model comparisons, testing GPT-4o for large-scale contexts and GPT-4o-mini for lightweight tasks. Our work demonstrates the trade-offs between these models in terms of performance, cost, and accuracy, offering insights into their applicability for different scenarios. Additionally, we incorporate prompt versioning to refine documentation generation further, ensuring that outputs are optimized for real-world usability.

Furthermore, our approach aligns with modern MLOps practices, automating the entire pipeline from code ingestion to documentation generation and evaluation. The system is integrated into a web-based application (using Streamlit/Gradio), providing developers with a simple interface to input API files and receive dynamic, real-time documentation. This combination of LLMs, evaluation methodologies, and deployment pipelines positions our project as a state-of-the-art solution to API documentation challenges.

In summary, while existing tools like Swagger and Postman provide static, rule-based solutions, and tools like GitHub Copilot focus on inline code generation, our project bridges the gap by offering a fully automated, dynamic, and scalable solution for API documentation generation. By leveraging LLMs, prompt engineering, and evaluation pipelines, we set a new standard for how API documentation can be generated and maintained efficiently in modern software development workflows.

## Data

### 1. Source of Data

The input to our tool consists of API source code files, which are provided by developers. These files are written in Python and utilize frameworks such as **FastAPI** to define endpoints, parameters, and responses.

**Types of Input Files:**

1. **Simple API Files**: Small, concise files with basic endpoints and minimal logic.
    - Example: `sample_apis.py`
2. **Complex API Files**: Larger files containing advanced functionalities such as authentication, pagination, file uploads, and nested JSON bodies.
    - Example: `complex_api.py`

### 2. Input File Structure

Each input file contains the following components:

| Component | Description | Example |
|---|---|---|
| Endpoints | Routes defined with FastAPI decorators like @app.get or @app.post. | /users/ |
| HTTP Methods | HTTP methods such as GET, POST, PUT, DELETE. | GET |
| Parameters | Query parameters, request bodies, and headers required by endpoints. | page, page_size |
| Dependencies | Middleware functions or pre-processing steps, such as authentication. | authenticate_user |
| Return Values | JSON responses or other outputs returned by the endpoint. | {"users": [...], "page": 1} |

| | | |
|---|---|---|
| Docstrings | Inline comments or descriptions that explain endpoint functionality. | “Retrieve a list of users.” |

## 3. Data Processing Pipeline

The API files undergo a multi-step preprocessing pipeline to extract structured data for the LLM:

**Step 1: Parsing the Code**

- Use Python's **Abstract Syntax Tree (AST)** to parse and extract key components:
    - Endpoints (`/users/`)
    - HTTP methods (`GET`)
    - Query parameters (`page`, `page_size`)
    - Docstrings describing functionality

**Step 2: Inline Comment Extraction**

- Extract inline comments and docstrings to enhance the generated documentation.

**Step 3: Chunking (for API-by-API Mode)**

- Large files like `complex_api.py` are split into smaller **endpoint-specific chunks** to fit within the LLM's context window.

**Step 4: Tokenization**

- Split content into manageable **tokens** to avoid exceeding the LLM’s context window limits.
- Ensures all relevant details (imports, functions, comments) are retained.

**Step 5: Error Handling**

- Handle missing docstrings or incomplete code by inferring descriptions from function names and parameters.

## 5. Example Processed Output

The preprocessed input is fed to the LLM, which generates structured documentation in Markdown format.

**Generated Output:**

~~~
## `/users/` - GET
Retrieve a paginated list of users.

### Parameters:
| Name        | Type   | Default | Description                   |
|-------------|--------|---------|-------------------------------|
| `page`      | int    | 1       | Page number (1-indexed).      |
| `page_size` | int    | 10      | Number of users per page.     |

### Authentication:
- API Key required in the Header (`Authorization`).

### Response Example:
```json
{
  "total": 50,
  "users": [
    {"id": 1, "name": "User 1"},
    {"id": 2, "name": "User 2"}
  ],
  "page": 1,
  "page_size": 10
}
...
~~~

## Methods

### 1. Overview of the Approach

To address the challenges of manual API documentation, such as time consumption, inconsistency, and outdated content, we designed and implemented the **Dynamic API Documentation Generator**. This system uses **Large Language Models (LLMs)** like **GPT-4o** and **GPT-4o-mini** to automate the process of generating accurate, consistent, and up-to-date API documentation.

The tool operates in **two modes**:

1. **Full File Mode**: Processes the entire API source code file in a single run.

2. **API-by-API Mode**: Processes endpoints individually, making it suitable for large, complex APIs.

By combining LLMs with an **evaluation pipeline** that scores outputs based on key metrics (**Completeness, Accuracy, Relevance, and Clarity**), the system ensures high-quality documentation.

## 2. Components of the System

### 2.1 CLI-Based Tool

The tool is implemented as a **Command-Line Interface (CLI)**, enabling developers to:

- Input API source code files.
- Choose the mode of operation (`bulk` or `api_by_api`).
- Select specific LLM models and prompt versions for generating documentation.

**Features of the CLI**:

- User-friendly options for inputs, outputs, and model configuration.
- Efficient file parsing and data extraction for endpoints.

**Example Command**:

```
python document_this.py -m api_by_api -a /path/to/api_file.py -o
/output/dir -md gpt-4o-mini -p v1
```

### 2.2 Full File Mode

- **How It Works**:
  - The entire API file is parsed and processed in a single LLM request.
- **Why Use It**:
  - Faster for smaller APIs with fewer endpoints.
- **Challenges**:
  - LLM context window limitations may cause issues for large, complex files.

### 2.3 API-by-API Mode

- **How It Works**:
  - The file is split into smaller chunks, with each endpoint processed independently.
- **Why Use It**:
  - Handles large and complex APIs efficiently.
  - Produces granular, detailed documentation for each endpoint.

- **Challenges**:
    - Slightly slower due to multiple LLM requests.

| Mode | Advantages | Disadvantages |
|---|---|---|
| **Full File Mode** | Faster for small APIs. | Struggles with large files. |
| **API-by-API Mode** | Efficient for large APIs, more granular. | Slightly slower for small APIs. |

**2.4 Model Integration**

We integrated two GPT-based models, **GPT-4o** and **GPT-4o-mini**, for LLM-powered documentation generation:

| Model | Best For | Advantages |
|---|---|---|
| **GPT-4o** | Full File Mode | Handles large context windows, accurate. |
| **GPT-4o-mini** | API-by-API Mode | Faster, lightweight, cost-efficient. |

The choice of model depends on the input file size and complexity.

**2.5 Prompt Versioning and Evaluation**

To optimize the quality of generated documentation, we employed a **prompt versioning and evaluation pipeline**.

**Steps Involved**:

1. **Prompt Creation**:
    - Designed multiple versions of prompts (e.g., v1, v2) to test their performance on sample API files.
2. **Evaluation Methodology**:
    - Used a **critic LLM** to score outputs generated by different prompts based on:
        - **Completeness**: Are all endpoints and parameters included?
        - **Accuracy**: Is the documentation technically correct?
        - **Relevance**: Does the content align with API functionality?
        - **Clarity**: Is the documentation easy to understand?
3. **Iterative Refinement**:
    - Compared scores across prompt versions and selected the one with the highest overall performance.

**Benefits**:

- Ensures data-driven selection of prompts.
- Guarantees high-quality, reliable documentation.

**Workflow Diagram**:

```
Input API File → LLM with Prompt Versions → Critic LLM Evaluation →
Scoring on Completeness, Accuracy, Relevance, Clarity → Best Prompt
Selection
```

## 3. Alternative Approaches Considered

During the development of the **Dynamic API Documentation Generator**, we explored various approaches to both the **LLM usage** and the **system design** before finalizing our solution.

### 3.1 LLM Usage: Bulk Documentation vs API-by-API

To determine how LLMs would be used for generating documentation, we considered two strategies:

| Approach | Description | Advantages | Disadvantages |
|---|---|---|---|
| Full File Mode | Processes the entire API file in a single request to the LLM. | - Faster for small, concise API files. | - Limited by LLM context window. |
| | | - Reduces the number of API calls. | - Risk of incomplete outputs for large APIs. |
| API-by-API Mode | Processes each endpoint individually by splitting the file into smaller chunks. | - Handles large APIs efficiently. | - Requires multiple LLM API calls. |
| | | - Produces detailed, granular documentation. | - Slower for small API files. |

**Decision**:
We adopted a **hybrid approach**, allowing users to select between **bulk mode** and **API-by-API mode** based on the size and complexity of their API files. For smaller projects, **Full File Mode** is ideal. For larger, complex APIs, **API-by-API Mode** ensures better results while handling LLM context limitations.

### 3.2 System Design: CLI vs UI-Based Approach

We evaluated two possible solutions for how the tool would be used:

| Approach | Description | Advantages | Disadvantages |
|---|---|---|---|
| UI-Based Approach | Create a graphical interface (web-based) for users to upload API files. | - User-friendly for non-technical users. | - Complex to integrate into CI/CD pipelines. |
| CLI-Based Approach | Implement a Command-Line Interface (CLI) for developers to run the tool via commands. | - Easy to integrate into existing pipelines. | - Requires familiarity with CLI tools. |
| | | - Lightweight and efficient. | |

**Decision**:
We chose a **CLI-based approach** because:

- It is highly **lightweight** and efficient for developers.
- It can be easily integrated into **CI/CD pipelines**, automating documentation generation for both new and existing projects.
- It aligns with our vision of enabling seamless, automated documentation workflows in modern software development.

By combining the flexibility of **LLM usage** (Bulk vs API-by-API) with the simplicity and pipeline readiness of a **CLI-based solution**, we ensured that our approach is both scalable and practical for real-world use cases.

## 4. Applied Skills and Ideas

The implementation of the system leveraged concepts and tools learned throughout the quarter:

- **Python Programming**: Core language for CLI development and API parsing.
- **FastAPI**: Used to understand input API files and dependencies.
- **LangChain**: Framework for integrating GPT-based models into the documentation pipeline.
- **OpenAI GPT-4o and GPT-4o-mini**: Leveraged for high-quality text generation.
- **Prompt Engineering**: Applied iterative refinement for optimizing LLM prompts.
- **Evaluation Pipelines**: Used critic LLMs to score and compare outputs.
- **Automation**: Ensured seamless integration of file parsing, LLM processing, and output generation.

## 5. Challenges and Solutions

| Challenge | Solution |
|---|---|
| Handling large API files | Implemented API-by-API mode for chunk-based processing. |
| LLM context window limitations | Choose GPT-4o for bulk and GPT-4o-mini for granular tasks. |
| Ensuring output quality | Designed prompt versioning with iterative evaluation. |
| Inconsistent code formatting | Preprocessed input files to standardize code structure. |

## Experiments and Results

### 1. Overview of Experiments

To evaluate the effectiveness of the **Dynamic API Documentation Generator**, we conducted a series of experiments focusing on:

1. **Prompt Optimization**: Comparing multiple prompt versions (`v1` and `v2`) for both Bulk and API-by-API modes.
2. **Model Performance**: Evaluating the output quality and efficiency of **GPT-4o** and **GPT-4o-mini**.
3. **Scalability**: Testing the tool's ability to handle both simple (`sample_apis.py`) and complex (`complex_api.py`) API files.
4. **Real-World Usability**: Generating documentation in Markdown format and scoring it using a critic LLM for key metrics:
    - Completeness
    - Clarity
    - Accuracy
    - Relevance

These experiments were designed to demonstrate the robustness and scalability of our solution across various scenarios.

### 2. Prompt Optimization

#### Experimental Setup

- **Prompts Tested**:
    - Bulk Mode Prompts (`bulk_api_prompts.json`).
    - API-by-API Mode Prompts (`api_by_api_prompts.json`).

- **Evaluation Process**:
    - Outputs generated using different prompt versions (`v1`, `v2`) were scored by a critic LLM using the prompt evaluation scripts (e.g., `prompt_evauation.py`).
    - Each output was assessed on four key metrics: Completeness, Clarity, Accuracy, and Relevance.

**Results**

| Metric | Version v1 | Version v2 | Improvement |
|---|---|---|---|
| Completeness | 75% | 92% | +17% |
| Clarity | 68% | 90% | +22% |
| Accuracy | 70% | 93% | +23% |
| Relevance | 72% | 91% | +19% |

**Key Observations:**

1. **Completeness** improved significantly in `v2`, as the prompt explicitly requested examples for all endpoints and parameters.
2. **Clarity** scores increased due to better structuring of headers and subheaders in Markdown format.
3. **Accuracy** benefited from `v2` prompts including additional instructions for precise parameter descriptions.
4. **Relevance** was enhanced by focusing on developer-centric phrasing in `v2`.

## 3. Model Performance

### Experimental Setup

- **Models Tested**:
    - **GPT-4o**: Evaluated for Bulk Mode.
    - **GPT-4o-mini**: Tested for API-by-API Mode.
- **Input Files**:
    - `sample_apis.py`: Small, simple API filelex_api.py`: Larger, multi-endpoint API file with dependencies and detailed logic.
    - Processing Speed
    - Cost Efficiency
    - Documentation Quality (assessed by critic LLM).

**Results**

| Metric | GPT-4o | GPT-4o-mini | Observation |
|---|---|---|---|
| Processing Speed | Moderate | High | **GPT-4o-mini** is faster for endpoint-level tasks. |
| Accuracy | High | Moderate | **GPT-4o** excels in detailed analysis. |
| Cost Efficiency | Low | High | **GPT-4o-mini** is cost-effective. |
| Output Consistency | High | Moderate | **GPT-4o** generates more consistent results. |

**Key Observations:**

1. **GPT-4o** performed better in Bulk Mode, especially for large files, due to its extended context capabilities.
2. **GPT-4o-mini** excelled in API-by-API Mode, providing faster and cost-efficient results for endpoint-specific tasks.

## 4. Scalability and Real-World Usability

### File Sizes and Results

| File Name | Size | Mode | Result |
|---|---|---|---|
| `sample_apis.py` | Small | Bulk | Successfully generated cohesive documentation in one request. |
| `complex_api.py` | Large | API-by-API | Produced detailed, endpoint-specific outputs in multiple calls. |

**Key Findings:**

1. **Bulk Mode** efficiently processed smaller files, generating documentation for the entire API in one request.
2. **API-by-API Mode** effectively handled larger, complex files by splitting them into manageable chunks for processing.

## 5. Failure Modes

1. **Missing Docstrings**:
    - Generated documentation lacked completeness for endpoints with insufficient comments.
    - **Mitigation**: Added fallback heuristics to infer missing descriptions.
2. **Complex Dependencies**:
    - Middleware layers (e.g., `authenticate_user`) required manual handling to include in the documentation.

    - **Mitigation**: Enhanced preprocessing to capture and document dependencies.
3. **Context Limitations**:
    - Bulk Mode occasionally hit the LLM's context limit for very large files.
    - **Mitigation**: Encouraged API-by-API Mode for complex files.

## 6. Visualizations

**Prompt Evaluation Results**

| Metric | v1 Score | v2 Score |
|---|---|---|
| Completeness | 75% | 92% |
| Clarity | 68% | 90% |
| Accuracy | 70% | 93% |
| Relevance | 72% | 91% |

**Model Performance**

| Metric | GPT-4o | GPT-4o-mini |
|---|---|---|
| Speed | Moderate | High |
| Cost Efficiency | Low | High |
| Output Consistency | High | Moderate |

## 7. Summary of Results

- **Prompt v2** delivered significant improvements in Completeness, Clarity, Accuracy, and Relevance.
- **GPT-4o** excelled in handling complex APIs in Bulk Mode, while **GPT-4o-mini** provided cost-effective and fast results for API-by-API Mode.
- The tool successfully automated API documentation for both simple and complex use cases, demonstrating its real-world applicability.

# Conclusion

The **Dynamic API Documentation Generator** successfully automates the traditionally manual process of API documentation creation, addressing key challenges like inconsistency, inaccuracy, and inefficiency. By leveraging Large Language Models (LLMs) such as GPT-4o and

GPT-4o-mini, and integrating robust prompt evaluation mechanisms, the tool produces high-quality, developer-friendly documentation in Markdown format.

## Key Results

1. **Prompt Optimization**:
   Iterative refinement of prompts demonstrated a substantial improvement in documentation quality, with **v2 prompts** achieving up to 92% Completeness, 90% Clarity, 93% Accuracy, and 91% Relevance—significantly outperforming earlier versions.
2. **Model Performance**:
   - **GPT-4o**: Ideal for Bulk Mode due to its superior accuracy and ability to handle large context windows.
   - **GPT-4o-mini**: A faster and cost-efficient alternative for API-by-API Mode, particularly effective for endpoint-level tasks.
3. **Scalability**:
   The tool efficiently processed both simple and complex API files, showcasing its ability to adapt to real-world use cases. Bulk Mode handled smaller APIs cohesively, while API-by-API Mode managed larger, complex APIs with precision.

## Lessons Learned

- **Preprocessing is Critical**: Accurate parsing and preprocessing of source files significantly enhance the quality of generated documentation.
- **Prompt Engineering Drives Success**: Fine-tuning prompts iteratively ensures outputs align with developer needs and expectations.
- **Trade-offs Between Speed and Accuracy**: While GPT-4o excels in detail and consistency, GPT-4o-mini is more suitable for faster, cost-effective operations.

## Future Extensions

1. **Multi-Language Support**:
   Expand compatibility to programming languages beyond Python, such as Java, JavaScript, and Go, to cater to a broader audience.
2. **Dependency Mapping and Visualization**:
   Include automated mapping of middleware and authentication flows, providing more context in the documentation.
3. **Advanced Prompt Engineering**:
   Explore chain-of-thought prompting and multi-step generation to handle more complex APIs and ensure even higher accuracy.
4. **UI-Based Alternative**:
   Add a web-based interface for non-technical users, complementing the CLI’s integration with CI/CD pipelines.

5. **Real-Time Integration**:
   Fully automate documentation updates during deployment to ensure synchronization with evolving APIs in real time.
6. **Expanded Evaluation Framework**:
   Include additional evaluation metrics, such as usability and developer feedback, to further refine documentation quality.

## Closing Statement

This project demonstrates the transformative potential of LLMs in software development workflows. By automating API documentation with a scalable and adaptable system, the **Dynamic API Documentation Generator** not only reduces developer workload but also sets a new standard for documentation quality. Future advancements will focus on expanding its applicability and refining its capabilities to serve even more diverse use cases in modern development ecosystems.