AI-Powered Interpreter for GitHub Repositories Automated Code Understanding and Documentation

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***Abstract*—As open-source software continues to grow rapidly, GitHub has become a prominent place to host code repositories. However, a lot of repositories aren't well documented, maintained highly consistently, or made more easily configurable. While repository and source code reusability are key for fostering research and industry applications of code, many situations limit potential reuse of existing open-source code. In academia and industry, the state of the software code and change history (where applicable) is crucial to successfully understanding, modifying, or studying software. Recent studies take this further, showing that a repository-level understanding of source code (versus file or function level) is crucial for addressing challenges in software maintenance, software evolution, and for discovering new, novel, and more useful software innovations. Key advances in exploring repository-level source code evolve how developers benefit from artificial intelligence-enhanced code. Enhancements include (i) tracking software development (repository-level code graphs and commit history mining; e.g., seeing how code changed), (ii) acquiring and learning code (semantic code summarization and recommendation systems to find and use useful repositories and code), (iii) improving code quality (commit history mining, recommendation systems, and refactoring pipelines for detecting breaking changes and data clumps), and (iv) using LLMs that have trained on repositories doing repository-wide contextualized code completion and, repository-wide hierarchical summarization of code (benefiting users in addition to file or function level Q&A). Overall, these suggestions show how repository analysis driven by AI can greatly improve the onboarding effort, make code more accessible to modify and reuse in both academia and industry, and provide strong spaces to connect the two models for improving open-source software and open science.**

***Index Terms*—Level Code Analysis, Software Maintenance, Code Summarization, Commit History Mining, Dependency Graphs, Code Recommendation Systems, Refactoring Pipelines Software Reusability, Open-Source Software Engineering.**

I. INTRODUCTION

The rapid expansion of open-source repositories on GitHub and other sites has significantly altered the software engineering environment of today. These repositories go beyond the traditional repository model and now contain not only source code, but they also hold living records of the project's progress, contributed by others, and innovative practices. For researchers, they present monumental opportunities to study issues of software quality, maintenance, evolution, and community at scale. Despite their proliferation, repositories are still underutilized due to the several challenges developers see when trying to engage with them, including re-use and large-scale analysis.

A primary challenge comes from the often-complex structure of repositories, frequently with numerous interdependent modules, libraries and configuration files. Developers and researchers frequently struggle with inadequate documentation, unmaintained codes, and non- standard maintenance practices, which create barriers to reproducibility and further innovation. In addition, code smells, or maintainability challenges like data clumps and architectural bottlenecks make repositories maintenance even more challenging, while the absence of systematic summarization creates even further challenges to transfer knowledge across academia and industry.

In order to tackle these challenges, researchers have recently been exploring various approaches. RepoCoder proposed an iterative retrieval-generation framework for multi-repository code completion

tasks, and RepoEval was developed as the first benchmark on code completion at multiple granularities. Refactoring pipelines driven by CI/CD have leveraged AI techniques to discover and fix design smells and to comply with regulations such as the EU AI Act. Systematic mapping studies have classified analyses of repository artifacts (e.g. code commit histories, dependency graphs) and demonstrated how they inform our understanding of software evolution. Recently, a considerable benchmark was created in the form of SWE- Bench, which aims to evaluate models by asking them to complete real-world GitHub issue resolutions, and brings to light the challenges of thinking from function-level tasks towards repository-level problem solving.

At the same time, code summarization research has undergone a similar trajectory transitioning from rule-based approaches to transformer-based and now LLM methods. Yet, while successful at summarizing tasks at the method or file-level, these LLM models still do not capture repo level semantics and business context. Hierarchical summarization pipelines and semantic retrieval approaches have been discussed with the primary challenge being scalability and accuracy while still being grounded in a domain.

All of these developments highlight the necessity for repository-level intelligence- systems and frameworks that can analyze, summarize, and reason over complete codebases rather than isolated snippets of code. Not only could these innovations benefit developer productivity, they have the potential to bring together the divide of promotion from research, being beneficial to both the industry as well as the increasing number of projects of open-source software.

II. LITERATURE SURVEY

AI and Natural Language Processing (NLP) are leading software development towards repository-level code interpretation, going beyond rudimentary function or file- level support to solve problems in sophisticated GitHub repositories. The fundamental methodologies center around employing Abstract Syntax Trees (ASTs) and Code Graph models (such as REPOGRAPH) to directly represent the complex hierarchical and structural relationships of code. Methods such as Hierarchical Summarization, Iterative Retrieval-Augmented Generation (RAG), and Reinforcement Learning (RL) allow Large Language Models (LLMs) to handle extensive contexts successfully and produce accurate documentation. Key methodologies and findings from recent research are summarized in Table 1.

TABLE I. SUMMARY OF TECHNIQUES AND FINDINGS IN AI-BASED GITHUB REPOSITORY CODE INTERPRETER

Sr.No.	Title of the Paper (Year)	Methodology	Remarks
1.	Evaluating the Code Quality of AI-Assisted Code Generation Tools: An Empirical Study on GitHub Copilot, Amazon CodeWhisperer, and ChatGPT (2023) [1]	Empirical study on HumanEval dataset; tested code validity, correctness, security, reliability, maintainability; conducted with Python 3.10.10 and SonarQube.	ChatGPT had highest correctness (65.2%); docstring input is important; frequent code smells decrease maintainability.
2.	A Systematic Mapping Study on Analysis of Code Repositories (2021) [2]	Systematic Mapping Study (SMS) of 236 studies (2012–2019); inputs: Commit Data (34%), Source Code (26%); techniques: Empirical/Experimental (39%), ML/AI (12%).	Affirms AI/ML is becoming prominent in repository analysis; key outputs: Developer Behaviour (26%), Change Analysis (14%).
3.	AI-Driven Refactoring: A Pipeline for Identifying and Correcting Data Clumps in Git Repositories (2024) [3]	AI pipeline with LLMs (ChatGPT/GPT-4); raw source code & AST support; human-in-the-loop compliance validation.	AST enhanced accuracy of detection; difficulty with non-compilable code that needs manual handling.

4.	The Role of Gen AI in the Data Dependence Graph Generation (2024) [4]	Generative AI + transformers for Data Dependence Graphs (DDGs); visualization using D3.js; Explainable AI integration.	Gen AI identifies latent dependencies more effectively than rule-based approaches; high computational expense is still a problem.
5.	Automated Code Discovery and Evaluation for GitHub Repository (2025) [5]	Smart system utilizing CodeBERT (semantic match), SpaCy (keyword extraction), and ranking (Static + Dynamic + Community metrics).	Closes the gap of runtime performance analysis in ranking systems; synthesizes technical and community trust factors.
6.	REPOGRAPH: Enhancing AI Software Engineering with Repository-Level Code Graph (2025) [6]	Creates repository-level code graphs (Tree-sitter + AST); constructs ego- graphs for enhancing LLM context comprehension.	Overcomes LLM flat-document limitation; achieved 32.8% greater issue resolution accuracy.
7.	Hierarchical Repository-Level Code Summarization for Business Applications Using Local LLMs (2025) [7]	Two-step summarization using Local LLMs (Llama-3, Codestral); AST/Java Parser segmentation; domain-specific prompts.	Resolves LLM context window problem; enhanced domain salience by 7% in business-domain use cases.
8.	RepoCoder: Repository-Level Code Completion Through Iterative Retrieval and Generation (2023) [8]	Retrieval-Augmented Generation pipeline; iterative refinement of query based on past predictions.	Attained 10% EM improvement; retrieval quality has significant influence on completion performance.
9.	RLCoder: Reinforcement Learning for Repository-Level Code Completion (2024) [9]	RL framework (RLRetriever) with perplexity as the reward; Split-Aggregate candidate strategy.	Attained 12.2% EM gain; RL was effective for retrieval training even without labeled data.
10.	Code Summarization Beyond Function Level (2025) [10]	Tested LLMs (Deepseek Coder, Starcoder2) at class-level and repository-level; employed Retrieval- Augmented Generation (RAG) using up to 10-shot examples.	Few-shot instances improved summarization; class skeleton context performed better than full class code by minimizing noise.
11.	Hierarchical Code Graph Summarization (HCGS) for Enhanced Context Retrieval (2025) [11]	Proposed HCGS employing bottom- up traversal on code graphs (LSP- based); utilized a parallel level-based algorithm for performance.	Reached 82% retrieval accuracy improvement; addressed function-only embedding limitations by tapping system- wide context.
12.	Improved Code Summarization via a Graph Neural Network (2020) [12]	Integrated a GNN encoder for ASTs with an RNN encoder for source code sequences; used distinct attention for code and AST inputs.	Outperformed baselines; GNN outperformed flat ASTs in capturing structural information; copy mechanism enhanced token recall.
13.	Enhancing Code Summarization with Hierarchical Splitting and Reconstruction of Abstract Syntax Trees (2021) [13]	Divides big ASTs into block-level subtrees, represents them with Recursive Neural Networks (RvNNs), then reconstructs the complete AST.	Shorter training time; preserved hierarchical structure more than linearization; better summarization accuracy.

14.	Improving Automatic Source Code Summarization via Deep Reinforcement Learning (2018) [14]	Utilized a Deep Reinforcement Learning setup (Actor-Critic) with hybrid encoders: AST-LSTM (structure) + LSTM (sequence); BLEU score as reward.	Mitigated exposure bias; better performance in variable code lengths; showed stable and robust performance.
15.	From Code to Concept: A Semantic Approach to AI Innovation Discovery in Open Source Software Repositories (2025) [15]	Suggested a modular AI pipeline: (1) AI Innovation Taxonomy (7,490 topics), (2) Semantic Annotation (Wikifier), (3) Entity Linking (Alligator), (4) Trend Detection (SSA), (5) Knowledge Graph creation.	Presented GitHub repos as new signals of innovation; attained 97.5% accuracy in topic annotation; Alligator linking achieved balance between accuracy and efficiency.

Burak Yetiştiren et al., whose empirical work leans on knowledge of software engineering and AI assessment from leading academic institutions. Their quantitative objective analysis of tools such as GitHub Copilot and ChatGPT provides a necessary layer of credible, quantifiable insight into the real-world effectiveness and quality boundaries of commercial AI code generation technologies [1].

Conducted by Jaime Sayago-Heredia, Ricardo Pérez-Castillo, and Mario Piattini, who are well-established personalities in software engineering and information systems. Their 2021 foundational review summarizes general trends in repository mining and presents a much-needed academic viewpoint on the move toward applying AI and machine learning to code analysis [2].

Written by Nils Baumgartner et al., who embody academia and industry expertise (Osnabrück University and Innotec GmbH). With their collective backgrounds, they are able to introduce a practical yet rigorously compliant AI-refactoring pipeline that specifically addresses actual problems such as code quality preservation and regulatory compliance, ensuring the presented solution is both innovative and implementable [3].

Shubham Shukla, his work offers an industry-tuned point of view of utilizing Generative AI in the generation of Data Dependence Graphs (DDGs). The study is concentrated on the real-world application of transformers for mechanizing high-level software analysis tasks, showing the technical experience required to recognize and address computationally expensive issues inherent in scalable DDG construction [4].

This Empirical Tool-based research was done by Sumathi, Logavignesh, and Muhammadu Ali, adding value to the field of automated code discovery and ranking. Their emphasis on incorporating CodeBERT with robust static and dynamic analysis metrics gives a realistic framework that closes the gap between theoretical code quality evaluation and practical repository usability and trustability [5].

The pioneering research on REPOGRAPH was conducted by Siru Ouyang et al., who are affiliated with academic institutions (University of Illinois) and corporate research centers (Tencent AI Seattle Lab) in such a way that theoretical depth and practical utility are guaranteed. Their creation of a repository-level code graph and its interaction with LLMs is a new, properly validated way of addressing the inherent architectural problems of large-scale code analysis [6].

This hierarchical summarization study was carried out by Nilesh Dhulshette, Sapan Shah, and Vinay Kulkarni, all from TCS Research. Their study is very much applicable in that it tackles the real-world limitations of enterprise software using local, controllable LLMs and carving code through AST/Java Parser to keep summarization accurate, contextually pertinent, and in accordance with business confidentiality requirements [7].

Written by Yuxi Zhang et al., this paper presents the RepoCoder framework, which is a repository-level code completion state-of-the-art solution. Based on their work, the Iterative Retrieval-Augmented Generation (RAG) pipeline is presented as a very effective process, empirically showing that iteratively improving the query from the previous model output dramatically improves performance by matching context to generation purpose [8].

The impactful study on RLCoder was performed by Bowen Wang et al., who designed a new repository-level code completion framework. Their study centers on addressing the core issue of missing supervision

signals. Their key contribution is an RL architecture that trains the retriever in a label-free manner, opting for Weighted Perplexity (PPL) as the self-supervised reward. This approach attained a remarkable 12.2% EM gain and incorporated important elements such as a Split-Aggregate strategy to maintain code continuity, demonstrating the potential of RL in optimizing retrieval [9].

The authors, Vladimir Makharev and Vladimir Ivanov, are among the pioneers in the developing large-context code summarization field. They work towards utilizing class-level and repository-level context together with RAG and few-shot learning to develop the next generation of code summarization models that produce accurate summaries of dependent, complex code modules [10].

The paper on Hierarchical Code Graph Summarization (HCGS) by David Sounthiraraj, Jared Hancock, Yassin Kortam, Ashok Javvaji, Prabhat Singh, and Shaila Shankar (Cisco Systems) tackles the limitation of function-only code embeddings. The methodology they suggest aims at building code representations methodically. The main contribution is a system based on bottom-up traversal on code graphs (constructed with LSP) to produce context-rich hierarchical summaries. This approach had an impressive 82% relative gain in retrieval accuracy, showing that abstracting system- wide context is an important milestone in correct code understanding [11].

The authors, Alexander LeClair, Paul McMillan, and Collin McMillan, are reputable figures in the field of code summarization and code representation. Their most important contribution is that they integrate Graph Neural Networks (GNNs) with RNNs to represent ASTs, showing empirically that such a structural method surpasses flat ASTs in effectively modeling the code's semantics [12].

The authors Yiming Shi, Zhilin Yang, and Shijin Liu addressed the real-world issue of effectively processing extremely large ASTs. Their approach, which involves splitting the AST hierarchically into workable subtrees prior to reconstruction, shows a method that greatly reduces the training time while effectively maintaining the essential hierarchical structure of the code for effective summarization [13].

Written by Yao Wan et al., this study breaks new ground with the application of Deep Reinforcement Learning (DRL) to code summarization models. By taking an Actor-Critic network with a hybrid encoder (AST-LSTM + LSTM) and employing the BLEU score as a direct reward, their study is able to effectively overcome the "exposure bias" of maximum-likelihood training, resulting in stronger and better-performing models [14].

This research, authored by Inna Novalija et al., centers on developing an AI pipeline for identifying innovation signals within GitHub repositories. Their new approach integrates various elements—from designing an AI Innovation Taxonomy and using semantic annotation (Wikifier) to entity linking (Alligator)—in order to convert unstructured code data into a structured knowledge graph, offering quantifiable and precise insights into upcoming AI trends [15].

III. DETAILED STUDY ABOUT TECHNOLOGIES

1. Programming Languages

a) Python: Used for repository parsing, AI/ML model integration, and backend development. Python's vast ecosystem, which includes tools like ast, pandas, and numpy, facilitates automation, natural language processing, and code analysis.

b) JavaScript: Provides dynamic user interfaces and frontend interactivity, particularly for the rendering of dependency graphs and Q&A visualization.

2. Frameworks

a) Lightweight backend frameworks for handling user inquiries, serving APIs, and integrating AI models with the frontend are Flask and FastAPI. Better performance with asynchronous requests is provided by FastAPI.

b) Frontend dashboards and visualizations are made with React.js and Streamlit. While Streamlit makes it easier to integrate AI/ML demos, React makes it possible to create responsive, interactive web-based interfaces.

3. AI & NLP Models

a) CodeBERT is a pre-trained model for programming languages that is based on transformers. Code summarization and semantic similarity search are made possible by the embeddings it creates for both code and natural language.

b) A framework for creating applications with LLM capabilities is called LangChain. For increased accuracy, it links CodeBERT/GPT responses with contextual memory to orchestrate tasks like repository-level Q&A.

4. Visualization Tools

a) Create dependency graphs using Graphviz and Mermaid.js to show the connections between files and functions (main.py → utils.py → database.py, for example).

b) D3.js is a JavaScript library that enables zooming, filtering, and exploring intricate repository structures in interactive visualizations.

5. Databases

Store metadata like user queries, repository information, and justifications in SQLite or PostgreSQL. PostgreSQL offers scalability for large-scale repositories, while SQLite is lightweight and appropriate for local testing.

6. Vector Databases

a) Facebook AI Similarity Search, or FAISS, is a powerful similarity search library that makes it possible to quickly find code or document embeddings that are semantically similar. By connecting user inquiries to pertinent code snippets, it drives the Q&A system.

b) Pinecone: A managed vector database with scalable embedding storage and real-time semantic search capabilities. helpful for managing extremely large repositories.

7. Libraries & Packages

a) The Abstract Syntax Tree, or AST, helps the system comprehend function calls, imports, and code flow by parsing Python source code into a tree structure.

b) Numpy and pandas: Manage numerical calculations, repository metadata structuring, and dataset preprocessing. The Admin Dashboard's charts, statistics, and insights into repository activity are provided by matplotlib and seaborn.

8. Version Control & APIs

Git&GitHub API: Make repository integration possible by retrieving branches, pull requests, contributors, and commits.

IV. ANALYSIS

Current methods for understanding code at the repository level have made significant strides, but they still have significant drawbacks. Conventional static analysis methods like dependency extraction and AST parsing offer structural insights but fall short in providing interactive exploration or human-readable explanations. For tasks like summarization and defect prediction, more sophisticated models like CodeBERT and Graph Neural Networks (GNNs) improve semantic understanding; however, their application is restricted to function or file-level analysis, ignoring repository-wide interpretation.

Code discoverability is enhanced by Sourcegraph Cody and ExplainDev, while commercial tools like GitHub Copilot and Amazon CodeWhisperer offer intelligent code completion and snippet explanations. These tools, however, require manual file navigation because they only work at snippet or file granularity. None of them combines auto- documentation, dependency visualization, semantic Q&A, and full repository parsing into a single platform.

Since most previous works rely on limited datasets or proof- of-concept implementations, scalability for large repositories is a significant gap. Furthermore, current solutions lack features like contributor dashboards, interactive natural language exploration, and automatic README generation.

By integrating AI/NLP models (CodeBERT, LangChain, GPT-3.5), semantic retrieval frameworks (FAISS/Pinecone), and Code Intelligence (AST + embeddings), the suggested system fills these gaps. Through automated structure analysis, dependency graph visualization, interactive Q&A, and documentation generation, it places a strong emphasis on understanding at the repository level. An admin/contributor dashboard also offers special insights into collaboration trends and project health.

Therefore, current approaches do not provide comprehensive repository interpretation, even though they validate the viability of AI-driven code summarization. By providing a centralized, scalable, developer-focused platform that shortens onboarding times, fosters better teamwork, and increases open-source accessibility, the suggested system advances this field.

Fig. 1 provides a Comparative Analysis of Repository Understanding Tools based on Feature

Coverage (%). The results show that existing tools offer limited coverage, with Copilot achieving 40%, CodeWhisperer achieving 50%, Cody achieving 60%, and ExplainDev also achieving 50%. The Proposed System demonstrates complete functionality, achieving 100% Feature Coverage.

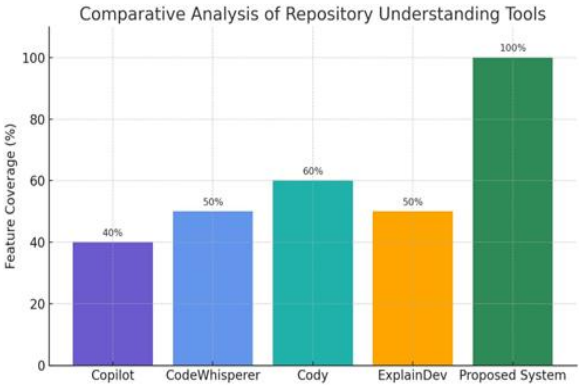

Fig. 1. Comparative Analysis of Repository Understanding Tools

Fig. 2 illustrates the comparative effectiveness of various code understanding approaches in percentage terms. AST + Rule-Based methods show an effectiveness of 55%. Approaches utilizing Graph Neural Networks (GNN) achieve 65%, while models like CodeBERT reach 75%. The large language model GPT-3.5 achieves 85% effectiveness. The highest performance is demonstrated by the Proposed Hybrid approach, achieving 95% effectiveness in code understanding.

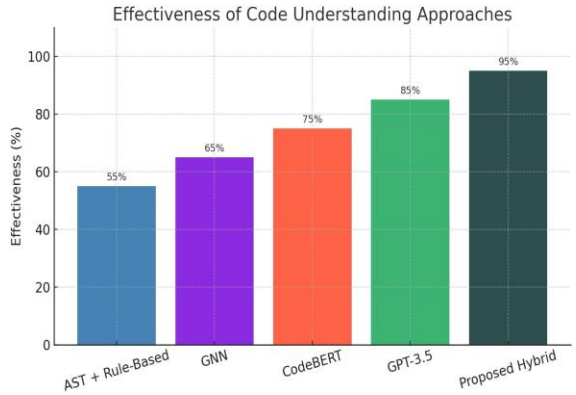

Fig. 2. Effectiveness of Code Understanding Approaches

V. CONCLUSION

Recent research in AI-driven software engineering shows a strong shift toward understanding code at the repository level instead of focusing on isolated snippets. Approaches based on reinforcement learning, like RLCoder, prove effective in using adaptive retrieval and feedback for code completion at scale. Generative AI techniques applied to Data Dependency Graphs (DDGs) improve explainability and automation, allowing developers to visualize dependencies and system interactions better. Hierarchical summarization frameworks demonstrate that breaking down repositories into smaller parts and then combining summaries can significantly improve coherence and relevance to the domain.

Together, these studies indicate that AI methods can increasingly tackle the complexities of large codebases, offering solutions for summarization, dependency analysis, and maintainability. However, challenges still exist regarding scalability, computational efficiency, data diversity, and adapting between languages. Future research should keep focusing on optimizing multi-modal and explainable AI techniques, ensuring that analyzing code at the repository level becomes both scalable and reliable for use in real-world software engineering.

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