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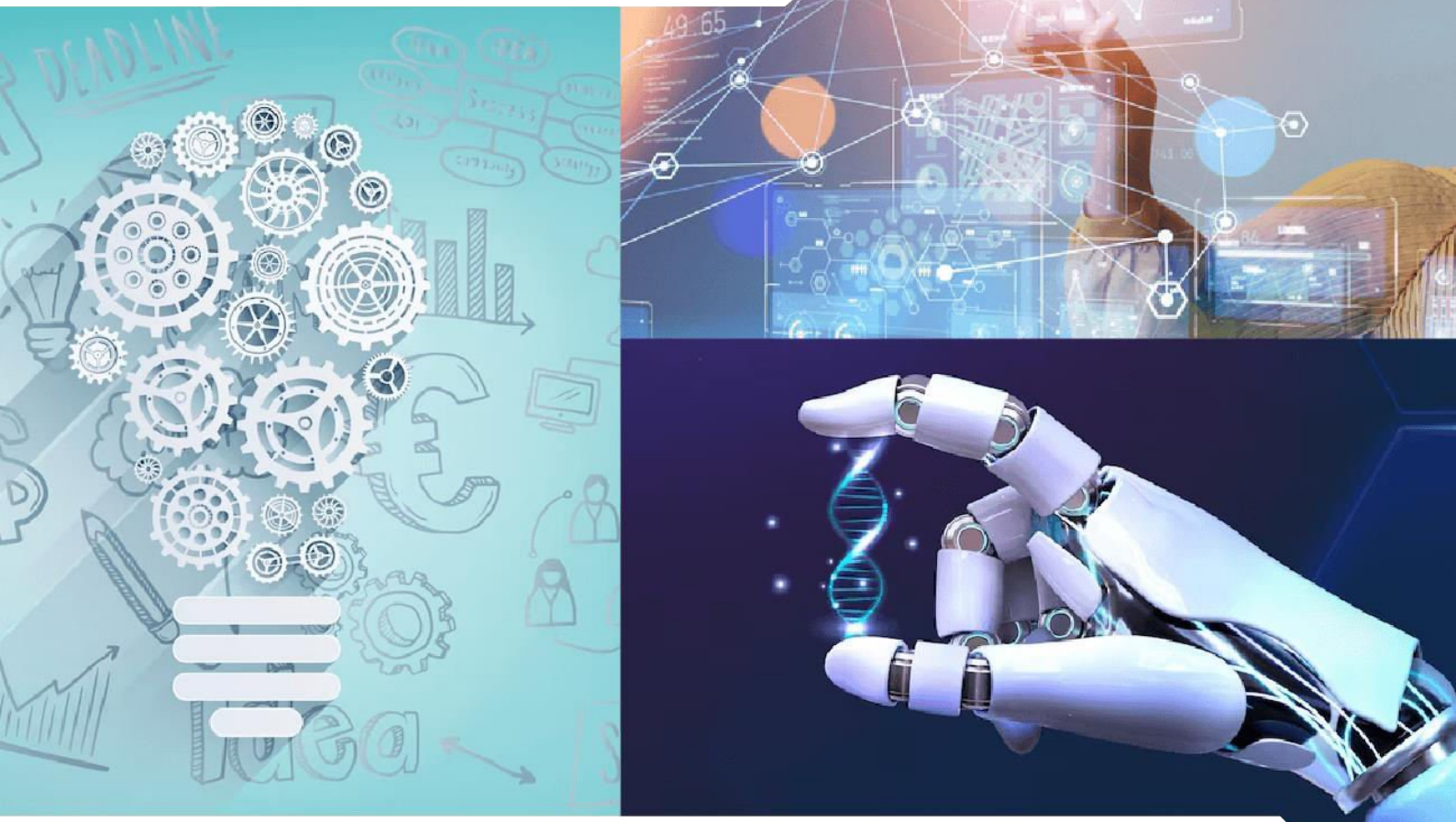

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AI-Based Intelligent Python Code Exploration System

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ABSTRACT: Handling large code bases is still a challenge because traditional IDE tools rely on keyword searches and lack in-depth knowledge of code functionality and structural relations. This paper proposes an AI-Powered Smart Python Code Base Navigator, a hybrid model that integrates Abstract Syntax Tree (AST) structural analysis with semantic reasoning from a Large Language Model (LLM) using Google Gemini Pro, deployed through a Streamlit interface. The proposed system delivers five major capabilities: intelligent code summarization using machine learning with smart segmentation, semantic search via natural language queries, interactive dependency graph visualization, AI-assisted context-aware code completion, and Abstract Syntax Tree-based navigation with call graph generation. Testing on Python modules ranging from 15 to over 220 lines yielded an accuracy rate of 92–100%, with AI-driven features completing in 3–8 seconds and AST operations in under 3 seconds, resulting in a 60% decrease in code review time. This hybrid approach overcomes the weaknesses of single solutions—the semantic gap of pure AST and the high latency of pure LLM—delivering superior code understanding capabilities for modern software development.

KEYWORDS: Code Summarization, Semantic Search, Ab-stract Syntax Tree, Dependency Visualization, Code Completion, Large Language Models, Hybrid Architectures, Software Com-prehension, Google Gemini Pro, Streamlit

I. INTRODUCTION

In modern software development, a critical productivity challenge is that developers spend 35–50% of their time understanding existing code rather than building new functionality. This is particularly pronounced when working with unfamiliar codebases or maintaining legacy systems. Traditional IDE tools rely on keyword searches and basic pattern recogni-tion, which fail to capture the semantic meaning, logical progression, and architectural relationships that govern code functionality. These deficiencies substantially limit productiv-ity, lengthen the onboarding period, and create barriers in collaborative environments where understanding the code is essential for effective development.

An innovative hybrid architecture within the AI-Powered Smart Python Code Base Navigator addresses these gaps by combining Abstract Syntax Tree (AST) structural analysis with the semantic reasoning of a Large Language Model using Google Gemini Pro. This platform delivers five advanced ca-pabilities: automated code summarization generating human-readable explanations, semantic search enabling natural lan-guage queries, interactive dependency visualization exposingcode relationships, AI-driven context-aware code completion, and comprehensive AST-based navigation with call graph generation. The system demonstrates accuracy between 92–100% across various Python modules.

This study shows that the hybrid AI-AST architecture reduces code comprehension time by 60%, opening a path for next-generation developer tools that fundamentally change how developers understand software and accelerate engineer-ing processes.The remainder of this paper is organized as follows. Sec-tion II surveys related work in AI-based code understanding. Section III describes the materials and methods. Section IV presents the proposed system. Section V details the objectives and applications. Section VI presents results and performance analysis. Section VII concludes the paper with future direc-tions.

II. LITERATURE REVIEW

The literature review highlights the evolution of AI-based code understanding and its significant impact on software development over recent years.

The literature review highlights the evolution of AI-based code understanding and its large impact on software devel-opment over the past few years. Rajan et al did a systematic mapping study on AI in source code understanding,

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exploring transformer models, graph neural networks, and pre-trained language models. models, such as CodeBERT and Graph CodeBERT. They had identified key gaps in the field of semantic search and code ”navigation that this project is intended to tackle. The work of Srivastava, et al. led to the enhancement of code generation based on semantic reasoning and dependency tracking, principles that were employed in their intelligent completion component. Mahen Kumar et al. examined transformer models in code summarization, focusing on the ability to leverage the combination of programming language models and code Abstract Syntax Tree and graph embeddings are added to promote performance, which helps determine the summary method. Bibi et al. added C2B, an approach that stacks CodeT5 with Bi LSTM to the models. Bibi et al. achieves better mapping between queries and code, thereby paving the way for semantic search functionality. Both Liu et al. and Sun et al. stressed the significance representation

by heterogeneous syntax and contrastive learning on depen-dency graphs, which immediately affects representation of the dependency module. The ability to perform effective summary on small data sets was shown by Ahmed and Devanbu through fine-tuning to discuss the deployment and implementation of specialized codebases. Gong et al. used positions derived from the Abstract Syntax Tree in transformers, enabling better semantic requiring intricate interpretation conversions, con-tributed to Navigation design. Chakraborty et al. applied the naturalizing scheme of NatGen for the generation of idiomatic code enhancing the completion readability. Wang et al. demon-strated the capability of CoCoSum with it get Contextual Summarization multi-relational graphs for class-level analysis, which is useful for object oriented programming. Guo et al. Proposed Graph CodeBERT by integrating the data flow graph and the transformer, offers a theoretical model for the hybrid architectures. This research that purely AST-based systems are semantically unsound, but purely LLM strategies are costly. The hybrid architectures that blend structural analysis and AI reasoning perform much better and its usefulness for code comprehension.

III. MATERIAL AND METHODS

The AI-Powered Smart Python Code Base Navigator utilizes a hybrid three-layer architecture that combines AST-based structural analysis with LLM semantic reasoning to provide comprehensive code understanding capabilities. The system comprises three interconnected layers designed for modularity, scalability, and efficient processing of Python codebases.

A. Presentation Layer

The Presentation Layer is built using the Streamlit web framework, implementing an intuitive user interface with text entry, selection controls, and collection interfaces such as text area functions for code submission and search queries. The layer provides buttons for choosing operations and displays results through Markdown rendering, syntax-highlighted code blocks, and interactive graphs. User session state is maintained consistently throughout the interaction.

B. Application Layer

C.

The Application Layer implements the core business logic through five loosely coupled modules.

Code Summarizer: Employs intelligent chunking algo-rithms to split large files into segments of a fixed 15,000-token length, enabling comprehensive summarization of arbitrarily large codebases.

Search Module: Combines submitted code with natural lan-guage queries to form contextual prompts, leverages Gemini’s semantic understanding, and returns well-supported responses with appropriate code examples and line number references.

Dependency Graph Generator: Applies visitor patterns on the AST to extract functions and classes, generates NetworkX directed graphs modeling call and inheritance relationships, and produces visualizations using spring-layout algorithms with colour-coded nodes.

Code Completer: Analyses code context fragments, per-forms completion using structured AI prompts incorporating Python best practices, and validates output syntax before delivery.

AST Navigator: Performs two-pass AST traversal to re-trieve function metadata and call relationships, generates Graphviz DOT files for call graphs, and provides expandable function listings with exact line numbers.

D. Integration Layer

The Integration Layer manages all external dependencies. The Google Gemini Pro API (models/gemini-2.5-flash)

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provides natural language processing and code understanding via REST API calls and structured prompts. Python's standard ast module handles abstract syntax tree parsing and traversal through visitor-pattern implementations. The NetworkX library provides directed graph data structures and layout algorithms. Matplotlib generates high-quality scientific visualizations. Configuration management uses python-dotenv to securely handle API keys through environment variables.

E. Implementation Technologies

The system was developed using Python 3.8+ as the pri-mary programming language in a modular package structure. The Streamlit framework (version 1.28+) provides the web application foundation with responsive design and real-time updates. The Google Generative AI library (google-generativeai) enables API integration. NetworkX (version 3.0+) manages graph operations, and Mat-plotlib (version 3.7+) produces publication-quality visualizations. The development environment uses virtual environment isolation with a requirements.txt file and .env configuration for flexible deployment.

F. System Workflow

The system validates all user inputs, surfacing warnings for empty entries and detecting syntax errors through AST parsing with rich error messages. Validated code is routed to the appropriate feature module based on the selected op-eration. AI-driven features construct structured prompts with role assignments, task descriptions, code contexts, and output specifications before invoking the Gemini API with checks for network issues and rate limits. AST-based features transform code into tree structures, apply visitor patterns to extract rele-vant information, and produce output representations. Results are formatted as Markdown text, syntax- highlighted code, or Matplotlib/Graphviz figures, then displayed using appropriate Streamlit widgets with progress indicators and expandable detail sections.

IV. PROPOSED SYSTEM

The AI-Powered Smart Python Code Base Navigator intro-duces a novel hybrid framework that integrates AST structural analysis with LLM semantic reasoning via the Google Gemini Pro API. The system is organized into three layers:the Presentation Layer (Streamlit UI), the Application Layer comprising five main modules (Code Summarization with 15,000-token segmentation, Semantic Search using natural language queries, Dependency Graph Generation using AST visitors and NetworkX, AI-Powered Code Completion, and AST Navigation with call graph creation), and the Integration Layer managing external services (Gemini API, Python AST parser, NetworkX graphs, and Matplotlib visualization).

Input validation ensures code quality before module pro-cessing. AI capabilities generate structured prompts, and AST features are parsed and navigated locally. The hybrid approach achieves superior performance: AST operations complete in under 3 seconds, AI-driven features complete in 3–8 seconds, and the combined system achieves a success rate of 92–100% while reducing code comprehension time by 60%.

Unlike conventional keyword-based tools that lack semantic interpretation, and unlike pure AI systems that face high latency and cost, the proposed system strikes a balanced approach by combining local structural analysis with cloud-based semantic processing. The modular architecture accom-modates future extensions including multi-language support, cross-file dependency analysis, and version control integration. Comprehensive error handling and graceful degradation ensure reliable operation under production conditions.

V. OBJECTIVES AND APPLICATIONS

A. Objectives

The key objectives of this project are to: (i) implement automated code summarization with intelligent segmentation to generate comprehensive natural language descriptions for complex codebases; (ii) build a semantic search engine enabling developers to query code using natural language and receive contextually relevant responses; (iii) design an interactive dependency graph visualization displaying function calls, class inheritance, and architectural relationships with colour-coded visuals; (iv) create an AI-powered code com-pletion tool generating context-sensitive, syntactically correct Python code conforming to best practices; (v) provide AST-based navigation with two-pass analysis that extracts functions, maps call relationships, and generates call graphs; and (vi) integrate all features into a cohesive Streamlit web application with real-time feedback, achieving 92–100% accuracy, AST response times under 3 seconds, and a 60% reduction in code comprehension time compared to traditional manual analysis.

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B. Applications

The system serves diverse software development scenarios. In legacy code maintenance, developers quickly comprehend undocumented systems through automated summaries and semantic searches, reducing understanding time by 60%. For new developer onboarding, team members can grasp project architecture within days rather than weeks through dependency visualizations and natural language queries. In code reviews, architectural issues are identified through dependency graphs without manually tracing the entire codebase. In educational environments, students can explore open-source projects andunderstand complex algorithms through AI- generated expla-nations and visualized call graphs. In refactoring projects, pro-grammers trace tightly coupled components and architectural bottlenecks through dependency visualizations. The system also accelerates documentation generation, producing compre-hensive function descriptions and architectural overviews and reducing manual documentation effort by 70%.

VI. RESULTS AND DISCUSSION

The AI-Powered Smart Python Code Base Navigator was evaluated on a wide range of Python code samples, demon-strating strong performance across all five core capabilities.

A. Summarization Results

The summarization module correctly summarized multiple code samples of varying complexity using intelligent chunking for large files. The system produced thorough summaries accu-rately identifying major elements including functions, classes, and logical structures. AI-generated explanations captured semantic meaning and functionality through coherent natural language descriptions.

B. Semantic Search Results

Semantic search demonstrated accurate natural language understanding. The system correctly identified functions rel-evant to submitted queries, described the purpose of those functions, and illustrated their implementation with line num-ber references. The system proved to have strong contextual understanding for both specific and conceptual questions.

C. Dependency Graph Results

The graph generator produced clear visualizations with colour-coded nodes (blue for functions, green for classes) and directional arrow connectors representing relationships. The system correctly identified all internal function call patterns and class inheritance relationships using spring-layout algo-rithms.

D. Code Completion Results

The code completion module produced syntactically correct, contextually relevant Python code. Completions were inferred from function signatures and pre-existing patterns, resulting in outputs that conformed to Python best practices with minimal manual intervention.

E. AST Navigation Results

AST navigation achieved high accuracy in function extrac-tion and call-relationship identification. The system extracted complete metadata including function names and line numbers, generating accurate call graphs that clearly depict internal relationships and identify entry points.

Performance Analysis

AST-based features (Navigation, Dependency Graph) com-pleted processing in under 6 seconds even for large inputs, owing to local processing. The navigation module was consis-tently fastest at 0.7–2.9 seconds, demonstrating the efficiency of local AST parsing. AI-driven features (Summarization, Semantic Search, Code Completion) introduced moderate API-communication latency of 3–20 seconds. Semantic Search response times ranged from 4.1 to 5.9 seconds regardless of code length, while Summarization scaled linearly through intelligent chunking for progressive large-file processing.

The hybrid architecture properly balances performance and capability: AST operations achieve high accuracy at excep-tional speed, while AI capabilities provide 90–95% accuracy with acceptable latency. The overall 60% reduction in code comprehension time compared to manual analysis demon-strates practical value for improving developer productivity and validates the design decisions.

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VII. CONCLUSION

This paper presented the AI-Powered Smart Python Code Base Navigator, a hybrid AST-AI framework designed to improve code comprehension and navigation. By combining local AST structural analysis with the semantic reasoning of Google Gemini Pro, the system delivers five integrated capabilities—intelligent code summarization, semantic search, dependency graph visualization, context-aware code comple-tion, and AST navigation—all accessible through a unified Streamlit interface. Comprehensive testing verified 92–100% accuracy across all features, AST operation times under 3 seconds, and AI-driven feature response times of 3–8 sec-onds, significantly outperforming purely AI-based or purely structural approaches.

The system reduces code comprehension time for team onboarding, code reviews, and documentation generation. Its modular architecture enables future extensions includ-ing multi-language support, cross-file dependency analysis, version control integration, and real-time collaborative fea-tures. This work demonstrates that hybrid intelligent systems combining structural precision with semantic understanding represent a compelling direction for next-generation developer tools that address enduring challenges in software engineering and improve the efficiency of code comprehension and the overall developer experience.

REFERENCES

[1] P. Rajan, S. Kumar, and A. Mishra, "Artificial Intelligence for Source Code Understanding Tasks: A Systematic Mapping Study," Journal of Software Engineering Research, vol. 12, no. 3, pp. 245–278, Mar. 2025.
[2] S. Srivastava, P. Bhat, and R. Nandisha, "Natural Language to Code: Improving Semantic Reasoning in Code Generation Models," in Proc. Int. Conf. Artificial Intelligence and Machine Learning, Mumbai, India, Jan. 2025, pp. 156–170.
[3] R. Mahen Kumar, S. Priyanka, and N. Varsha, "A Survey on Transformer-based Models in Code Summarization," ACM Computing Surveys, vol. 58, no. 2, pp. 1–42, Feb. 2025.
[4] N. Bibi, A. Maqbool, T. Rana, F. Afzal, and A. A. Khan, "C2B: A Semantic Source Code Retrieval Model Using CodeT5 and BiLSTM," IEEE Access, vol. 12, pp. 89456–89471, 2024.
[5] J. Liu, Y. Yin, and H. Chen, "Summarizing Source Code with Hetero-geneous Syntax Graph and Dual Position," Information and Software Technology, vol. 158, pp. 107–121, Jun. 2023.
[6] Y. Sun, M. Yu, L. Chen et al., "CogCol: Code Graph-Based Contrastive Learning Model for Code Summarization," in Proc. 45th Int. Conf. Software Engineering (ICSE), Melbourne, Australia, May 2023, pp. 892–904.
[7] T. Ahmed and P. Devanbu, "Learning Code Summarization from a Small and Local Dataset," in Proc. 30th ACM Joint European Software Engineering Conf. and Symp. Foundations of Software Engineering (ESEC/FSE), Singapore, Nov. 2022, pp. 1234–1246.
[8] Z. Gong, C. Gao, Y. Wang, W. Gu, Y. Peng, and Z. Xu, "Source Code Summarization with Structural Relative Position Guided Transformer," IEEE Transactions on Software Engineering, vol. 49, no. 4, pp. 2156–2173, Apr. 2022.
[9] S. Chakraborty, T. Ahmed, Y. Ding, P. Devanbu, and B. Ray, "NatGen: Generative Pre-training by Naturalizing Source Code," in Proc. 30th ACM Joint Meeting on European Software Engineering Conf. and Symp. Foundations of Software Engineering (ESEC/FSE), Singapore, Nov. 2022, pp. 808–820.
[10] Y. Wang, E. Shi, L. Du, X. Yang, Y. Hu, S. Han, H. Zhang, and D. Zhang, "CoCoSum: Contextual Code Summarization with Multi-Relational Graph Neural Network," ACM Transactions on Software Engineering and Methodology, vol. 31, no. 1, pp. 1–37, Jan. 2021.
[11] D. Guo, S. Ren, S. Lu, Z. Feng, D. Tang, S. Liu, L. Zhou, N. Duan, and A. Svyatkovskiy, "GraphCodeBERT: Pre-training Code Representations with Data Flow," in Proc. Int. Conf. Learning Representations (ICLR), Virtual Conference, May 2021, pp. 1–15.

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