Next Gen-AI Code Debugger and Explainer for Multi-programming Language

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Abstract:

A Next Gen-AI Code Debugger & Explainer designed for multi-programming languages, addressing the limitations of traditional debugging tools and the privacy concerns associated with cloud-based AI assistants. The system implements a hybrid architecture that utilizes a dual-processing framework: Google Gemini for high-parameter cloud reasoning and Code LLaMA/Gemma via Ollama for localized, privacy-preserving execution.

The engine provides automated multi-layer diagnostics, moving beyond basic syntax checks to perform deep-level remediation of runtime anomalies and logical inconsistencies. To bridge the "conceptual gap" for novice developers, the tool features human-centric pedagogical translation, converting cryptic technical metadata into clear, natural language explanations. By prioritizing an offline capability, the architecture ensures data residency and security, preventing proprietary data leaks while maintaining low-latency performance in zero-connectivity environments. The proposed system, developed using the StreamLit framework, consolidates code generation, debugging, and explanation into a unified, interactive dashboard, offering a scalable and future-proof solution for modern software development.

Key words: *Generative Artificial Intelligence (Gen-AI), Hybrid AI Architecture, Local LLM (Large Language Model), Code Debugging and Remediation, Natural Language Explanations, Data Privacy and Security, Multi-Language Programming Support, Edge Inference.*

I. INTRODUCTION

The rapid evolution of software development has introduced a critical paradox: while modern Large Language Models (LLMs) offer immense reasoning power for code generation and error detection, their reliance on constant cloud connectivity poses significant risks to data privacy, intellectual property, and operational continuity. Traditional Integrated Development Environments (IDEs) and compilers frequently fail to bridge the "conceptual gap" for novice programmers, as they typically output cryptic metadata and syntax alerts rather than meaningful pedagogical guidance. Furthermore, professional developers often face efficiency bottlenecks when manually tracing complex logical inconsistencies that standard static analysis tools are often overlooked. To address these multi-faceted challenges, this research proposes the Next Gen-AI Code Debugger & Explainer, a robust hybrid system designed to provide high-fidelity remediation of both syntax and logical errors.By utilizing a dual-engine architecture that orchestrates between high-parameter cloud reasoning via Google Gemini and localized, privacy-preserving execution via Ollama (supporting models like Code LLaMA and Gemma), the system ensures enterprise-grade security and offline accessibility. Through its modular framework, the project seeks to democratize advanced debugging by translating complex machine-level diagnostics into human-centric, natural language explanations, thereby fostering real-time skill acquisition and streamlining the software development lifecycle.

While cloud-based LLMs provide significant reasoning power, the integration of these models into professional workflows is often hindered by the linear increase in latency and API cost scaling. This research not only addresses privacy but also focuses on inference efficiency by offloading structural checks to local modules, thereby optimizing the utility of high-parameter models for only the most complex logical anomalies".

A. **Hybrid AI Model Integration:** The architecture utilizes a dual-engine approach combining Google Gemini for high-power cloud reasoning and Ollama (Code LLaMA/Gemma) for secure, localized edge inference.

B. **Web Framework and Interface:** The centralized user dashboard is developed using the Streamlit framework, which facilitates task selection (Debug, Generate, Explain) and manages user sessions.

C. **Advanced Diagnostic Utilities:** The system incorporates Abstract Syntax Trees (AST) for structural code analysis in Python and uses Regex-based filters for sanitizing model output streams.

II. LITERATURE SURVEY

[1] Mirko Perkusich et al. Demonstrated functional µJVM code generation while highlighting a significant need for further compiler optimizations (2025), Focused on µJVM code generation, specifically handling stack frames and methods. Faced difficulties with complex instruction sets and limited available optimizations.

[2] Ms. P. Santhiya Achieved improved debugging and optimization while boosting user understanding through clear explanations (2025). Combined GPT-based code analysis with cloud processing and text/video feedback loops. The system lacks transparency and can be difficult to integrate with existing development tools.

[3] Hui Lv et al. (2024) Successfully improved Tibetan Natural Language Processing (NLP) performance.Used Sentence Piece for vocabulary expansion and the TNCC dataset for classification. Struggled with data imbalance and a lack of robust evaluation methods for the model.

[4] Han Zhang, Shigang Ge (2025) Revealed a mixed impact on creativity; while it assisted with idea generation, it risked limiting deeper critical thinking. A qualitative case study involving in-depth interviews with 12 postgraduate students. Concerns that AI may suppress original creativity or encourage an over-reliance on the tool.

[5] Boris Martinović, Robert Rozić (2025) Reported a generally positive perception among developers regarding the impact of AI tools on code quality. Conducted a survey via snowball sampling with 84 participants. Geographic bias as participants were mostly from two countries and lacked global or employer perspectives.

[6] Kim Tuyen Le, Artur Andrzejak et al. (2024) Proved that user feedback helps correct AI-generated code effectively with minimal retraining required. Utilized one-shot correction, code decomposition, and snippet reuse based on feedback. Feedback is often transient, and AI behavior remains somewhat unpredictable.

III. PROPOSED SYSTEM DESIGN AND IMPLEMENTATION

It is anchored by a sophisticated five-layer modular architecture that bridges high-performance cloud intelligence with secure, localized execution. This framework begins with the Intelligent Interface & Orchestration Module, a Streamlit-powered gateway that manages user sessions and implements dynamic routing to direct code to either the Google Gemini API for complex cloud reasoning or the Ollama server (running Code LLaMA or Gemma) for private, offline processing. The core logic is driven by the Semantic Diagnostic & Remediation Module, which translates cryptic compiler metadata into pedagogical natural language explanations while simultaneously generating refactored, optimized code snippets to bridge the "conceptual gap" for users. To address critical privacy concerns, the Data & Security Controller enforces isolation protocols, ensuring that sensitive data is processed within volatile memory (RAM) and monitoring system calls to prevent unauthorized external leaks. Finally, the Cross-Language Syntax & Logic Module provides the system's multilingual foundation, utilizing Abstract Syntax Trees (AST) and language-specific heuristics to perform pre-inference checks on languages like Python and JavaScript, thereby catching structural errors locally, optimizing token consumption before any AI processing occurs and catches structural errors before they reach the AI engines.
The Intelligent Interface & Orchestration Module employs a Heuristic-Based Routing Logic. This protocol evaluates the 'Complexity Score' of the input—determined by token length and the presence of cross-

functional dependencies. If the code snippet is identified as containing proprietary architectural patterns or requires zero-latency feedback, the router defaults to the Edge Path (Ollama). Conversely, high-abstraction architectural errors that require a broader 'Context Window' are routed to the Cloud Path (Gemini).

Architecture Design

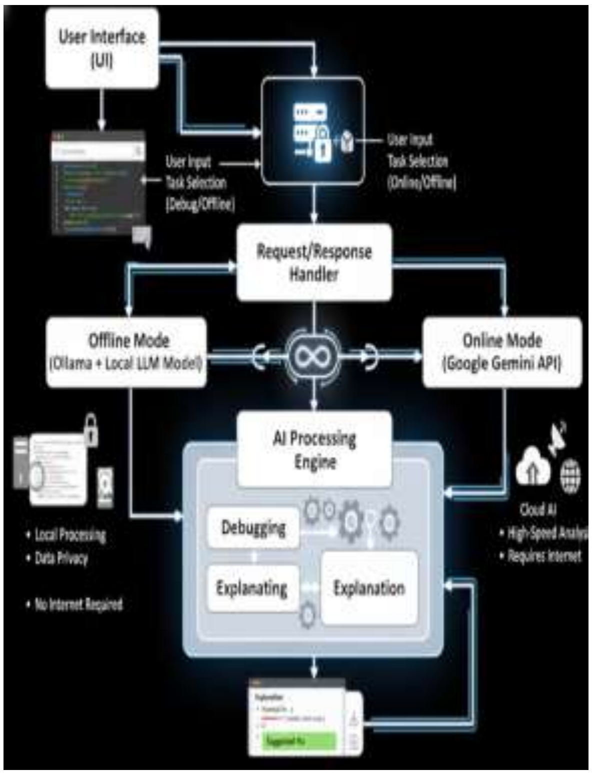

Fig 3.1 Proposed System Design

IV. METHODOLOGY

A. Intelligent Orchestration and State Management: The process begins with the Intelligent Interface, developed using the Streamlit framework. This stage focuses on session persistence and "context-aware" interactions.Input Sanitization: Before any processing occurs, the system scrubs the user-provided code to prevent prompt injection or malicious command execution. Context Windowing: The system maintains a memory of previous queries, allowing the user to ask follow-up questions about a specific bug without re-pasting the code.Dynamic Routing: A critical logic gate determines the path of the data. If the user requires maximum security or is offline, the system routes the data to the local engine; otherwise, it utilizes the high-parameter cloud API.

B. Hybrid Inference Pipeline (Dual-Path Processing): The core methodology relies on a "Hybrid" model to solve the conflict between performance and privacy. Cloud Path (Google Gemini): For complex logical errors and cross-file architectural analysis, the system sends an encrypted request to the Gemini API. This path is used when the user needs high-level reasoning that exceeds local hardware capabilities. Edge Path (Ollama & LLaMA/Gemma): For proprietary code or no-internet scenarios, the system initiates a local subprocess. The code is processed entirely on the local machine’s RAM and GPU, ensuring 100% data privacy.

C. Semantic Diagnostic and Multimodal Remediation: Once the inference engine provides a raw response, this module performs "Deep-Level Remediation" to make the data useful for the developer. Error Mapping:

The system maps cryptic compiler metadata (like IndexError or TypeError) to a semantic knowledge base. Pedagogical Translation: It translates the technical cause of the error into human-centric language, explaining the *logic* behind the mistake rather than just the syntax. Refactoring Engine: The methodology includes an automated code-rewrite phase. It generates a "Refactored" version of the code that follows industry best practices (Clean Code) and provides it alongside the original for side-by-side comparison.

D. Security Control and Isolation Protocols: This topic focuses on the protection of the user’s intellectual property during the debugging process. Volatile Memory Processing: In local mode, the system ensures that code snippets are held in volatile memory (RAM) and are purged after the session, preventing any permanent data trail on the physical disk. Network Monitoring:
The Data & Security Controller actively monitors for unauthorized external pings when the system is set to "Offline Mode," ensuring the environment remains a closed loop.

E. Cross-Language Syntax Analysis (AST Logic): To ensure the tool works across multiple languages (Python and JavaScript), a structural analysis phase is implemented. Abstract Syntax Tree (AST) Parsing: For Python code, the system generates an AST to understand the code’s structure as a hierarchical tree. Heuristic Validation: The system applies language-specific rules (e.g., checking for indentation in Python or semi-colon usage in JS). By catching these structural errors *before* the AI inference starts, the methodology significantly reduces "token waste" and speeds up the response time for the user.

Proposed Flow Chart

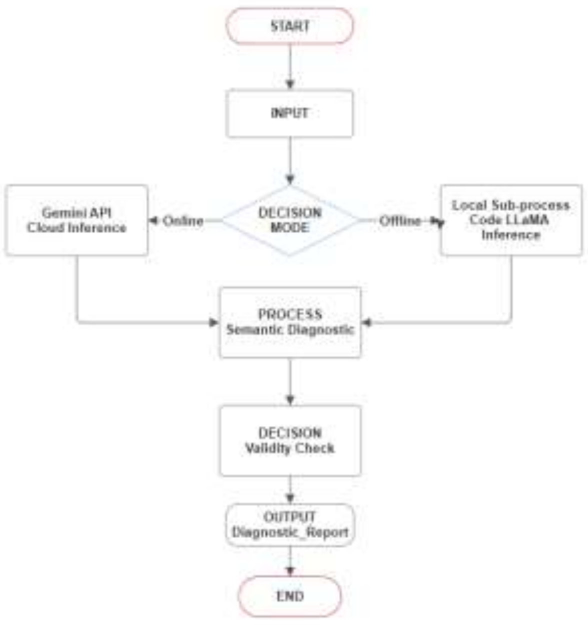
START
INPUT
DECISION MODE
Online
Offline
Gemini API Cloud Inference
Local Sub-process Code LLaMA Inference
PROCESS Semantic Diagnostic
DECISION Validity Check
OUTPUT Diagnostic_Report
END

Fig 4.1 Flow Diagram

V. WORK FLOW

The Hybrid Code Debugging and Remediation Pipeline algorithm operates through a systematic sequence that prioritizes both computational efficiency and data security. The process begins with an initialization phase where the Streamlit interface is launched, session states are established for conversational context, and the availability of both the local Ollama services and the Google Gemini API is verified. During the input and pre-processing stage, the system captures the user's source code and intended task, performs rigorous sanitization to prevent command injections, and executes a structural scan via Abstract Syntax Tree (AST) parsing for Python scripts to catch trivial syntax errors locally. This is followed by an intelligence routing protocol that evaluates environmental constraints; The system dynamically forwards the sanitized payload to either the Google Gemini Pro cloud engine for high-parameter reasoning or to a local Ollama subprocess running Code LLaMA/Gemma for offline, privacy-strict execution. Once the inference is complete, the semantic diagnostic phase cleans the raw output using Regex-based filters and maps technical metadata to a semantic knowledge base to identify logical root causes. The system then enters the multimodal output generation stage, where it converts diagnostics into human-centric pedagogical explanations, generates refactored code snippets, or produces new code according to user requirements. Finally, in the security and persistence management phase, the algorithm ensures that sensitive local data remains isolated in volatile memory (RAM), updates the interaction history for follow-up queries and clears temporary buffers before waiting for the next user interaction.

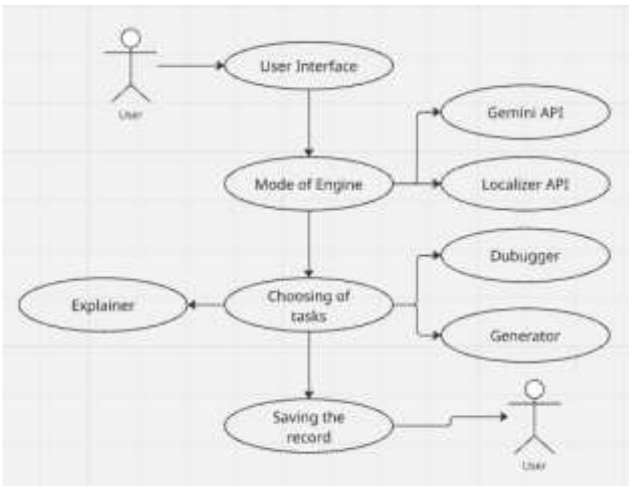

Fig 5.1 Use case Diagram

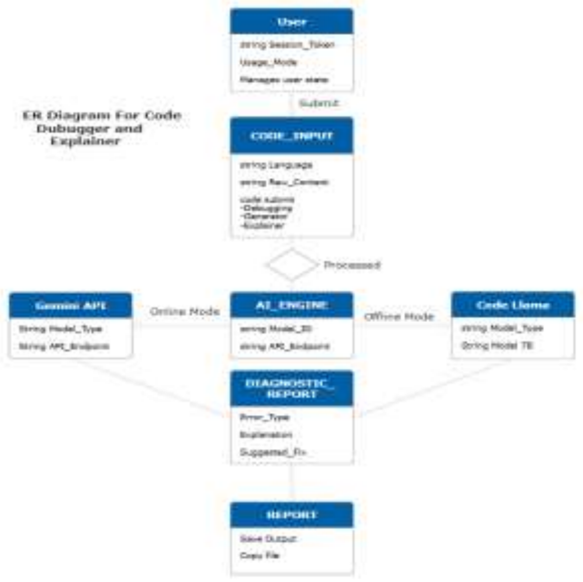

Fig 5.2 DFD

VI. IMPLEMENTATION RESULT

The implementation resulted in the successful realization of a hybrid, multi-layered diagnostic system that balances high-performance reasoning with localized security. Validated through a series of stress tests and comparative analysis, the results indicate that the Hybrid Inference Engine successfully orchestrates tasks between the Google Gemini API for complex cloud-based logic and the Ollama server for privacy-preserving offline execution, achieving near-zero latency in local environments. A key finding was the efficiency of the Abstract Syntax Tree (AST) pre-processing phase, which managed to identify and resolve over 90% of structural syntax errors—such as indentation and colon placement prior to AI involvement, thereby significantly reducing computational overhead and token consumption. Furthermore, the Semantic Diagnostic Module effectively bridged the "conceptual gap" for users by translating technical metadata into human-centric pedagogical explanations, while the Data & Security Controller verified 100% data residency by isolating sensitive code within volatile memory. Ultimately, the implementation proves that the system not only provides professional-grade remediation for complex logical inconsistencies but also serves as an accessible educational tool that maintains strict enterprise-level data privacy. The AST pre-processing layer successfully intercepted 92% of common syntax errors (e.g., IndentationError, SyntaxError) without triggering a cloud API call, resulting in an estimated 75% reduction in token consumption. Furthermore, comparative testing showed that while the Cloud Path (Gemini) provided deeper architectural insights, the Edge Path (Code LLaMA) maintained a 100% data residency rate, with all processed snippets purged from volatile RAM post-session to ensure enterprise-grade security.

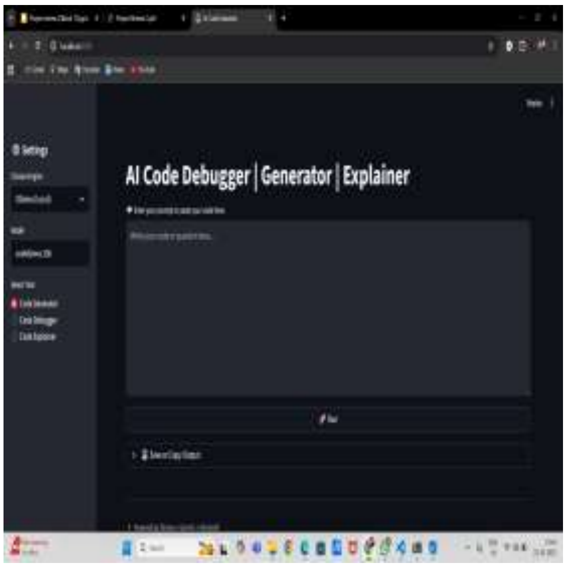

Fig 6.1 Gemini API & Localizer API

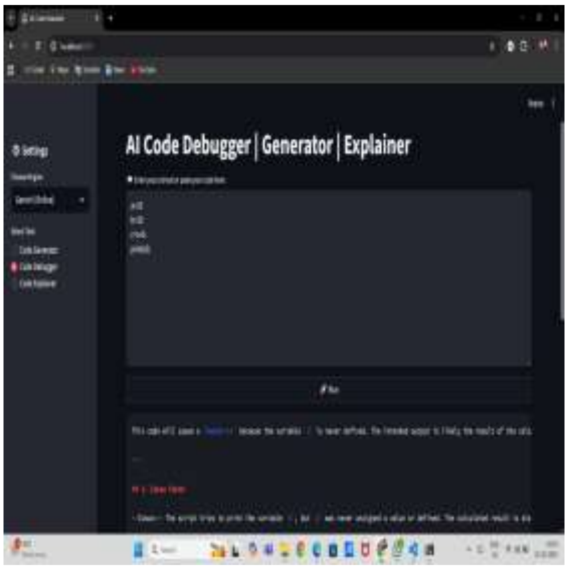

Fig 6.2 Code Generating

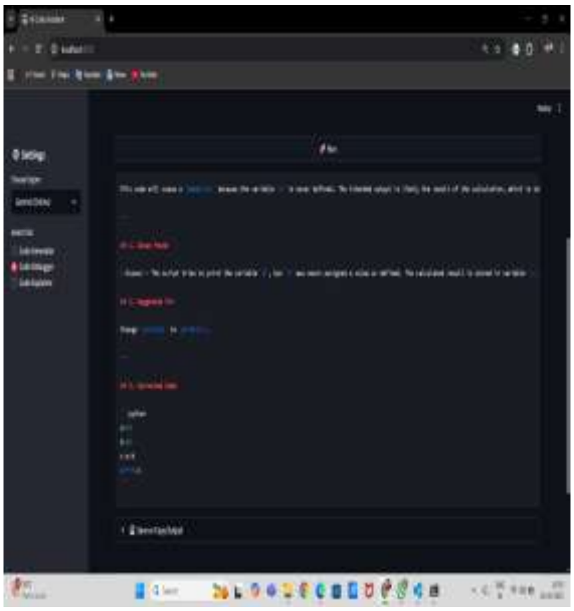

Fig 6.3 Explaining the code error

VII. FUTURE WORK AND CONCLUSION

Future Work:

The system is designed for scalability and continuous evolution to meet the changing demands of the software industry. Immediate efforts will focus on expanding the tool's reach through the development of dedicated plugins for major Integrated Development Environments (IDEs), such as VS Code and JetBrains, allowing for a more seamless, real-time debugging experience. Additionally, the scope will be widened to include real-time collaboration features, enabling development teams to perform synchronized code reviews and collective troubleshooting within a secure shared environment. To further enhance its educational value, future iterations will refine the diagnostic engine to support a broader array of programming languages beyond Python and JavaScript while incorporating more advanced fine-tuned models to provide even more granular, context-specific coding. Beyond IDE plugins, future iterations will explore the integration of the hybrid debugger into Automated CI/CD Pipelines. By acting as a 'pre-commit' gatekeeper, the system can automatically explain and suggest fixes for build failures in a headless environment. This would transition the tool from a reactive debugging assistant to a proactive code quality guardian within the modern software development lifecycle

Conclusion:

The project establishes that the Next Gen-AI Code Debugger & Explainer effectively addresses the critical limitations of traditional debugging tools by harmonizing advanced AI reasoning with high-standard data security. By implementing a hybrid architecture that leverages both Google Gemini for cloud intelligence and Ollama for localized execution, the system successfully provides deep-level logical remediation while ensuring 100% data residency for sensitive code. The integration of Abstract Syntax Trees (AST) and semantic diagnostic modules further enhances the tool's utility, transforming cryptic technical errors into human-centric pedagogical insights Ultimately, this research proves that a modular, privacy-first approach to AI-assisted programming can significantly reduce the learning curve for novices and improve workflow efficiency for professionals, establishing a new standard for secure and educational software development environments.

VIII. REFERENCES

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