Streamlining Software Development: An AI-Powered Code Generation Platform

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Contents

Introduction

Advancements in artificial intelligence, particularly with LLMs like Claude, Codex,GPT-4 and Deepseek, have revolutionized how software is created. This project harnesses these models to create a web application capable of generating Html, Css, Javascript or Python code from natural language prompts.

The platform offers an intuitive interface where users can specify their programming needs, generate code in real-time, and debug it immediately. Tailored to accommodate users of all skill levels, it simplifies software development by automating a huge majority of its various processes.

Literature Review

No.	Title	Methodology	Results	Advantages and Disadvantages
1	Balancing Security and Correctness in Code Generation	• Evaluated five commercial LLMs (GPT-3.5, GPT-4, Claude Instant, Claude Opus, and Gemini 1.0). • Designed prompts that intentionally generated security vulnerabilities based on Common Weakness Enumerations (CWEs). • Applied different prompt strategies to improve security and assessed their impact on functionality. • Generated 4,235 code samples and tested them using unit tests for correctness, security, and robustness.	• Security-focused prompts significantly reduced vulnerabilities but often negatively impacted code correctness. • GPT-4 produced the most secure and functional code, whereas Gemini 1.0 frequently rejected security-related prompts. • Increasing temperature settings slightly improved security but had minimal effect on correctness. • Some security measures introduced unnecessary complexity, leading to non-functional or difficult-to-debug code.	*Advantages* • **Enhanced Security:** Prompt engineering significantly reduced the occurrence of CWEs in generated code. • **Comparative Evaluation:** Demonstrated the strengths and weaknesses of different commercial LLMs for secure code generation. • **Practical Applications:** Insights can be used to develop better prompt strategies for security-aware code generation. *Disadvantages* • **Reduced Correctness:** Security improvements often came at the cost of program correctness. • **Model Dependence:** Different LLMs produced varying security and correctness levels, requiring careful model selection. • **Overhead in Execution:** More secure prompts led to increased response times and computational costs.

No.	Title	Methodology	Results	Advantages and Disadvantages
2	Code Generation using Machine Learning: A Systematic Review (2022)	• **Search Approach:** The study used the PRISMA framework to systematically review 37 papers from the IEEE Xplore and arXiv databases, applying strict inclusion and exclusion criteria. • **Application Categories:** Papers were grouped into three paradigms: description-to-code, code-to-description, and code-to-code. • **Model Evaluation:** Examined different machine learning (ML) models (e.g., RNNs, Transformers) and their performance on tasks like program synthesis, automatic program repair, and documentation generation. • **Data:** Data sources included GitHub, StackOverflow, and manually created or synthetic datasets.	• **Performance Trends:** Transformers generally outperformed RNNs for generating code and descriptions. • **Applications:** Tasks like code generation from natural language and documentation generation showed notable advancements.	*Advantages* • **Wide Applicability:** ML models enable automatic software development tasks, enhancing productivity. • **Adaptability:** Models work on various paradigms (e.g., natural language to code). *Disadvantages* • **Data Limitations:** Many datasets are mined automatically and lack quality, affecting model reliability. • **Computational Costs:** Training models like transformers demands significant computational resources.

No.	Title	Methodology	Results	Advantages and Disadvantages
3	Knowledge aware code generation using Large Language Models (2024)	• **Data & Knowledge Library:** The authors create **CodeF**, a Python-based dataset (1,523 problems) from CodeForces, carefully split at September 2021 to avoid overlap with ChatGPT's training data. They also construct a **Knowledge Library** for 33 common algorithms and data structures, including short descriptions, pseudo-code, and step-by-step guides. • **Approach (KareCoder):** The process has two main stages. First, a **Prompt Engineering Stage**: ChatGPT acts as a "prompt engineer," reading the problem plus the relevant knowledge to generate a problem-solving prompt. Second, a **Coding Stage**: ChatGPT uses that prompt to write the final code. • **Baselines & Setup:** They compare KareCoder with direct ChatGPT usage, Plan (Self-planning idea), SCOT (Structured Chain-of-Thought), and SCOT&KareCoder. Pass@1, Pass@3, and Pass@5 are used as primary metrics.	●**On CodeF Post-2021:** KareCoder notably boosts Pass@1 (first-try accuracy) compared to direct ChatGPT usage and other planning-based methods, demonstrating that injecting targeted algorithm/data-structure knowledge aids code generation on new tasks. However, ChatGPT alone can sometimes yield higher Pass@3 and Pass@5, since a single flawed intermediate prompt in KareCoder can affect all subsequent code attempts. ●**On APPS (500 Problems):** ChatGPT's performance remains strong, likely due to overlap with its training data. Even so, KareCoder often equals or exceeds other structured-prompt baselines, underscoring the value of integrating a Knowledge Library for tasks that ChatGPT has not seen.	• **Enhanced Performance on Unseen Problems:** Using algorithm /data-structure knowledge helps solve new problems ChatGPT has not seen in training. • **Modularity:** The Knowledge Library is easily updated; the approach can adapt to other algorithm domains. • **Strong Pass@1 Gains:** The method particularly boosts the first successful generation rate (Pass@1).

No.	Title	Methodology	Results	Advantages and Disadvantages
4	Low-Cost Language Models: Survey and Performance Evaluation on Python Code Generation (Science Direct 2024)	• **Dataset Creation:** Introduced a new dataset of 60 Python programming problems with varying difficulty levels. • **Chain-of-Thought Prompting:** Designed a prompt strategy to guide models in generating Python code. • **Evaluation:** Conducted semi-manual evaluation using GPT-3.5-Turbo for correctness assessment, validated with test cases. • **Comparison:** Tested low-cost CPU-friendly models (e.g., Mistral, Llama, Phi) against advanced models (e.g., ChatGPT, Gemini) on HumanEval and EvalPlus	• **Low-Cost Models:** Some CPU-friendly models (e.g., Mistral-7B, Llama-3.1, Phi-2) achieved competitive results compared to advanced models like ChatGPT-3.5 and Gemini. • **Quantization Impact:** Quantized models (e.g., 4-bit Mistral, 5-bit Phi-2) performed well, with minimal performance drop compared to non-quantized versions. • **Dataset Performance:** Low-cost models excelled in generating correct code but struggled with output format adherence. • **Inference Time:** CPU-friendly models demonstrated efficient inference times, making them practical for standard machines.	***Advantages*** • **Accessibility:** Low-cost models enable Python code generation on standard CPUs, reducing resource requirements. • **Competitive Performance:** Some models (e.g., Mistral-7B, Llama-3.1, Phi-2) rival advanced models in code generation tasks. • **Dataset Contribution:** New dataset extends benchmarks, enabling deeper evaluation of model capabilities. ***Disadvantages*** • **Output Format Issues:** Models like Dolphin-2.6-Mistral and Phi-2 struggled with adhering to specific output formats despite generating correct code. • **Limited Scope:** Focused on Python; underrepresented languages and paradigms were not evaluated. • **Rapid Model Evolution:** New models and updates may outpace the study's findings.

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Problem Statement

Building projects from scratch is time-consuming and complex, especially for beginners. This project aims to develop an AI-powered platform that generates, executes, and fine-tunes code based on natural language prompts, simplifying the development process.

Objective

The project's key objectives are:

- To develop a platform that generates code based on user prompts.
- To enable real-time error detection.
- To create an interactive environment for code generation, debugging, refinement, report generation and test case generation.

Methodology

The Methodology for the project can be divided into 4 parts:

1. **Requirement Gathering and Research**
2. **System Design and Architecture**
3. **Backend Development**
4. **Frontend Development**

1. Requirement Gathering and Research

Objective: Evaluate AI models for automated code generation, debugging, and execution.

Outcome: Selected models based on accuracy, speed, and Python compatibility for backend integration.

Process:

- Tested publicly available LLMs via Together AI.
- Analyzed model performance with user prompts.
- Generated requirement docs to define software needs.

AI Models Tested

1. **Llama 3.3-70B-Instruct Turbo Free**
- *Info*: A high-performance, FP8-quantized version of Meta's Llama 3.3 70B. Optimized for fast inference with a 128K token context window. Excels in multilingual dialogue and instruction-following tasks.
- *Use*: Generates accurate requirement docs and code with reduced latency.

2. **DeepSeek V3**
- *Info*: A 671B parameter Mixture-of-Experts (MoE) model with 37B active parameters per token. Trained on 14.8T tokens, supports 128K context. Strong in reasoning, math, and coding.
- *Use*: Ideal for complex code generation and synthetic data tasks.

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3. **Gemma-2 Instruct 27B**

- *Info*: Google's lightweight, open-source model with 27B parameters. Multimodal (text/image), 128K context, excels in reasoning and chat tasks.
- *Use*: Efficient for smaller-scale code generation with high accuracy.

4. **Qwen 2.5 72B**

- *Info*: Alibaba's 72B parameter model from the Qwen series. Enhanced for code generation, reasoning, and math. Supports 128K context and multilingual tasks.
- *Use*: Powers robust code and test case generation (e.g., your script's generate_code).

2. System Design and Architecture

Objective: Design a scalable system for automated code generation and documentation.
Outcome: A modular system ready for web integration, supporting full-stack automation.

Features:

- Real-time code generation and execution.
- Automated error detection and correction.
- Structured documentation for requirements, specs, code, and tests.
- Python-centric design with extensible architecture.

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Key Functionalities:

1. **Prompt Processing**: Converts user input into structured requirements (generate_req_doc).
2. **Software Specification**: Defines tools and algorithms for implementation (generate_software_doc).
3. **Code Generation**: Produces Python code using LLMs (generate_code).
4. **Self-Correcting Debugging**: Iteratively fixes errors with a validation loop (auto_generate_code).
5. **Test Case Creation**: Generates test cases to validate code (generate_test_cases).
6. **Execution**: Runs code and captures output/errors (execute_code).
7. **PDF Documentation**: Formats outputs into professional PDFs with headers, footers, and timestamps (create_pdf).

3. Backend Development

Objective: Build a robust backend to support the web application’s pipeline.

Outcome: A functional backend powering the pipeline, ready for frontend integration.

1. **Professional Interface (Chat-Based)**:

- Backend: Handles prompt submission (POST to /generate), processes it with LLMs, and returns responses to the chat box.
- Script Tie-In: Uses generate_req_doc for initial requirement generation.

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2. **Requirements Page**:

- Backend: Generates requirement docs from user prompts and suggestions, saves as Requirements.pdf, and serves for download.
- Script Tie-In: generate_req_doc and create_pdf.

3. **Software Specification Page**:

- Backend: Creates specs based on requirements, updates with feedback, and outputs Software_Spec.pdf.
- Script Tie-In: generate_software_doc and create_pdf.

4. **Code Generation Page**:

- Backend: Generates Python code with framework options (e.g., Flask/Django), supports real-time preview and download (Code.pdf).
- Script Tie-In: generate_code, auto_generate_code, create_pdf.

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5. **Test Cases Page**:

- Backend: Produces test cases from generated code, updates with prompts, and saves as Test_Cases.pdf.
- Script Tie-In: generate_test_cases and create_pdf.

4. Frontend Development

This website's frontend is built using a static, document-centric approach that emphasizes accessibility, clarity, and simplicity. Developed entirely with HTML and minimal use of JavaScript or external libraries, it is lightweight, easy to deploy, and highly portable. Each page—Project Overview, Requirements, SRS, Code, and Test Case Generation—is treated as a standalone document, allowing users to access well-structured content without complex navigation. The design follows a sequential, linear layout using standard HTML elements like headings, paragraphs, lists, and tables.

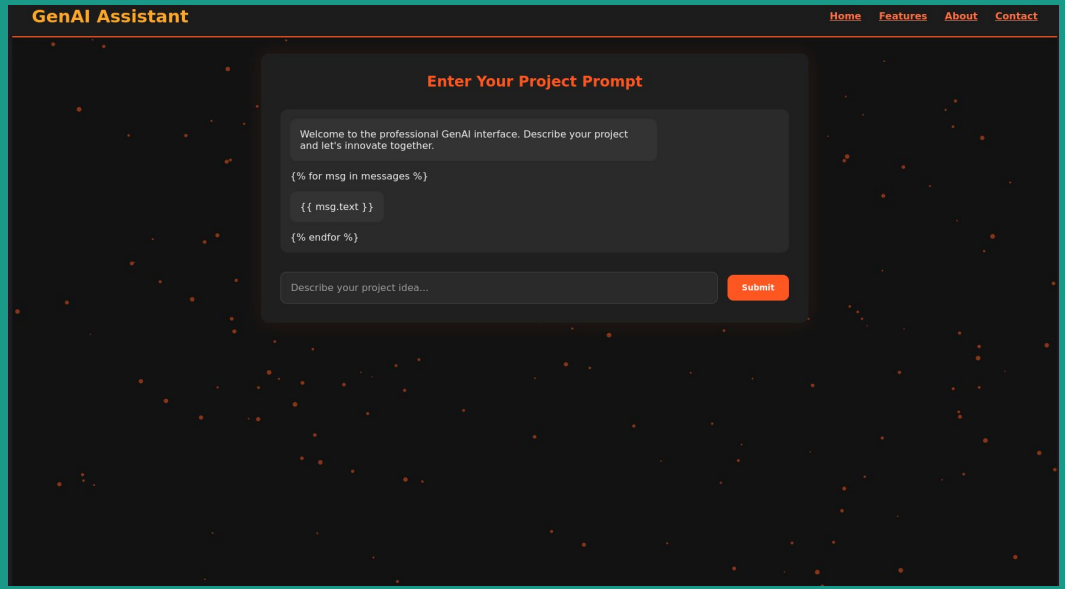
Each section serves a distinct role in the software development lifecycle. The **Project Overview** introduces the application’s purpose, while the **Requirements** page outlines necessary system specifications. The **SRS** provides detailed functional and non-functional requirements in an organized format. The **Code** section showcases properly formatted code snippets for better readability. A key feature is the **Test Case Generation** module, where users can input functional prompts or code to generate test cases. It includes fields for prompt entry, customization settings, and a preview area displaying generated tests.

Results

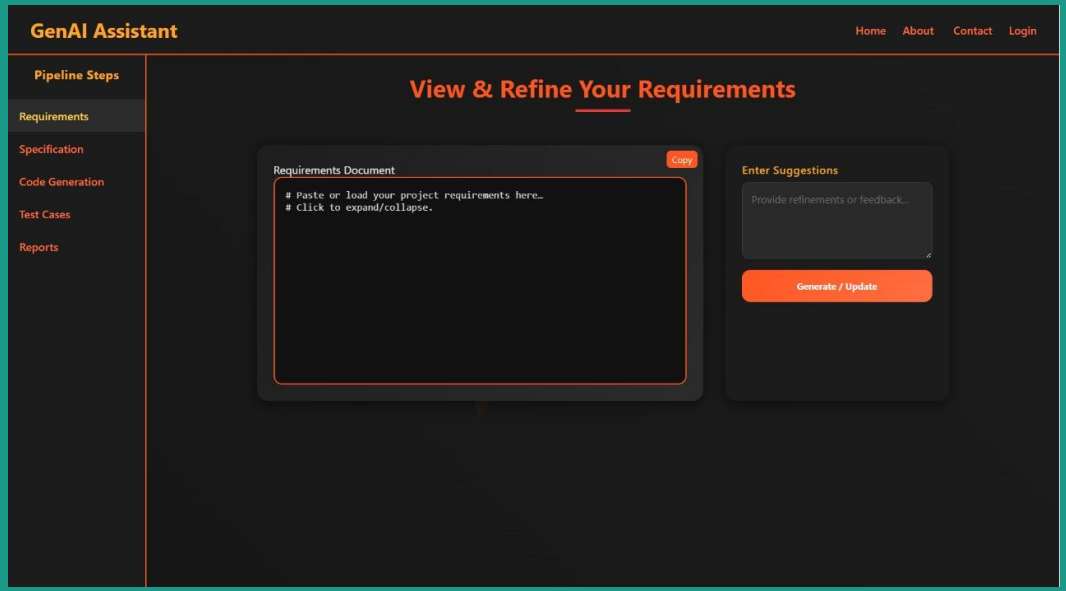
The goal of this project was to develop a platform that generates code based on user prompts, enabling real-time error detection. The platform was designed to provide an interactive environment for code generation, debugging, refinement, report generation, and test case creation, offering a seamless user experience across multiple interfaces.

1. Receiving the prompt from the user

The user interface presents a intuitive dialog box designed to collect detailed input for code generation. At the top, a welcoming message invites users to describe their project idea. Beneath this, a dynamic message display area is reserved for ongoing conversational context, helping users keep track of their interactions. The primary input field allows users to enter a comprehensive prompt, including relevant project details and requirements. Once the prompt is ready, the user can click the **Submit** button to initiate the generation process.

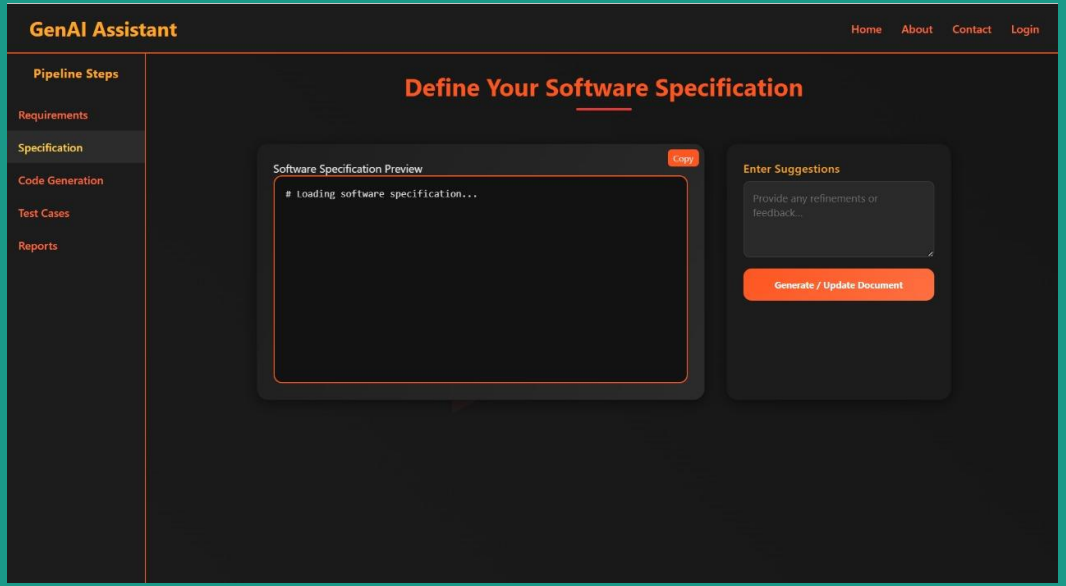

GenAI Assistant
Home
Features
About
Contact
Enter Your Project Prompt
Welcome to the professional GenAI interface. Describe your project and let's innovate together.
{% for msg in messages %}
{{ msg.text }}
{% endfor %}
Describe your project idea...
Submit

2. Generation of Requirement document



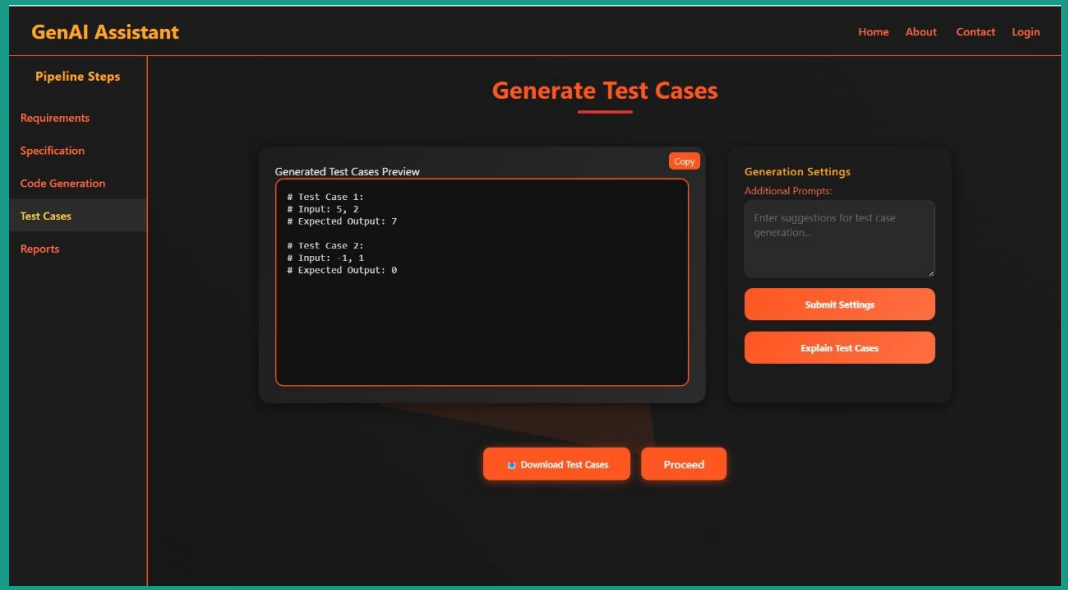
The user is presented with a central editor where they can paste or write their project requirements in detail. This section supports a code-like format for structured input. On the right panel, users can provide specific suggestions, refinements, or feedback related to the requirements. Once the suggestions are entered, clicking the "Generate / Update" button processes the input and updates the requirements accordingly.

3. Generation of SRS document



This interface allows users to define or refine their software specification. In the center, a preview panel displays the generated specification in a code-like format, currently showing a loading message. On the right, users can enter feedback or suggestions to improve the document. Once entered, clicking the **“Generate / Update Document”** button will regenerate the specification based on the input provided. The **Copy** button enables quick copying of the specification preview for external use or further editing.

4. Generation of Test Cases



This interface is designed for generating and previewing software test cases. The center panel displays the test cases in a formatted preview with a **Copy** button for quick copying. On the right, users can input additional prompts to customize the generation process. Two buttons—**Submit Settings** and **Explain Test Cases**—enable user-driven refinement. At the bottom, **Download Test Cases** allows saving the output, while **Proceed** moves the workflow forward based on the generated test cases.

Conclusion

This AI-powered platform will bridge the gap between coding expertise and accessibility by allowing users to generate code effortlessly.

By combining LLM-driven code generation with error debugging, report generation and test case generation, the platform offers a streamlined and intuitive solution for software development. This project has the potential to revolutionize how coding is taught, learned, and executed, ultimately making programming accessible to a broader audience.

Future Scope

The project's future is to develop a single interface that can support code execution, thus enabling users to execute code within the application to accelerate the development process.

The interface will feature multi-language support to cater to the varied needs of developers and will include improved performance through profiling tools and automated tests to enhance execution speed and resource usage.

Additionally, the platform will incorporate real-time collaborative features, allowing multiple users to interact and work on the same codebase simultaneously. Finally, it will offer easy deployment options for the publication and management of applications across different environments.

References

- **Knowledge aware code generation using Large language models.**
  Tao Huang, Zhihong Sun, Zhi Jin, Ge Li, Chen Lyu
  Source: https://arxiv.org/abs/2401.15940
- **Extending the Frontier of ChatGPT: Code Generation and Debugging**
  Fardin Ahsan Sakib, Saadat Hasan Khan and A. H. M. Rezaul Karim
  Source: https://arxiv.org/abs/2307.08260
- **Code Generation using Machine Learning: A Systematic Review**
  Enrique Dehaerne, Bappaditya Dey, Stefan De Gendt and Wannes Meert
  Source: https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9849664

Thank You!