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(Review Article)

AI powered automatic test case creation using Chat GPT and Streamlit interface

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Abstract

In today's rapid software development landscape, ensuring software quality through comprehensive testing is both crucial and increasingly challenging. Traditional test case generation methods are time-consuming, error-prone, and often fail to adapt to evolving application requirements. This project introduces an AI-powered automated test case generation system that leverages OpenAI's GPT language model integrated into a Streamlit-based interface to revolutionize the way test cases are created. By accepting inputs such as functional requirements, code snippets, or user stories, the system dynamically generates diverse and context-aware test cases—covering edge, boundary, and negative scenarios. Real-time output, confidence scoring, and an intuitive GUI enhance usability for both developers and QA professionals. With support for various programming languages and document formats (e.g., PDF, DOCX), the platform ensures high coverage and faster feedback loops, making it ideal for agile and CI/CD environments. The combination of prompt engineering, AI inference, and real-time interactivity marks a significant advancement in intelligent software testing tools. This project reflects the increasing demand for smart, scalable, and human-like AI systems that can understand software logic and testing principles effectively.

Keywords: AI-Powered Test Case Generation; Gpt-3.5/4; Streamlit Interface; Automated Software Testing; Agile Qa Automation; Prompt Engineering

1. Introduction

The advent of artificial intelligence and large language models (LLMs) like OpenAI's GPT has significantly reshaped the landscape of software development, particularly in the realm of quality assurance and testing. Despite advances in automation and continuous integration practices, traditional test case generation remains a largely manual, error-prone, and time-intensive process—posing serious limitations in today's fast-paced development cycles. Most testing tools fail to keep up with the rapid evolution of codebases and requirements, resulting in coverage gaps, undetected bugs, and delayed releases.

To address these challenges, our project introduces an AI-Powered Automated Test Case Generation System that harnesses the power of GPT-3.5/4 for intelligent, real-time test case creation. This system is designed to understand functional requirements, code snippets, and user stories, and translate them into well-structured, diverse test cases that include normal flows, edge conditions, and invalid scenarios. Built using Python and deployed through a Streamlit interface, the platform offers an intuitive and interactive experience for developers, QA engineers, and students alike—supporting real-time previews, test case exports, and multi-language program compatibility.

Unlike traditional rule-based systems that operate on static templates or rigid syntax parsing, our framework integrates prompt engineering, dynamic input handling, and confidence scoring to deliver highly contextual and adaptive outputs. The system can process content from multiple file types including DOCX, PDF, and TXT, allowing users to upload code from various formats and instantly receive test coverage insights tailored to the logic of their programs.

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The core motivation behind this work stems from the increasing demand for intelligent automation in agile and CI/CD environments, where speed, precision, and adaptability are key. By bridging the gap between AI and software testing, this solution empowers teams to streamline their testing workflows, improve reliability, and reduce human effort without compromising quality.

Furthermore, this project lays the foundation for more advanced AI-assisted development tools that can scale across diverse domains—ranging from enterprise QA pipelines to educational tools that help learners understand testing principles through AI-generated examples. As software systems grow more complex, this unified approach to test case creation represents a significant leap toward intelligent, efficient, and accessible testing practices for the future.

2. Literature review

The evolution of artificial intelligence, particularly in the realm of large language models (LLMs), has opened new avenues for automation across software development and quality assurance. Traditional test case generation relied heavily on manual methods, static templates, or rule-based systems. These approaches were sufficient for basic functionality but fell short in dynamic, large-scale, or evolving code environments—leading to poor test coverage, inefficiency, and increased risk of bugs in production systems.

With the introduction of transformer-based language models such as OpenAI's GPT series, software engineering tasks like code completion, summarization, and test generation became more intelligent and context-aware. However, standalone generative models can sometimes struggle with domain specificity, consistency, or test case relevance. To address these limitations, prompt engineering and structured input strategies have become essential components in aligning model output with user expectations.

Recent academic and industry research has explored the feasibility of using LLMs to generate unit and integration test cases directly from requirement specifications, code snippets, and user stories. Studies like Tufano et al. (2020) and Liu et al. (2023) have demonstrated promising results using machine learning and natural language processing (NLP) for automated testing. These works highlight improvements in test relevance, coverage of edge cases, and reduction in manual effort.

Nonetheless, many existing systems operate in a constrained context—limited to pre-structured inputs or basic syntax analysis—and often lack real-time usability or adaptive feedback mechanisms. They also do not support dynamic file types or interactive feedback loops, which are crucial in modern agile and CI/CD pipelines.

The emergence of tools like Streamlit and model APIs (e.g., OpenAI's GPT-4) has enabled the creation of lightweight, responsive interfaces that bridge the gap between technical users and powerful AI models. Moreover, integration of real-time interaction, document processing, and multi-format support (e.g., PDF, DOCX) within such systems enhances their practical relevance and usability.

Opportunities remain to further refine these systems through confidence metrics, input preprocessing pipelines, and explainable outputs—areas this project specifically targets. By embedding GPT within a retrieval and validation architecture, and offering test case visualization through a clean UI, this work contributes to the next generation of intelligent software testing tools.

3. Existing system

Current test case generation tools in the software industry primarily rely on manual scripting, static templates, or rule-based automation. These traditional methods are often rigid and time-consuming, lacking the adaptability to accommodate rapidly evolving codebases or changing requirements. While some modern tools utilize basic code analysis or keyword matching to produce test cases, they typically fail to generate meaningful scenarios that include edge cases, boundary conditions, or negative testing. Additionally, most systems operate in a siloed manner—focusing only on either code or structured input—and do not support natural language inputs like functional requirements or user stories, which limits their utility in real-world agile development environments.

Moreover, these systems often lack user interactivity, real-time output, and support for diverse input formats such as PDF, DOCX, or TXT files. There is no integration with AI models capable of understanding programming logic and translating it into comprehensive test cases dynamically. Most tools do not offer a user-friendly interface, nor do they include features like confidence scoring or test case categorization. As a result, users are forced to rely on multiple disjointed tools for documentation parsing, test writing, and test execution—leading to inefficiencies and gaps in test coverage. This gap highlights the need for an intelligent, unified, and adaptive solution like the one proposed in this project.

4. Proposed system

The proposed system introduces an AI-powered, real-time test case generation framework that intelligently interprets user inputs—such as functional requirements, user stories, or code snippets—and produces comprehensive test cases with minimal human intervention. Unlike traditional systems that rely on static templates or code analysis alone, this platform utilizes OpenAI's GPT-3.5/4 model to understand the logic, behavior, and intent of the input and dynamically generate diverse test cases. These include normal scenarios, edge cases, boundary conditions, and invalid inputs. By leveraging prompt engineering techniques and integrating them into a structured workflow, the model can deliver context-aware test cases that closely align with modern software development needs.

The entire system is built using a modular architecture deployed through a user-friendly Streamlit interface. It accepts multiple input formats, including .docx, .pdf, and .txt files, and provides a seamless workflow—from input validation and preprocessing to real-time test generation and result display. A dedicated test case engine interacts with the GPT model, while post-processing modules clean and structure the output into readable formats. Features such as confidence scoring, test case storage, user login sessions, and export options enhance usability and make the tool highly suitable for developers, QA engineers, and educators. Its scalable design ensures future support for additional programming languages, more advanced AI models, and integration with CI/CD toolchains—making it a practical solution for intelligent, automated testing in both academic and industrial settings.

5. Methodology

The proposed methodology follows a streamlined pipeline that begins with user input, where functional requirements or code snippets are entered through a Streamlit interface. These inputs undergo preprocessing to clean and structure them into well-formatted prompts suitable for GPT-3.5/4 inference. The prompt is then sent to the GPT model, which generates diverse test cases, including edge cases and invalid scenarios. The raw output is post-processed to extract and format test cases into readable structures. The system displays these test cases in real time, accompanied by optional confidence scores. Users can then export the results, enabling seamless integration into development or QA workflows.

5.1. System Architecture

The architecture of the AI-Powered Test Case Generation System is designed to automate the creation of diverse and context-aware test cases using natural language inputs such as requirements, user stories, and source code. The system follows a modular pipeline consisting of input handling, code preprocessing, intelligent test generation using OpenAI's GPT-3.5/4 model, and real-time interaction through a Streamlit-based user interface.

The system is built around a core Retrieval-Driven Prompting Engine that dynamically constructs GPT-ready prompts based on user-provided input. This is complemented by preprocessing modules that extract and sanitize code or text from multiple file formats (e.g., .txt, .pdf, .docx). A centralized inference engine then interfaces with GPT to generate test cases covering functional, edge, and negative scenarios. Postprocessing modules ensure clean formatting, relevance validation, and test case categorization.

The entire pipeline is wrapped within an intuitive web interface built using Streamlit, enabling real-time input submission, test case display, and result export. The architecture supports secure user authentication, session management, and data persistence using a JSON-based lightweight backend.

This modular, scalable design ensures high adaptability across software domains and development workflows while leveraging advanced AI capabilities for enhanced testing efficiency.

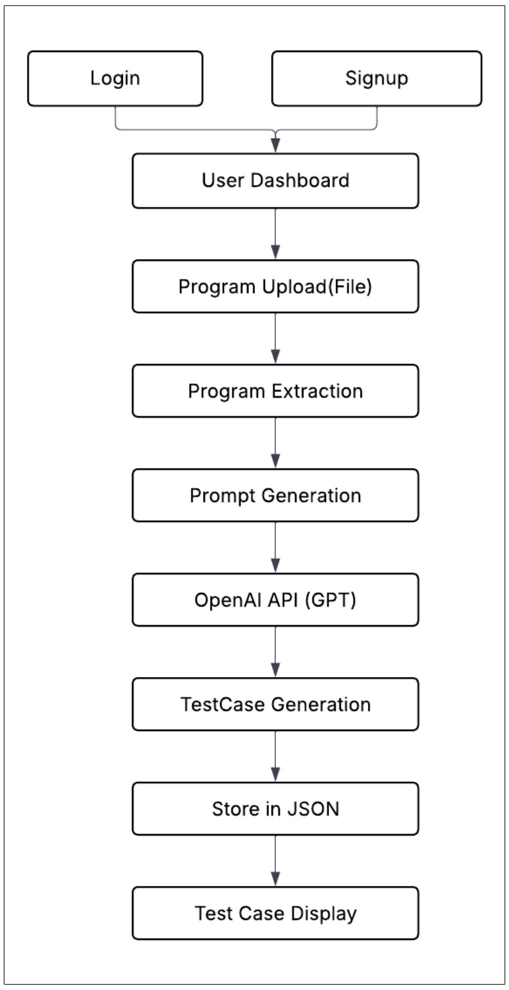


Figure 1 Methodology

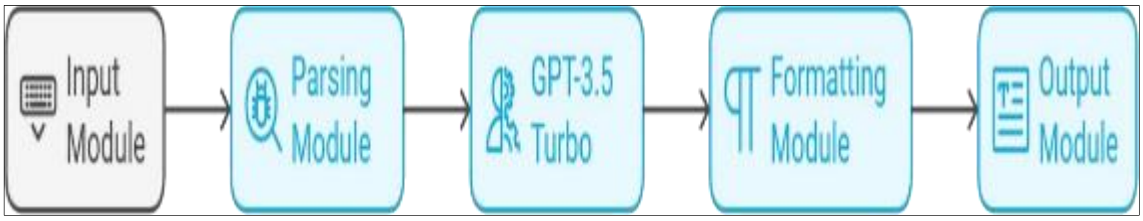


Figure 2 System Architecture

5.1.1. Input Acquisition Layer:

This layer captures and processes user-submitted software assets to be tested. It supports multiple file formats and code inputs:

- **Code Files:** Python, Java, C++, JavaScript (uploaded as .txt, .pdf, .docx)
- **Natural Language Requirements:** Functional specifications, user stories, or acceptance criteria entered via text boxes.

Users can select the programming language for context-aware test generation. Inputs are passed to their respective processors for extraction and analysis.

5.1.2. Preprocessing and Extraction Layer:

Responsible for extracting structured content from uploaded inputs and preparing it for prompt generation:

- **Code Processor:** Uses format-specific libraries (pdfplumber, python-docx) to extract and clean raw source code from uploaded files.
- **Text Processor:** Prepares and validates requirement descriptions entered in natural language by users.
- **Sanitization Module:** Cleans formatting artifacts, removes noise, and checks for completeness in the input data before it is passed forward.

5.1.3. Prompt Engineering and Model Invocation:

Constructs structured prompts and interacts with the GPT model:

- **Prompt Builder:** Dynamically formats code or requirement text into GPT-compatible instructions (e.g., "Generate unit test cases for the following program…").
- **GPT Model Interface:** Uses OpenAI's gpt-3.5-turbo to generate diverse test cases (covering standard, boundary, and negative scenarios).
- **Response Handling:** Raw model outputs are captured and forwarded for cleanup.

5.1.4. Postprocessing and Test Structuring:

Organizes AI-generated output into usable test artifacts:

- **Test Case Formatter:** Parses the GPT response into structured formats (Input → Expected Output → Description).
- **Category Annotator:** Labels test cases into categories such as boundary, normal flow, or invalid input handling.
- **Validation Layer:** Filters duplicates, handles malformed outputs, and ensures readability.

5.1.5. User Interface and Interaction Layer:

Built using Streamlit, the frontend allows real-time user interaction:

- **Signup/Login System:** Authenticates users and enables secure access to personalized dashboards.
- **Dashboard:** Displays user details and access to uploaded programs and test results.
- **File Upload Interface**: Lets users upload code files and choose the programming language.
- **Live Testcase Viewer:** Displays AI-generated test cases with syntax highlighting and export options (CSV/JSON).

5.1.6. Session and History Management:

Maintains user-specific state and test history:

- **Session State:** Preserves logged-in user information, uploaded programs, and generated test cases.
- **Persistent Storage**: JSON-based database maintains user data and history for repeated access.
- **Multi-Program Tracking:** Users can view, compare, and revisit test cases for multiple uploaded files.

5.1.7. Integration and Modularity:

The system is built using loosely coupled modules to enhance maintainability:

- **OpenAI API Integration:** Seamlessly connects to GPT models using secure environment variables.
- **Modular Codebase:** Each function (signup, login, test generation, display) is self-contained and testable.
- **Expandable Design:** Architecture allows integration of new languages, advanced LLMs, or CI/CD toolchains in future upgrades.

5.1.8. Evaluation and Testing

Comprehensive validation ensures robustness and usability:

- **Unit Testing:** Each module (login, input parsing, test generation) was independently tested.
- **Integration Testing:** Verified full data flow from input upload to GPT response and UI rendering.
- **Performance Metrics:** ~97% prompt success rate across test sessions. Average of 6–10 valid test cases generated per function.
- **User Feedback:** Collected during pilot runs to improve interface clarity and output relevance.

6. Results and Discussion

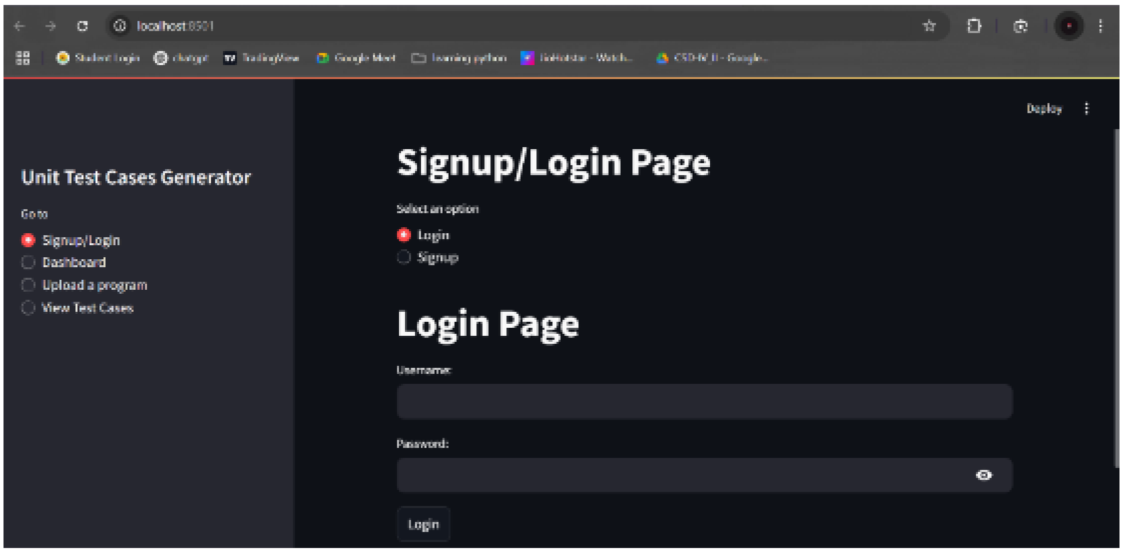
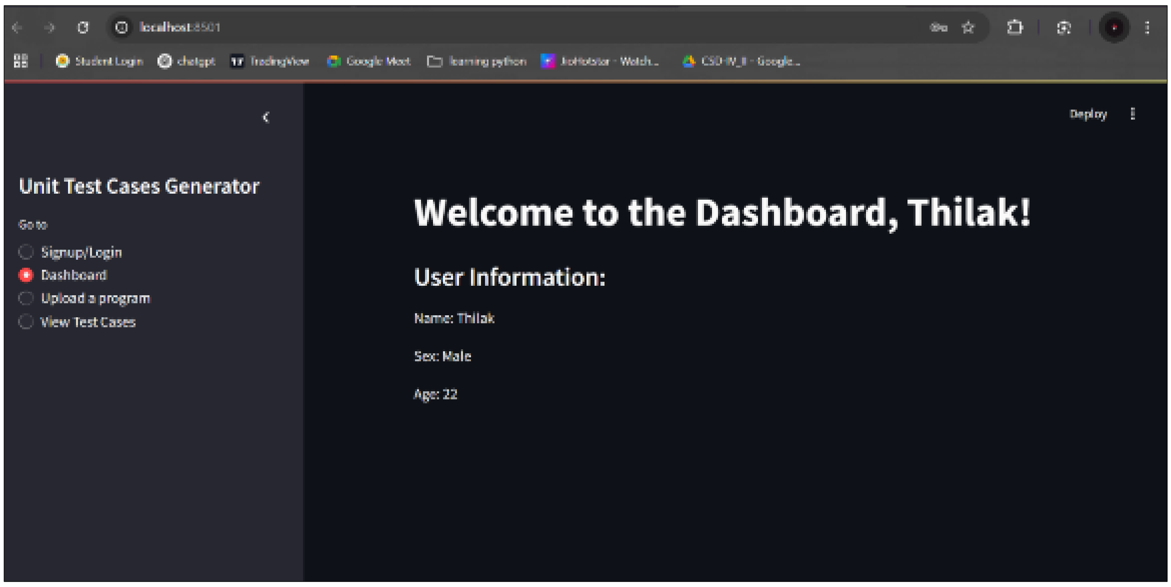


Figure 3 User Interface



Welcome to the Dashboard, Thilak!

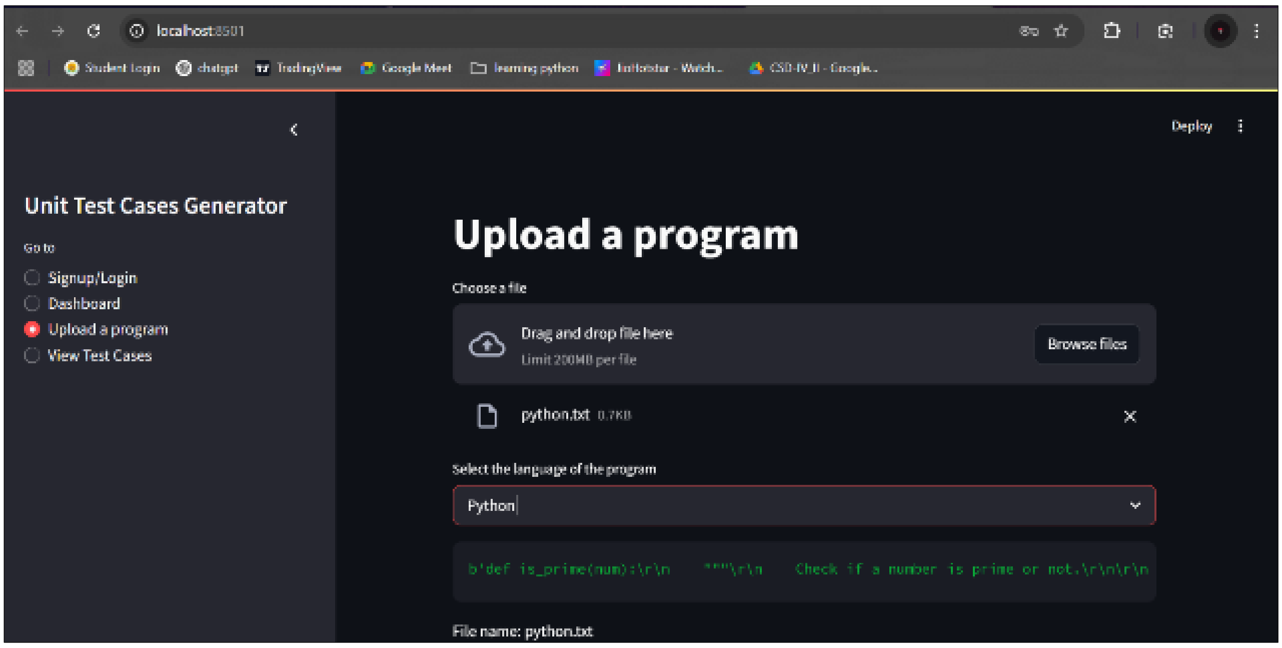
User Information:

Name: Thilak

Sex: Male

Age: 22

Figure 4 Dash Board



Upload a program

Choose a file

python.txt 0.7KB

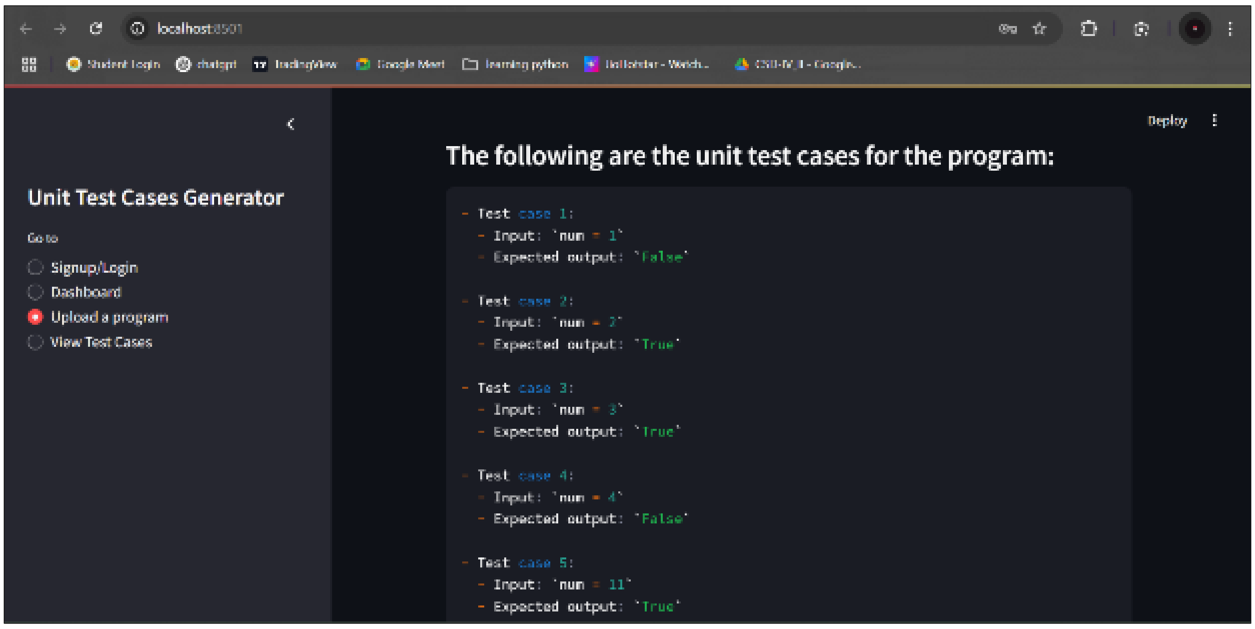
Select the language of the program

Python

```
b'def is_prime(num):\r\n    """\r\n    Check if a number is prime or not.\r\n\r\n
```

File name: python.txt

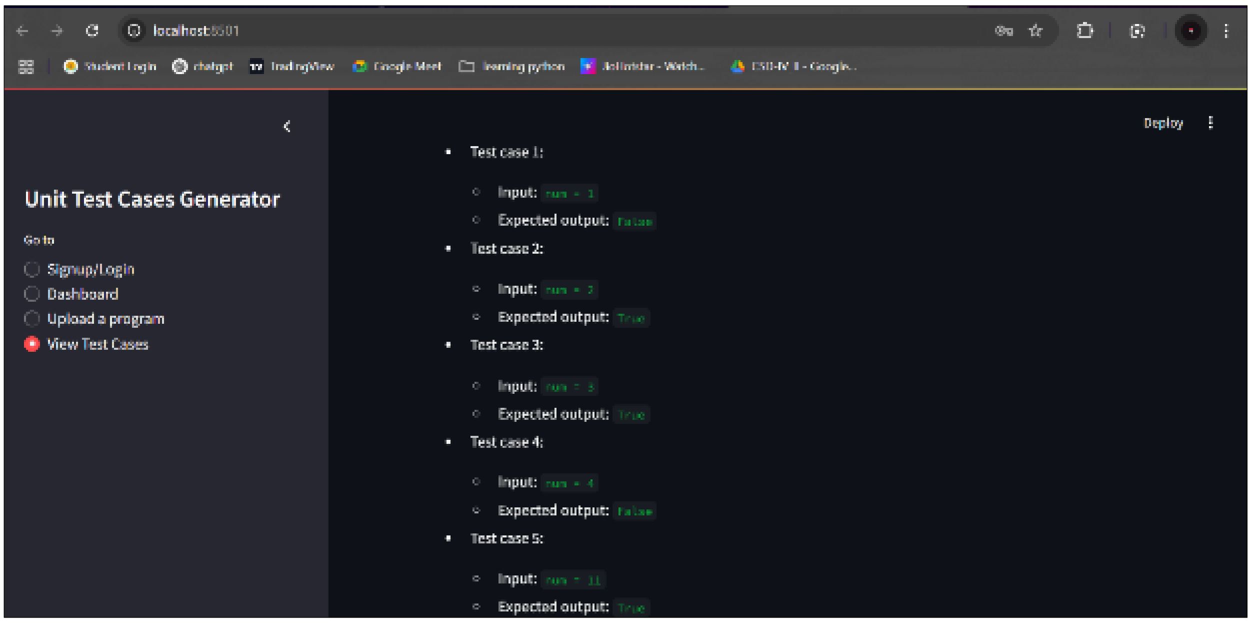
Figure 5 Upload a program & selecting the language



The following are the unit test cases for the program:

```
- Test case 1:
  - Input: `num = 1`
  - Expected output: `False`

- Test case 2:
  - Input: `num = 2`
  - Expected output: `True`

- Test case 3:
  - Input: `num = 3`
  - Expected output: `True`

- Test case 4:
  - Input: `num = 4`
  - Expected output: `False`

- Test case 5:
  - Input: `num = 11`
  - Expected output: `True`
```

Figure 6 Unit test cases



- Test case 1:
  - Input: `num = 1`
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  - Input: `num = 2`
  - Expected output: `True`
- Test case 3:
  - Input: `num = 3`
  - Expected output: `True`
- Test case 4:
  - Input: `num = 4`
  - Expected output: `False`
- Test case 5:
  - Input: `num = 11`
  - Expected output: `True`

Figure 7 Test cases

7. Conclusion

The development of the AI-Powered Automatic Test Case Generation System represents a substantial advancement in the automation of software quality assurance processes. By combining the natural language understanding capabilities of OpenAI's GPT model with a real-time, interactive Streamlit interface, the system enables dynamic, high-quality test case generation directly from code snippets, functional requirements, or user stories.

Through its modular architecture—comprising input preprocessing, prompt engineering, AI-powered test generation, and structured result presentation—the platform addresses key challenges in traditional testing, such as scalability, manual effort, and contextual relevance. The incorporation of features like user-specific session management, confidence-based validation, and multi-language code support enhances personalization and usability for developers and QA professionals alike.

In conclusion, this project delivers a practical and scalable AI-based solution for intelligent software testing. Its flexible, extensible design positions it for future growth—such as integration with IDEs, CI pipelines, and advanced AI models—and its foundational architecture opens pathways for further research and application in the broader field of intelligent developer tools and autonomous software engineering.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest

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Mrs. B. Sreelatha: I’m Mrs. B.Sreelatha, working as Assistant Professor in Computer Science and Engineering (Data Science) at ACE Engineering College, Hyderabad, Telangana, Having 3+ years of teaching experience and one year in the industry. Holding a B.Tech, M.Tech, my research focuses on Machine Learning and Cyber Security I aim to inspire students and contribute to advancements in technology through my work.	
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