

# PROJECT REPORT: Deep-100 Based Autonomous Code Analysis and Repair Agent (Code Doctor)

## 1. Introduction and Project Objective

The objective of this project is to transform Large Language Models (LLMs) from passive structures that merely generate text into **autonomous agents** capable of executing code, correcting errors, and retrieving information from external sources (RAG). The **Deep-100** model (based on DeepSeek/Qwen2.5) was utilized as the base model, and the **ReAct (Reasoning + Acting)** architecture was implemented.

The goal is to develop a system that analyzes faulty or incomplete user code requests, executes them in a secure virtual environment (Sandbox), and fixes errors through **Self-Correction**.

## 2. Architectural Design and Methodology

The project is built upon a hybrid architecture consisting of three main components:

### A. Orchestration (The Brain)

**Model:** The Deep-100 model, optimized using the Unsloth library, was employed.

**Loop:** The system operates within a **Thought -> Action -> Observation** loop.

**Memory:** To prevent the model from losing context, conversation history is managed dynamically using a "Sliding Window" method.

### B. Tools

Two fundamental tools were developed to enable the agent to interact with the external world:

**python\_executor\_tool:** Executes generated Python code within an isolated subprocess. For security, a `timeout=5s` constraint was enforced, and regex filters were added to block dangerous libraries (e.g., `sys`, `os`, `input`).

**rag\_retrieval\_tool:** Documents were vectorized using SentenceTransformers (all-MiniLM-L6-v2), and semantic search was integrated to answer theoretical questions.

## C. Security Layer

Before direct execution, the code generated by the model passes through a "Smart Regex" filter. Even if the Markdown formatting is missing, code blocks are detected; however, blocks requiring interaction such as `sys.argv` or `input()` are automatically blocked.

## 3. Experimental Scenarios and Analysis (Trace Outputs)

To test the success and limitations of the project, the following edge-case scenarios were applied:

### Scenario 1: Training Bias and Constraint Management

**Situation:** When asked to write a simple Fibonacci code, the model persistently attempted to use `sys.argv` (command-line arguments) due to habits acquired from its training data (scripts).

**Intervention:** System security blocked this code. The behavior was corrected via negative prompting by the user ("Do not use sys, hardcode values").

**Result:** The model understood the constraints, simplified the code, and executed it successfully.

(Insert screenshot of the log showing the sys error and subsequent correction here)

### Scenario 2: Performance Optimization and Time-Out Test

**Situation:** The model was asked to write a "Recursive Fibonacci 100" code.

**Observation:** The model selected the Naive Recursion method without using `lru_cache` (Memoization). Since the complexity of this algorithm is  $O(2^n)$ , the process could not complete in a reasonable time.

**Result:** The 5-second timeout mechanism in the `python_executor` was triggered, protecting the system from an infinite loop. This demonstrated that the agent's optimization capability requires guidance.

(Insert screenshot of the "Timeout" error here)

### **Scenario 3: Stateless Execution Challenge**

**Situation:** The agent defined a function in one step and attempted to call that function in the subsequent step.

**Error:** A NameError was received because the Python execution environment is reset (Stateless) at every step.

**Solution:** The agent was instructed to use the previous result (hardcoded value), overcoming the issue.

## **4. Challenges and Solutions**

## **5. Conclusion**

The **Code Doctor** developed in this project has gone beyond being a simple code generator. Its ability to execute written code (**Action**), read and fix errors when they occur (**Self-Correction**), and operate within security boundaries is a successful implementation of the modern ReAct Agent architecture. In particular, thanks to RAG integration, a hybrid structure possessing both theoretical knowledge and practical application capabilities has been achieved.