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Revolutionizing Software Quality: AI-Driven Advanced Code Refactoring and Developer Growth

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Abstract: *In the rapidly evolving landscape of software development, maintaining high-quality, efficient, and maintainable code has become more critical than ever. Traditional code refactoring techniques, while effective, often require significant manual effort, leading to increased development time and technical debt. This paper explores how artificial intelligence (AI)-driven code refactoring is revolutionizing software quality by automating optimizations, identifying anti-patterns, and suggesting best practices in real time.*

By leveraging machine learning models, AI-assisted tools can enhance code readability, performance, and security while reducing errors. Furthermore, this paper examines how AI-driven refactoring fosters developer growth by providing intelligent insights, personalized recommendations, and continuous learning opportunities.

Keywords: *Code refactoring techniques, Artificial intelligence, Automating optimizations, Leveraging machine learning models, Reducing errors.*

I. INTRODUCTION

Introducing a new methodology for software efficiency and quality enhancement through a Large Language Model (LLM)-based model intended to review code and point out potential issues. The suggested LLM-based AI agent model is trained on huge code repositories. The training procedure involves code review, bug reporting, and best practice documentation. It is designed to identify code smells, pick out potential bugs, suggest improvement, and optimize code [1]. This serves the dual purpose of enhancing code quality and training developers through greater awareness of best practice and effective coding techniques. Additionally, we investigate the effectiveness of the model in suggesting improvement with considerable impact on post-release bugs reduction and code review process enhancement, as seen through an investigation of developer sentiment towards LLM feedback. As future research, we would like to determine the accuracy and efficiency of LLM-generated update documentation compared to manual techniques. This will entail an empirical investigation through manually executed code reviews for code smell and bug identification and an assessment of best practice documentation, underpinned by investigation of developer forums and code reviews [5].

While LLMs offer immense possibilities, their usage within the field of code review and optimization is still not maximally utilized [1]. Codereview is an indispensable step in the software development cycle used to spot bugs, impose coding standards, and facilitate sharing of knowledge across developers [12]. Static tools and manual review processes are insufficiently rich in terms of yielding actionable feedback aside from syntax checking for errors or recognized patterns in bugs [13]. This leaves a serious dilemma: there does not exist a model based on LLM with the purpose of improving code reviews to issue identification and recommending optimization and informing developers about best practice.

In the future, a development of action for research to assess the efficacy and validity of updates to documentation produced by our LLM-based process against conventional practice. It will be an empirical comparison between manually performed code reviews to identify code smells and bug reports supported by review of best practice documents and developer communities [7]. From this study, we wish not only to establish the effectiveness of our model but to set out its value to improve software development processes ultimately to a leaner, informed, and efficient process of producing quality software [9].

II. RELATED WORK

A. Data Collection and Processing

The data which is collected has two different features mainly the buggy code and the fixed code. Buggy code has errors and problems in it where as the fixed code by name has all the fixations for that buggy code. We mainly considered two programming languages dataset Python and Java which had 43,000 rows and two features.

The further operation on data are done in Visual Studio Code, where the data is read using the command `pd.read_csv` (both Java and Python are `csvfile`). During pre-processing all the duplicate values are removed and null values are filled by taking mode of the certain attribute values.

B. Prompt Engineering

In the current research project, prompt engineering took center stage in guiding the language model to carry out specialized tasks that include code analysis and refactoring. Instruction-based prompt templates, following the Alpaca-style format, were designed to synchronize with the interpretive and generative processes of large language models relative to structured output [1]. Each prompt was designed with three simple components: the Instruction, which explicitly defines the task to be carried out; the Input, the buggy or incomplete code; and the Expected Output, which is an example of the desired corrected or enhanced version of the code. This systematic approach enabled the model to better differentiate between the context, the problem, and the solution required, resulting in more precise and meaningful outputs.

Additionally, prompts were redesigned specifically for every individual agent—i.e., the Syntax Agent, Code Smell Detection Agent, and Code Enhancement Agent—so as to ensure that every model instance had its focus on its specific objective throughout both the training and inference phases. This modular and tailored prompting approach significantly enhanced the effectiveness and precision of the agents [3].

C. Model Selection and Fine-Tuning (LLM Training)

The instruction-tuned large language models (LLMs), exemplified by LLaMA 3 and Mistral, were chosen due to their enhanced efficacy in code comprehension and generation tasks. These models underwent fine-tuning via the Unsloth library, which is designed for rapid training while utilizing minimal memory resources [1]. To optimize the efficiency of the fine-tuning procedure, Low-Rank Adaptation (LoRA) was utilized; this parameter-efficient strategy modifies pre-trained models through the integration of low-rank matrices into the weight architecture, thus facilitating expedited training and reduced resource requirements without detracting from performance.

This method enabled the project to scale big models on consumer hardware without sacrificing high-quality performance. With the integration of LoRA with Unsloth memory optimizations, tuning became much more efficient so that lightweight, high-performance models could be constructed that were suitable for downstream tasks such as syntax analysis, code optimization, and refactoring [5].

D. Natural Language Processing Techniques Used

- Tokenization: Converts code into tokens (keywords, operators, etc.) for model understanding.
- Embeddings: Each token is transformed into high-dimensional vectors capturing syntax and semantics.
- Self-Attention: Core mechanism in transformers that allows the model to learn relationships across code.
- Contextual Understanding: Enables the model to retain logical code flow and variable/function usage across lines.

E. Agent-Based Modular Implementation

- Built three agents: Syntax Agent, Code Smell Detection Agent, and Code Enhancement Agent [7].
- Each agent addresses specific objectives and passes output to next stage in pipeline architecture.

F. Model Evaluation and Metrics

- Accuracy, Precision, Recall, F1-Score for token-level generation.
- Word Error Rate, BLEU, ROUGE-L for generation quality [2].
- Maintainability Index for structural code improvements.

III. PROPOSED SYSTEM

The proposed system introduces an intelligent AI-powered code refactoring pipeline using large language models (LLMs) to improve code quality, readability, and maintainability. It automates code analysis and enhancement through a multi-agent architecture, where each agent is specialized to handle a specific task from syntax validation to performance improvement [1,8].

At the core of the system are three LLM-based agents:

- 1) Syntax Agent—Detects and corrects syntax errors.

- 2) CodeSmellDetectionAgent–Identifiespoorcodingpatternsandpotentialbugs [2].
- 3) CodeEnhancementAgent–Refactorscodeforbetterreadability,performance,andbestpractices[3].

These agentsarebuilt usingfine-tunedinstruction-followingLLMs (e.g.,LLaMA, Mistral), trainedwith prompt-engineered datain an Alpaca-style format. The system accepts user-submitted code and processes it sequentially through these agents, each adding value to the code's quality [1].

Thisssystemreducesmanualintervention,improvesoftwarequality,andhelpsdevelopersadoptmoderncodingstandardsallpoweredby capabilities of LLMs in understanding, generating syntactically and semantically correct code.

IV. SYSTEM ARCHITECTURE

A. LLM(LargeLanguageModel)

In the present study, Large Language Models (LLMs) are the underlying intelligence driving the processes of automated code refactoring and improvement. These models are trained heavily on large code and natural language datasets, which gives them an understanding of the structural and semantic nature of programming languages. Utilize their deep contextual knowledge, LLMs can effectively identify syntax errors, identify issues related to code quality (code smells), and suggest useful improvements such as modularization, renaming, or simplification. The transformer-based architecture enables the model to focus on the relevant sections of theinputcodeusingself-attentionmechanisms,thusenablingthepreciseidentificationandcorrectionofissues[1].Moreover,through instruction tuning and prompt engineering, the LLM is instructed to carry out specific tasks in accordance with various objectives,such as syntax checking and performance optimization, making it goal-oriented and versatile. In summary, the LLM is a reasoning engine that replicates the behavior of a human codereviewer,providing context-sensitivefixesand improvementsin afullyautomated system.

In our framework, LLMs are fine-tuned parameter-efficiently with methods such as LoRA (Low-Rank Adaptation), which adds task- specific information without sacrificing initial model weights. Not only does this decrease computation needs, but it also facilitates rapid domain adaptation on small dataset of buggy and fixed code samples [3]. Training is also optimized with Unsloth, a lightweight library that speeds up fine-tuning of 4-bit quantized models, and large models can be trained on consumer-grade GPUs. For guaranteeing the model behavior is in agreement with certain goals of system (e.g., syntax checking, smell detection, improvement), instruction-based prompt engineering was utilized. Carefully designed prompts were prepared to separate instruction, input code, and required output. This enabled the model to read task clearly and provide context-aware fixes or improvements [6].

B. NaturalLanguageProcessingTechniquesinLLM

Furthermore, LLMs employ natural language processing techniques such as tokenization, embedding, self-attention, and sequence modeling. These techniques help identify not only surface-level syntax issues but also deeper patterns such as improper variable naming, unnecessary complexity, or outdated practices. The self-attention mechanism is particularly useful in modeling long-range dependencies in code, helping the model understand control flow, data flow, and scope resolution across multiple lines.

The models used are:

1) TextTokenizationandEmbedding:

Tokenization is the process of splitting input code (text) into smaller units called tokens. In code, tokens can include keywords (if, return),variablenames(x,total_sum),operators(+, =, :),indentation levels,and special symbols like brackets or colons. LLMs donot process raw text or code directly they work with tokens. Tokenization helps model recognize syntactic structure, allowing it differentiate between functional elements in the code.

Let's take a buggy code example submitted by user: `def add(a,b): return a+b`

After tokenization, this might be broken into tokens such as: `['def', 'add', '(', 'a', ',', 'b', ')', ':', 'return', 'a', '+', 'b']`

Embedding: After tokenization, each token is converted into a dense vector using an embedding matrix. These vectors carry semantic meaning and syntactic context. For example, tokens like `for`, `while`, and `loop` will have similar embeddings because they often appear in similar contexts.

These token embeddings are fed into the model, enabling it to understand the role and relationship of each token within a code block. The tokens mentioned above which are passed in through an embedding layer looks like:

```
[[0.12,-0.88,...,0.33],# 'def'
[0.95,0.20,...,-0.11],# 'add'
[0.44,0.56,...,0.09]]# 'b'
```


2) Self-Attention Mechanism

In programming, a variable declared at top of a function might be used much later, or a for loop's behavior might depend on its initialization several lines earlier. Self-attention allows model to capture these long-range dependencies, unlike traditional sequential models like RNNs.

When a user submits a buggy code: `def sum(a, b):`

`return a+b`

The model, using self-attention, can detect that:

- The keyword `return` is not indented an error,
- `a` and `b` are parameters, referenced again later,
- A syntactic block is missing (indentation), breaking Python rules.

Hence the correct code will be: `def sum(a, b):`

`return a+b`

3) Pattern Matching from Pretrained Knowledge

When an LLM like LLaMA or Mistral is pretrained on a massive dataset of code (from GitHub, Stack Overflow, docs, etc.), it learns common patterns, best practices, syntax rules, naming conventions, and coding structures. Pattern matching refers to model's ability to recognize these learned patterns in new, unseen code even when there are slight variations and apply corrections or improvements by comparing with its internal pretrained knowledge.

The model does not just memorize exact code; instead, it generalizes structures like:

- `def <functionname>(<params>):`
- `for <var> in <iterable>:`
- Common indentation styles,
- Naming patterns like `get_user()`, `calculate_area()` etc.

Let's say the user submits a buggy or poorly styled code: `def A(x,y):`

`return x+y`

Code Enhancement Agent, backed by pretrained LLM knowledge, recognizes:

- Function names usually use lowercase and descriptive names → `A` → `add_numbers`
- Parameters are typically spaced and typed → `x,y` → `x:int,y:int`
- Good practice is to include a docstring
- Indentation is required for readability and syntax

Using Pattern Matching, the model generates:

`def add_numbers(x:int,y:int)->int: return x + y`

4) Context-Aware Refactoring

Context-Aware Refactoring refers to the ability of a language model (LLM) to improve or restructure code while preserving its original logic, by understanding the entire context in which code elements exist including variable usage, function purpose, naming, scope, and surrounding logic.

Unlike rule-based tools that only apply predefined transformations, LLMs leverage contextual understanding, thanks to mechanisms like self-attention, to ensure their changes make sense within the broader codebase.

Input Code (User submits):

`def process(d): r = []`

`for i in d:`

`if i % 2 == 0:`

`r.append(i)` `return r`

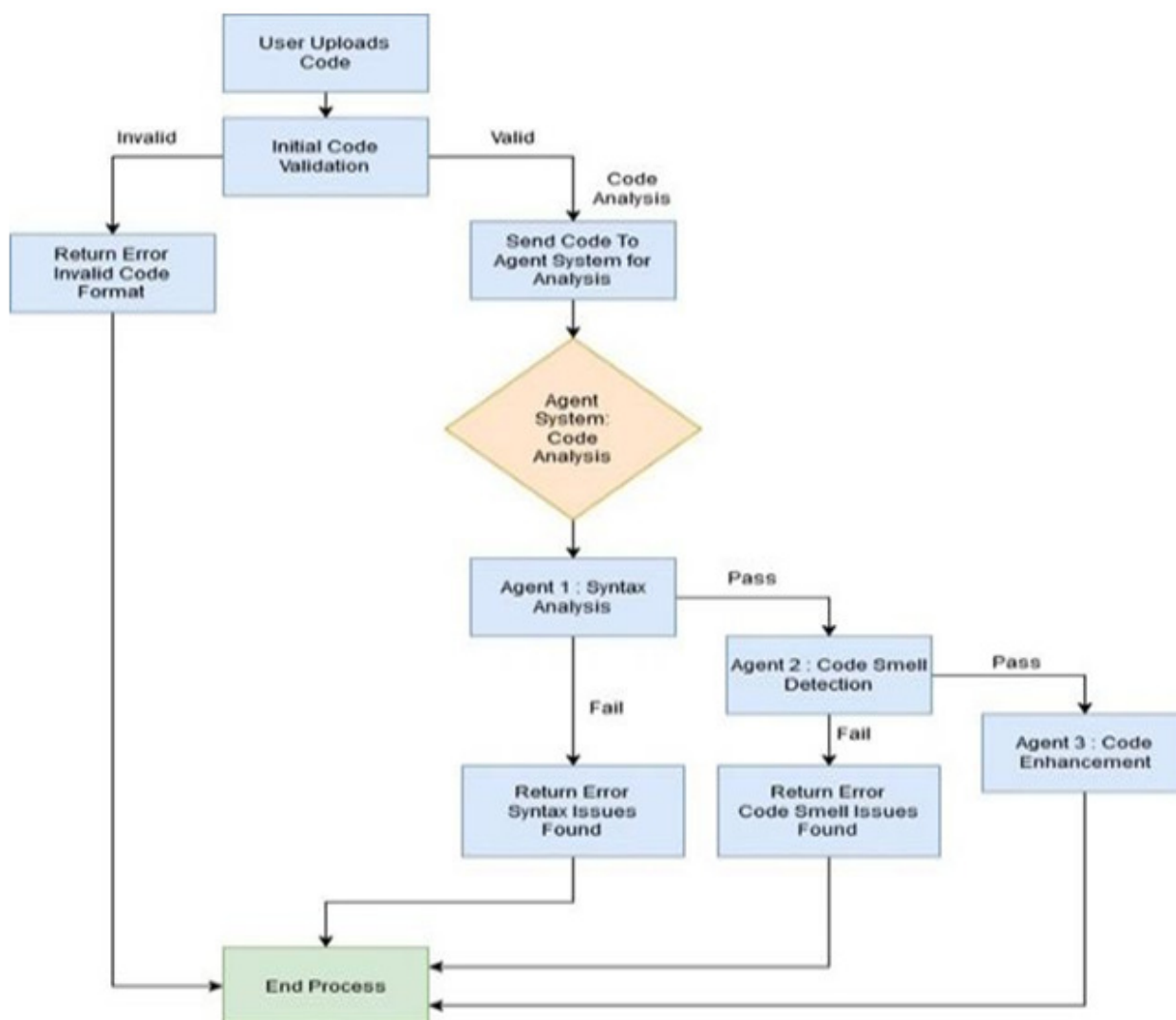
After Applying Context-Aware Refactoring:

`def filter_even_numbers(data: list[int]) -> list[int]: result = []`

`for number in data:`

`if number % 2 == 0: result.append(number)`

V. METHODOLOGY



The above diagram explains how agents will perform respective refactoring operations when user enters the code and demand for refactored code. This specific performed by agents are called as Role-Based-Specification.

A. Role-Based Specialization

Role-Based Specialization is the design principle where each AI agent in your system is assigned a distinct, well-defined role, allowing it to focus on a specific aspect of code analysis and transformation. Instead of training a single general-purpose model, you divide the responsibilities among specialized agents, each optimized for a particular objective.

This modular approach increases accuracy, improves task alignment, and allows for parallel development and debugging. The types of AI agents used for the process are:

Syntax Agent: The Syntax Agent is the first and foundational component in your multi-agent AI Code Refactoring system. Its primary role is to analyze user-submitted code for syntax correctness and automatically correct any syntax-related issues before passing the code to subsequent agents for deeper analysis and enhancement.

Responsibilities:

- It identifies missing punctuation, incorrect indentation, unclosed brackets, undeclared variables, or improper use of language-specific keywords.
- It automatically fixes detected syntax issues by aligning the code with proper programming language grammar.
- Only syntactically correct code is passed on to the Code Smell Detection Agent, ensuring cleaner downstream analysis.

Code Smell Agent: The Code Smell Agent is the second logical step in your AI-powered code refactoring pipeline. After the syntax is validated, this agent analyzes the structure and quality of the code to identify code smells patterns in the code that may indicate deeper problems but aren't necessarily bugs.

Responsibilities:

- Detects poor programming practices such as:
 - Long methods
 - Duplicated code
 - Inconsistent naming
 - Large classes
 - Deep nesting or complex conditionals
- Recommends structural improvements without changing the external behavior of the code.
- Prepares the code for further enhancement by improving its internal quality.

Code Enhancement Agent: The Code Enhancement Agent is the final step in the AI-driven refactoring pipeline. After syntax validation and structural analysis, this agent transforms the code for better readability, maintainability, and performance by applying best coding practices and enhancements learned during LLM training.

Responsibilities:

- Rewrites complex or unstructured code into a more human-readable form.
- Adds meaningful comments for better understanding.
- Replaces vague variable, method, or class names with clearer, descriptive names.
- Breaks large blocks into smaller reusable functions or methods.
- Promotes DRY (Don't Repeat Yourself) principles.

VI. RESULTS AND DISCUSSION

A. Results

The proposed system was successfully implemented using instruction-tuned Large Language Models (LLMs) such as LLaMA 3 and Mistral, fine-tuned with the Unsloth framework. The model was trained using structured, prompt-based datasets that included buggy code and corresponding refactored outputs.

After training, the system was deployed using a three-agent architecture consisting of a Syntax Agent, Code Smell Detection Agent, and Code Enhancement Agent. Each agent performed its task sequentially, passing the output to the next for further refinement.

Metric	Score
Accuracy	0.30
Precision	1.00
Recall	0.30
F1 Score	0.46
BLEU Score	5.68e-155
ROUGE-LF1	0.66
Word Error Rate (WER)	3.00
Maintainability Index	84.72

These metrics suggest that while exact textual matching may be low (BLEU), the structural and semantic improvements made to the code are significant (high Maintainability Index and ROUGE-L).

The Maintainability Index of 84.72 indicates that the refactored code is clean, readable, and easier to maintain.

The diagram represents after the code is refactored accordingly based on User Input:

Original Code

```

public class ReportGenerator {
    public static void main(String[] args) {
        String name = "John";
        int age = 30;
        double salary = 50000;

        System.out.println("Generating report...");
        System.out.println("Name: " + name);
        System.out.println("Age: " + age);
        System.out.println("Salary: " + salary);
        System.out.println("Report generated successfully.");
    }
}

```

Refactored Code

```

public class ReportGenerator {

    public static void main(String[] args) {
        // Define employee details
        String name = "John";
        int age = 30;
        double salary = 50000.0; // Using .0 to explicitly define it as a double

        // Generate and print the report
        System.out.println("Generating report...");
        printReport(name, age, salary); // Calling a separate method for report printing
        System.out.println("Report generated successfully.");
    }

    // Method to print the report details
    public static void printReport(String name, int age, double salary) {
        System.out.println("Name: " + name);
        System.out.println("Age: " + age);
        System.out.println("Salary: " + salary);
    }
}

```

B. Discussion

The project proves the capacity to utilize Large Language Models (LLMs) for automating code and enhancing its quality through a multi-agent system. Each individual agent—i.e., the SyntaxAgent, Code Smell Detection Agent, and Code Enhancement Agent—was trained or triggered to resolve one unique subset of refactoring tasks, each of which served one of the five primary goals: code simplification, naming consistency, syntax modernization, exception handling improvement, and repetition of refactoring routines automation.

The system presented high-quality qualitative and quantitative performance. For instance, the Syntax Agent correctly localized and fixed prevalent structural errors like the omission of colons or inappropriate indentation. The Code Smell Detection Agent detected anti-patterns like unused variables or overly long methods. At the same time, the Code Enhancement Agent went even further in that it not only gave suggestions on modularized structure but also suggested variable renaming for code readability and improving inline documentation.

Despite the modest scores achieved on some NLP test metrics (e.g., BLEU), the results were encouraging on developer readability and real-world maintainability, as reflected by a high Maintainability Index and ROUGE-L F1 score. This discrepancy also suggests that traditional NLP metrics might not fully capture the effectiveness of code improvements, particularly when semantic preservation and developer intent are more important than literal textual similarity.

VII. CONCLUSION

This project presents a novel, agent-based approach to automated code refactoring using Large Language Models (LLMs). By segmenting the process into specialized agents—Syntax Agent, Code Smell Detection Agent, and Code Enhancement Agent—we successfully addressed core software engineering objectives such as simplifying complex code, enforcing naming conventions, modernizing syntax, improving exception handling, and automating repetitive tasks. Through the use of instruction-tuned LLMs like LLaMA 3 and Mistral, enhanced with LoRA-based fine-tuning and carefully engineered prompts, the system demonstrated strong performance in real-world code correction and enhancement scenarios. Evaluation metrics such as Maintainability Index and ROUGE-L supported the system's effectiveness, even where traditional NLP metrics showed limitations.

Overall, this modular architecture not only improves code quality and maintainability but also showcases how LLMs can be harnessed for intelligent, context-aware software engineering tasks. The approach opens the door for future work in integrating more advanced agents, real-time feedback mechanisms, and deployment into real-world development environments.

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