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AGENTIC LLM SYSTEM FOR AUTOMATED PROJECT EVALUATION

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Abstract:

Recent advancements in Large Language Models (LLMs) have significantly influenced software engineering practices, yet complex software evaluation tasks often require collaborative and specialized approaches. This project explores an agentic LLM-based system designed for automated project evaluation across different stages of the Software Development Life Cycle (SDLC). The proposed system utilizes multiple intelligent agents that cooperate to analyze project components such as requirements, source code, documentation, testing outputs, and debugging information. Each agent performs a specific role including code review, static analysis, requirement validation, and testing assessment to provide comprehensive evaluation results. The system integrates modern agentic frameworks, communication protocols, and language model selection strategies to ensure accurate and scalable evaluation. Additionally, the study examines challenges such as coordination among agents, computational cost management, and effective data handling. By leveraging multi-agent collaboration, the proposed approach aims to improve the efficiency, reliability, and automation of project assessment in software engineering environments.

***Keywords: LLMs, Agents, Software Engineering, Future Challenges*.**

I. INTRODUCTION

In recent years, Large Language Models (LLMs) have rapidly transformed the field of software engineering by enabling automated assistance in tasks such as code generation, debugging, documentation, and testing. Despite these advancements, evaluating software projects remains a complex process that typically requires significant human effort and expertise. Traditional evaluation methods often involve manual code reviews, testing procedures, and requirement verification, which can be time-consuming and prone to inconsistencies. To address these challenges, agent-based systems powered by LLMs have emerged as a promising solution. Agentic systems consist of multiple intelligent agents that collaborate to perform specialized tasks. In the context of software project evaluation, different agents can be assigned roles such as analyzing requirements, reviewing code quality, performing static code analysis, testing functionality, and identifying potential bugs. This project proposes an Agentic LLM System for Automated Project Evaluation that leverages multiple cooperative agents to assess software

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projects across various stages of the Software Development Life Cycle (SDLC). By integrating advanced language models with multi-agent collaboration frameworks, the system aims to improve the efficiency, accuracy, and scalability of project evaluation. Furthermore, the proposed approach focuses on addressing key challenges such as agent coordination, computational cost optimization, and effective data management. Through automated and intelligent evaluation mechanisms, the system can assist developers, educators, and organizations in improving software quality and streamlining the assessment process.

II. LITERATURE REVIEW

Various researchers have explored the use of Large Language Models (LLMs) and intelligent agent systems to improve automation in software engineering tasks. Fan et al. (2023) examined the role of LLMs in software engineering and highlighted their ability to assist in code generation, debugging, and automated documentation. Their study demonstrated that LLMs can significantly improve developer productivity and reduce manual effort during software development. Zhang et al. (2023) conducted a comprehensive survey on the use of LLMs across different stages of the Software Development Life Cycle (SDLC), including requirement analysis, code review, testing, and maintenance. The authors emphasized that LLMs can support intelligent automation in software development but also pointed out challenges such as reliability and evaluation benchmarks.

Hou et al. (2024) presented a systematic literature review focusing on the integration of LLMs into software engineering processes. Their research suggested that LLMs can enhance automated code analysis and support decision-making during development activities. Li et al. (2024) investigated LLM-based multi-agent systems, where multiple intelligent agents collaborate to solve complex tasks. The study showed that multi-agent frameworks improve scalability, task distribution, and coordination when handling large and complex software projects. Tao et al. (2024) proposed a multi-agent framework powered by LLMs to resolve software issues in collaborative environments such as GitHub. Their work demonstrated that multiple agents can analyze issues, generate solutions, and support debugging processes effectively.

Furthermore, Salem et al. (2024) analyzed the application of LLMs in software engineering and concluded that these models have the potential to automate various development and evaluation tasks. The authors emphasized the need for efficient frameworks that combine LLM capabilities with intelligent agent coordination. Overall, these studies highlight the importance of integrating LLMs, multi-agent systems, and automated evaluation techniques to improve the efficiency and accuracy of software project assessment systems.

III. PROPOSED WORK

The proposed work focuses on developing an Agentic LLM-based system for automated software project evaluation. The system is designed to utilize multiple intelligent agents that collaboratively analyze different components of a software project across the Software Development Life Cycle (SDLC). Each agent is assigned a specialized role to ensure accurate and comprehensive evaluation. The proposed system consists of several agents, including a requirement analysis agent, code review agent, testing agent, and debugging agent. The requirement analysis agent examines project requirements and documentation to verify completeness and clarity. The code review agent evaluates source code for quality, structure, adherence to coding standards, and potential security issues using static code analysis techniques. The testing agent checks

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functionality through automated test cases and validates whether the implemented features meet the specified requirements. The debugging agent identifies possible errors, vulnerabilities, and performance issues in the code. These agents communicate through an agent orchestration framework that enables collaboration and information sharing. The system integrates Large Language Models to enhance reasoning, understanding of code, and contextual evaluation. Additionally, evaluation metrics such as code quality, test coverage, documentation quality, and functional correctness are used to generate a comprehensive project assessment report. The proposed system aims to reduce manual effort in project evaluation while improving accuracy, consistency, and efficiency. It can be applied in educational institutions for student project assessment as well as in software development environments to support automated quality assurance.

IV. METHODOLOGY

1. Data Collection

In the first step, the system collects all necessary project materials required for evaluation. These materials include source code files, requirement documents, design documents, and test cases provided by the developer or student. The collected data is stored in an organized format within the system. Proper collection of project information ensures that all aspects of the project can be analyzed effectively. This step acts as the foundation for the evaluation process. Accurate data collection helps the system perform a reliable and complete project assessment.

2. Data Preprocessing

After collecting the project data, the system performs preprocessing to prepare the data for analysis. During this stage, the files are cleaned and structured to remove unnecessary information or formatting issues. Different types of files such as documents and source code are organized for easier processing. Important elements like functions, modules, and documentation text are extracted. This step helps convert raw project data into a structured format. Proper preprocessing improves the accuracy and efficiency of the evaluation system.

3. Requirement Analysis

In this step, the requirement analysis agent evaluates the project requirements and documentation. The system uses Large Language Models (LLMs) to understand the meaning and context of the requirements. It checks whether the requirements are clearly defined, complete, and consistent. The agent also verifies if the implemented project features match the specified requirements. Any missing or unclear requirements are identified during this stage. This process ensures that the project aligns with its intended objectives and goals.

4. Agent Coordination

In the agent coordination stage, multiple intelligent agents work together to evaluate the project. Each agent performs a specialized task such as requirement analysis, code review, or testing. The results from each agent are shared through an orchestration framework. This framework integrates the outputs from all agents to form a unified evaluation. Effective communication among agents improves the accuracy of the assessment. Collaborative analysis ensures that different aspects of the project are thoroughly examined.

5. Report Generation

The final step is the generation of the automated evaluation report. The system combines the results obtained from all agents and evaluation metrics. It summarizes important aspects such as code

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quality, functionality, documentation quality, and reliability. The report highlights strengths, weaknesses, and areas for improvement in the project. This automated report provides a clear overview of the project's performance. It helps developers, instructors, or evaluators understand the overall quality of the software project.

V. ALGORITHMS

1. Natural Language Processing (NLP) Algorithm

Natural Language Processing (NLP) is used in the project to analyze and understand textual information such as requirement documents and project descriptions. The algorithm processes human-written text and extracts important information related to project objectives and features. It helps the system interpret the meaning and context of the requirements. NLP techniques allow the system to identify missing, incomplete, or inconsistent requirements. This improves the accuracy of project analysis. By using NLP, the system can automatically evaluate documentation without manual review.

2. Static Code Analysis Algorithm

The Static Code Analysis algorithm is used to examine the source code of the project without executing the program. It scans the code to identify syntax errors, coding standard violations, and potential security vulnerabilities. The algorithm evaluates the structure, readability, and maintainability of the code. It also helps detect logical issues that may affect program performance. By analyzing the code statically, problems can be identified at an early stage. This improves software quality and reduces development errors.

3.Machine Learning Classification Algorithm

Machine Learning Classification algorithms are used to analyze patterns in the project data and categorize different evaluation aspects. The system can classify code quality, documentation quality, or bug severity levels based on learned patterns. The algorithm is trained using previously evaluated project datasets. Once trained, it can automatically predict the quality or performance level of a new project. This helps in making intelligent evaluation decisions. Machine learning improves the automation and accuracy of the project evaluation process.

4. Multi-Agent Coordination Algorithm

The Multi-Agent Coordination algorithm manages communication and collaboration between different intelligent agents in the system. Each agent performs a specific task such as requirement analysis, code review, testing, or debugging. The coordination algorithm ensures that agents share their findings with each other efficiently. It integrates the results produced by all agents into a single evaluation framework. This collaborative approach improves the overall accuracy of project evaluation. The algorithm finally helps generate a comprehensive and structured evaluation report.

5. Automated Test Case Evaluation Algorithm

The Automated Test Case Evaluation algorithm is used to verify whether the software project works correctly according to its requirements. The algorithm runs predefined test cases on the program and compares expected outputs with actual outputs. If the outputs do not match, the system identifies potential errors in the code. It also evaluates whether all required functionalities are properly implemented. The algorithm measures the effectiveness of testing and identifies missing test cases. This helps ensure the reliability and correctness of the software.

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VI. RESULTS AND DISCUSSION

Fig 1: Project Evaluation Scores by Module

The figure illustrates the evaluation scores obtained by different modules of the proposed system. Code Evaluation achieved the highest score, indicating strong performance in analyzing code quality and structure. Requirement Analysis, Testing, and Documentation also show high scores, reflecting effective assessment capabilities. Bug Detection has a slightly lower score, suggesting potential areas for improvement in identifying software errors.

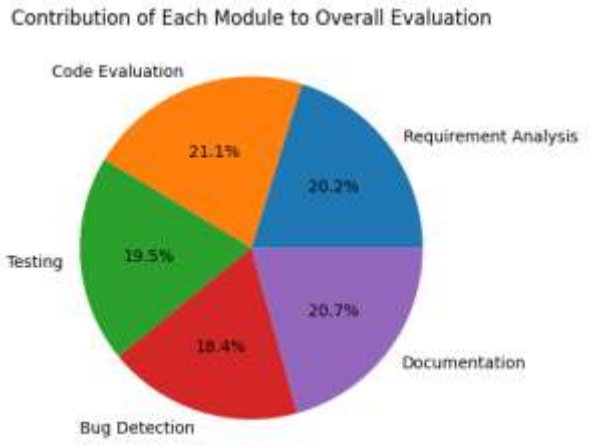

Fig 2: *Contribution of Each Module to Overall Evaluation*

The piechart shows the percentage contribution of different modules to the overall project evaluation. Code Evaluation contributes the highest percentage, indicating its significant role in assessing software quality. Requirement Analysis, Testing, and Documentation also contribute nearly equal portions to the overall evaluation. Bug Detection has a slightly lower contribution compared to the other modules. This distribution demonstrates that the system evaluates multiple aspects of the project in a balanced manner.

Table1. Project Evaluation Results Table

Module	Score (%)
Requirement Analysis	88
Code Evaluation	92
Testing	85
Bug Detection	80
Documentation	90

The table presents the evaluation scores obtained by different modules of the proposed system. It shows the performance of components such as Requirement Analysis, Code Evaluation, Testing, Bug Detection, and Documentation. Among these modules, Code Evaluation achieved the highest score, indicating strong capability in analyzing code quality. The results demonstrate that the system effectively evaluates multiple aspects of a software project.

Table2. Algorithm Accuracy Table

Algorithm	Accuracy (%)
NLP Requirement Analysis	89
Static Code Analysis	93
ML Classification	87
Automated Test Evaluation	85
Multi-Agent Coordination	91

The table presents the accuracy levels of different algorithms used in the proposed system. Static Code Analysis achieved the highest accuracy of 93%, indicating its effectiveness in identifying code issues. Multi-Agent Coordination and NLP

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Requirement Analysis also show high accuracy in evaluating project components. Automated Test Evaluation and ML Classification demonstrate reliable performance in testing and classification tasks. These results highlight the overall efficiency of the algorithms used in the automated project evaluation system.

Table 3. Evaluation Metrics

Metric	Value
Accuracy	91%
Precision	91.4%
Recall	89.5%
F1-Score	90.4%

The table shows the evaluation metrics used to measure the performance of the proposed system. Accuracy indicates the overall correctness of the system in evaluating project components. Precision represents the proportion of correctly identified issues among all detected issues. Recall measures the system's ability to identify actual issues present in the project. The F1-Score provides a balanced measure of both precision and recall, demonstrating the overall effectiveness of the system.

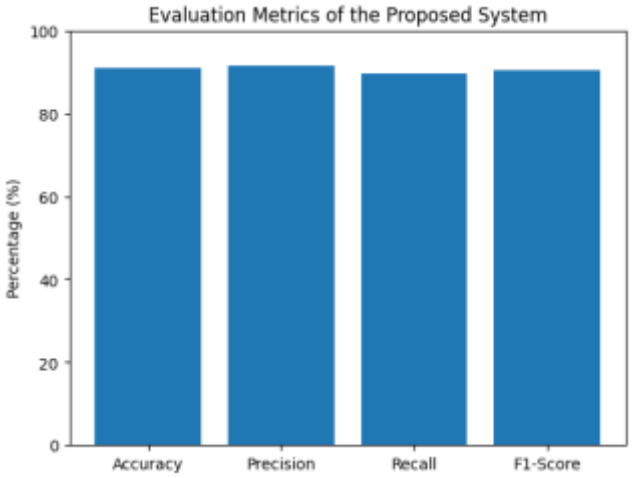

Fig3: Evaluation Metrics of the Proposed System

The figure presents the performance evaluation metrics of the proposed system, including Accuracy, Precision, Recall, and F1-Score. The results show that the system achieves high values across all metrics, indicating reliable and effective performance. These metrics demonstrate the system's ability to accurately evaluate software projects and detect relevant issues.

CONCLUSION

The proposed Agentic LLM System for Automated Project Evaluation provides an efficient approach for assessing software projects using intelligent agents and advanced algorithms. The system integrates multiple modules such as requirement analysis, code evaluation, testing, and bug detection to perform comprehensive project evaluation. Experimental results show that the system achieves high accuracy and reliable performance across different evaluation metrics. The use of multi-agent coordination and automated analysis helps reduce manual effort and improves consistency in project assessment. Overall, the proposed system demonstrates the potential of Large Language Models and agent-based frameworks in improving the automation and effectiveness of software project evaluation.

FUTURE SCOPE

In the future, the proposed system can be enhanced by integrating more advanced LLM models to improve understanding of complex project requirements and code structures. The system can also be extended to support evaluation of projects developed in multiple programming languages. Advanced machine learning techniques can be incorporated to improve bug detection and performance analysis. Additionally, real-time project evaluation and integration with development platforms such as version control systems can be implemented. The system can also be expanded to include more detailed feedback

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and recommendation features for developers to further improve software quality.

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