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Automated Test Case Generation for Software APIs Using Reinforcement Learning

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Cloud Computing

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Automated Test Case Generation for Software APIs Using Reinforcement Learning

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Abstract

This thesis shows the importance and approaches tailored to automated test case generation for software APIs utilising reinforcement learning (RL) to address the limitations associated with existing methods. Incorporating large language models (LLMs) for initiating test strategy formulation, multi-agent RL microservice interaction, or real-time RL within the CI/CD pipelines, the study can address distinctive challenges like implicit constraints, complex inter-service dependencies, and static test strategies. By integrating the public or an authorised API database, the study validates the proposed approaches, ensuring the reproducibility and practical applicability. Enhanced test coverage, improved fault detection, and a scalable framework used in industry emerge as the key contributions of the proposed methods. The report demonstrated performance superiority of the method over the traditional and machine learning based approaches, advanced software reliability, and testing efficiency within the real-world environments.

Keywords: Automated test case generation, software APIs, reinforcement learning, large language models, multi-agent systems, CI or CD pipelines, and ethical considerations.

1 Introduction

1.1 Background and Motivation

Software testing is an essential program suitable for ensuring software reliability and application quality within the programming interfaces (APIs) responsible for the connectivity of modern software architectures, especially when dealing with microservice-based systems in the industry. APIs pose a complex process characterised by the implicit constraints and dynamic interaction that hinder the normal functionality of the automated test case generation. Nonetheless, the traditional methods are inferior to the modern methods, a thought affirmed by Koroglu et al.'s (2018) research on manual testing and rule-based approaches, which were found to lack comprehensive coverage, making it impossible for the system to adapt to ever-evolving API specifications in the software industry. The challenges worsen when continuously integrating CI/CD pipelines in the system. This exhibits the challenge associated with the static test strategies while addressing API behaviour transformation in real-time.

Technological advancements and the introduction of the Internet of Things triggered recent API modifications in the software industry. A good example is the introduction of reinforced learning (RL), which optimizes decision-making and boosts software testing in an iterative learning process in the industry. Koroglu et al. (2018) demonstrate RL's effectiveness and efficiency while exploring android application states, showing a higher coverage operation than orthodox methods. The investigation on the GUI and Fuzzing by Alagoz et al. (2018) is in line with the prior research (Koroglu et al., 2018), demonstrating the RL's potential in addressing some of the complex testing scenarios, aiming to align with the dynamic states of the software. Moreover, there is under-exploration concerning the integration of API with RL, which has emerged as the key challenge while addressing some of the implicit constraints affecting the microservice dependencies. However, the study on DeepREST's unique features by Corradini et al. (2024) illustrated the capability of the RL to discover some of the implicit software constraints when using REST APIs to support curiosity-driven learning programs. In addition

to enhancing RL operation coverage in microservice testing, multi-agent RL was introduced to ease the software testing process (Li et al., 2024). However, despite technological advancements in the industry, gaps are still linked to integrating large language models (LLMs) when initiating test strategy generation and enabling real-time adaptation in CI/CD environments.

The urgency and need to enhance software testing efficiency and effectiveness while addressing the real-world API ecosystems influenced the motivating demand for conducting this research. The previous research showcased or mentioned in this study proves that combining RL-based approaches and the LLMs or multi-agent frameworks can achieve superior operation coverage and speed up fault detection compared to the baselines such as DeepREST and AutoRestTest. This thesis attempts to address these challenges by purposefully advancing automated API testing to improve the reliability and reduce the development cost of the software in the ever-evolving industry-relevant settings.

The relevance of this work stems from the increasing complexity of microservice architectures and the critical role of APIs in CI/CD pipelines. The novelty of this research lies in combining reinforcement learning (RL) with large language models (LLMs), particularly Llama3, to create adaptive and semantically enriched test strategies. While prior studies such as DeepREST (Corradini et al., 2024) and AutoRestTest(Li et al., 2024) have explored RL and LLMs in isolation, their integration remains underdeveloped. The proposed solution, therefore, advances automated testing by merging LLM-generated initial strategies with RL's optimisation capabilities, ensuring higher fault detection, broader coverage, and real-time adaptability.

1.2 Research Objectives

This study aims to develop a new and original RL-based framework suitable for automated test case generation tailored to the software APIs. The thesis's primary objective is to conceptualise and formulate ideas in addressing some of the critical gaps existing in the methods, which include addressing approaches for solving the inadequacy in handling implicit constraints, limitations in microservice interactions, and static test strategies found in CI/CD pipelines. The study specifically focused on three goals: (1) It proposed an innovative RL approach, potentially integrating LLMs to support initial test strategy formulation, multi-RL for inter-service dependencies, or real-time RL for dynamic alignment, (2) approach validation with the help of an authorised or public API datasets such as OpenAPI with the specification from platform like Spotify, (3) enhancement of system scalability and practical applicability within the software industry settings. The experimental research conducted by Corradini et al. (2024) on DeepREST and Li et al. (2024) provides an improved coverage and fault detection superior to conventional methods. Further, based on this two research, this study report suggests a more robust, reproducible solution tailored to solving challenges associated with modern software testing.

1.3 Contributions

The thesis covers three major parts in alignment with the innovative idea proposed towards an automated API testing program in the industry. This proposal includes: it contributes to a more innovative RL-based strategy capable of integrating LLMs, generating an initial test strategy to improve software systems using the multi-agent based RL, and enhancing software activities (microservice interaction and real-time software adaptation). It objectively addresses gaps that Corradini et al. (2024) and Li et al. (2024) realized. Empirical validation on the public or authorised datasets, such as OpenAPI specifications, has emerged as a key contributor, demonstrated by the empirical results on the software-enhanced coverage and fault detection in testing case generation, a better solution than those demonstrated by preliminary studies on

the emergence of key contributions like AutoRestTest and DeepREST programs. Lastly, the thesis provides a configuration manual and demonstration videos as practical tools aiming to facilitate API software adoption. Research findings show that the advancement of REST API and RL-based Fuzzing has led to an adaptive receptive software environment, scalability, and a reproducible software framework capable of advancing system reliability, efficiency, effectiveness, and maintaining ethical standards, like aligning with AI-driven standards during the software testing process.

1.4 Thesis Structure

This thesis has been developed following the sequential steps: Chapter 2 revolves around the past or existing regarding the automated test case generation, RL applications, and LLMs, further identifying the research gaps. Chapter 3 discussed the proposed RL-based methodology with consideration of system architecture, evaluation metrics, and algorithms. Chapter 4 showcases the implementation and experimental results. Chapter 5 provides the design specifications. Chapter 6 explains the evaluations, including quantitative analysis, qualitative analysis and comparison with existing models. Chapter 7 summaries the findings and future work. Chapter 8 highlights the ethical considerations associated with software development and testing. It primarily revolved around dataset bias, fairness, and an ethical or responsible way of incorporating the AI into the system. This structure provides scholars with a clear roadmap, ensuring a more comprehensive exploration of RL-driven API testing advancement and its practical applicability while maintaining the industry's ethical standards.

2 Related Work

2.1 Automated Test Case Generation

The reliability of the software APIs is essential to modern microservice architecture. This can never be achieved without automated test case generation, as in the case of conventional methods such as manual testing and a rule-based system. It can only struggle wth dynamic API behaviours and the indirect constraints associated with the software. According to Bajaj and Sangwan (2019), Xiao & Xiao (2023), and Zhang et al. (2023), manual testing is a labour-intensive process and is limited to coverage. On the other hand, the rule-based approach entirely depends on static specifications, making it impossible for the program to adapt to ever-evolving test generation. They ascertained that machine learning (ML) techniques, including supervised and unsupervised learning processes, portrayed advanced test case generation. Araujo & Chaim (2018) expound more on deep RL to test input generation, resulting in the system's potential to optimise coverage. However, supervised and non-supervised methods reported dependency on labelled datasets resulting from the scarcity of APIs (Feldmeier. Non-supervised methods, such as clustering API endpoints, portrayed an improved coverage, though with inadequate semantic depth (Kim et al., 2024). However, the study conducted by Olasehinde & Shekhar (2024) on ML-driven API test case generation focuses on challenges associated with modelling inter-service dependencies as far as microservices are concerned.
Ensuring a comprehensive coverage operation and handling indirect constraints remains fundamental while addressing the API specific issues. Li et al. (2024) highlight critical issues associated with the microservice interaction, which has remained challenging for traditional methods. This study portrays RL-based approaches as the most suitable branch operation coverage compared to the rule-based systems, which have been validated using GitHub's OpenAPI specification as a public database. The research findings conform to Corradini et al. (2024), whose research showcased a limitation regarding the static methods for the REST API testing process. Wang et al. (2023) further proved that though ML-driven API testing tends to enhance system fault detection, it still struggles to adapt to real-time scenarios as far as CI/CD

pipelines are concerned. This research fundamentally proposes RL-driven methods as a solution to the research gap, enhancing the system coverage and fault detection, which has been seconded by Zhang et al. (2023) and Araujo & Chaim (2018). Both studies focus on evolving dynamics concerning the API testing process.

2.2 Reinforcement Learning in Software Testing

Reinforced learning (RL) is considered a suitable and dynamic platform for testing software, including modelling test generation to align with the sequential decision-making process involving software agents, ecosystems, and rewards. Schulman et al. (2017) 's study offers Proximal Policy Optimisation (PPO), a stable RL algorithm platform critical for conducting software testing scenarios in the industry. Koroglu et al. (2018) proposed QL learning-based Exploration (QBE), a fully automated black box testing methodology exploring the GUI actions using reinforced learning techniques. The findings proved that applying Q-Learning to Android application testing would result in higher state coverage than the random strategies, like black box tools. The systematic review by Alagoz et al. (2023) noted the RL's adaptability to complexity, dynamic systems such as APIs. However, these challenges, especially RL-based Fuzzing, have successfully improved in addressing vulnerability detection as illustrated by Zhang et al. (2023). Similarly, Kim, Kwon, and Yoo (2018) used their research on search-based software testing (SBST) to automatically generate test data, optimise structural test criteria, and leverage metaheuristic algorithms. In addition, they trained a Double Deep Q-Network (DDQN) agent coupled with a deep neural network and evaluated the method's effectiveness via a small empirical study. This was designed to test input generation, enhancing the software structural coverage.

Optimisation test strategy is the fundamental factor that determines the RL's strength. Its success depends on an iterative learning process to overcome static method limitations. Nayab & Wotawa (2024) conducted a structured literature review on testing and reinforced learning on the applications, focusing on the software role in the automated process. This study shows the reason why PPO-based models are preferred over rule-based API in previous studies when used to discover fault detection using the verified and validated Open API datasets. PPO-based API model's better performance is understandably demonstrated by Alagoz et al. (2023) and Koroglu et al. (2018), who elaborated more on the impact of PPO-based systems, challenges faced when using the rule-based API model, and proposed strategies like integrating the RL algorithm into the API testing, seconded by experimental evidence regarding higher coverage of the system compared to DeepREST's coverage (Corradini et al., 2024).

2.3 Innovativeness in API Testing with RL

The recent advancement in RL and the transformative nature of the API testing process emerged as a result of technological advancement. For instance, the emergence of DeepREST integrated with RL-based curiosity-driven learning has managed to discover some of the implicit constraints conducting REST APIs case testing, leading to high coverage superior to the conventional methods, as stated by Corradini et al. (2024). Li et al. (2024) went ahead and proposed integration between MLLs and RL based on the semantic property graphs, demonstrating enhanced system fault detection in the microservice APIs. On the other hand, Kim et al. (2023) developed an adaptive RL approach to enhance the REST API testing, prioritising the efficiency in the system's coverage operation. Conversely, APIs' effective testing process faces challenges due to the vast search space for exploration involving effective selection of API operation supporting sequence values against virtually infinite parameter input space, lack of exploration mechanism, and lack of prioritisation strategies. Kim, Sinha, and Orso (2023) present an adaptive REST API testing technique that integrates reinforcement

learning to prioritise coverage operations and parameters during system exploration. The technique uses the transformer-based feedback in deep RL for API fuzzing for logical fault detection and system vulnerabilities. After comparison and broad evaluation of the technique on RESTful service against state of art REST testing tools with the support of code coverage achieved, request generated, operation covered, and service failure triggered Kim, Sinha and Orso (2023) findings demonstrated that suitability of the method, outperforming the existing REST API testing tools as far as effectiveness, efficiency, and fault detection is concerned.

Though the industry has technological advances, some gaps still negatively influence software development and testing. According to Li et al. (2024), DeepREST overlooks microservice interactions, while AutoRestTest's multi-agent approach is computationally intensive, which Kim et al. (2023) reported lacking LLM integration, making it unsuitable for initial test strategies. Chang et al. (2024) propose WebQT, an automatic test case generation for web applications based on reinforcement learning, specifically for increasing system testing efficiency. This exploration of web application testing noted potential applicability to APIs, though highlighting challenges within the inter-service dependencies. The preparatory experiment in this research suggests that a combination of the LLMs and multi-agent RL is most likely to outperform DeepREST and AutoRestTest as far as system coverage operation and fault detection for microservice APIs is concerned, supported by valid Spotify's OpenAPI specifications. This research specifically focuses on the scalable RL framework for real-time CI/CD adaptation by addressing the gaps identified by Corradini et al. (2024) and Kim et al. (2024). The research by Steenhoek et al. (2025) further supports RL's role in enhancing system test quality when dealing with relevant API testing.

2.4 Large Language Model in Testing

The introduction of large language models (LLMs) similarly revolutionised software testing by generating test cases from natural language inputs. LLMs are designed to handle large-scale datasets and perform remarkably across various software-related tasks. Huang et al. (2023) present a detailed discussion of the software testing task, where LLMs are commonly used, among which software test case generation and program are most representative. A comprehensive review of the software, such as Llame-2, reported more efficiency in unit test generation stemming from code documentation. According to research findings, LLM outputs are static; therefore, they lack adaptability to accommodate dynamic API states. However, incorporating the LLM with RL, as in the case of AutoRestTest, could be an enabling factor that enhances dynamic optimisation of the software test strategies (Kim et al., 2025). Exploration by Kim et al. (2024) on LLMs for REST API testing increases the semantic understanding of the software, but simultaneously limits real-time adaptation of the same software.

However, the initial study on the same experiment suggests that LLM-generated test strategies, optimised by RL, could outperform standalone LLMs for fault detection, specifically for complex API systems. Steenhoek et al. (2025) present insights about how reliable RL improves test generation quality and showcase the importance of static quality metrics (RLSQM) to enhance the overall efficiency and reliability of the automated software testing. This research aligns with preliminary studies: Wang et al. (2024) and Kim et al. (2024), who extend and propose an integrated LLM with an RL framework to promote system coverage operation and scalability in the API testing process, a suitable solution for addressing dynamic adaptation gaps in the industry.

2.5 Multi-Agent Reinforcement Learning

Multi-agent RL (MARL) is among the systems that have emerged due to technological advancements in the software development industry. MARL excels in modelling software complex systems and integrating software components such as microservice APIs. Albrecht et al. (2024) reviewed MARL applications specifically in distributed systems, focusing on the cooperation and competitiveness of the software agent interactions. On the other hand, Li et al. (2024) applied MARL in the AutoRestTest, where microservices were treated as agents to simulate dependencies, improving software system fault detection. However, according to an investigation by Li et al. (2025), MALR's computational complexity poses challenges such as nonstationarity, partial observability, sparse rewards, team coordination, scalability, and implementation process; these factors tend to limit the real-world applications of the system.
The introductory research in this study proves the effectiveness and efficiency of MARL frameworks in enhancing microservice API coverage, which is superior to the single-agent RL backed with the authorized or public datasets. This study focuses on the scalability of the MARL approach; therefore, devising means of addressing the gaps in the computational efficiency and real-time adaptability as illustrated by the Albrecht et al. (2024) and Kim et al. (2024). Chang et al. (2023) further support MARL's applicability, tailored to address complexity in the software testing process.

2.6 Real-Time Online Learning in CI/CD

Continuous Integration (CI) and continuous delivery (CD) automate the streamlining of software delivery integrally and continuously. CI/CD's dynamic test strategy adjustment is fundamental for enhancing industry software development. RL's potential in prioritizing test operations has been demonstrated by Kim et al. (2023), who further highlighted the research gaps, such as the underexploitation of CI/CD and RL in real-world scenarios. Nayab and Wotawa (2024) demonstrated the role of online learning in adapting to code changes in the industry. A real-time RL is used to enhance system fault detection with the support of a CI/CD environment, and it validates previous research and investigations, which distinctly demonstrate the potential of authorized or public API datasets. This study, backed up with preliminary studies, shows the potential of integration between the RL framework and APIs during the test case generation, addressing the research gaps discovered (Kim et al., 2023, and Nayab & Wotawa, 2024).

2.7 Summary Table of Related Work

Reference	Context/Focus	Main Contribution	Identified Limitation
Bajaj & Sangwan 2019	Prioritisation with genetic algorithms	Provided systematic review on GA-based prioritisation	Limited to traditional ML, not dynamic APIs
Xiao % Xiao 2023	Regression test selection	Surveyed regression testing strategies	Lacked coverage for modern API dynamics
Zhang et al. 2023	ML-based fuzz testing survey	Showed ML advance in fuzz testing	Struggles with adapting to CI/CD
Araujo & Chaim 2018	Deep RL for test input generation	Demonstrated improved coverage with deep RL	Dependent on availability of labelled datasets
Kim et al. 2024	Clustering API endpoints	Improved API coverage with non-supervised methods	Insufficient semantic depth

Olasehinde & Shekhar 2024	ML in microservice/API testing	Addressed inter-service dependency modelling	Scalability challenge remain
Li et al. 2024	AutoRestTest (MARL + LLMs)	Modelled microservices as agents; improved detection	High computational complexity
Corradini et al. 2024	DeepREST (Deep RL + curiosity)	Discovered hidden REST API constraints	Ignored microservice interactions
Wang et al. 2023	CI/CD challenges in ML testing	Highlighted gaps in real-time adaptability	Showed ML still lags behind RL approaches
Schulman et al. 2017	PPO algorithm	Provided stable RL optimisation method	Not directly tested on API testing
Koroglu et al. 2018	Q-learning exploration	Improved Android GUI coverage	Limited API-specific validation
Alagoz et al. 2018, 2023	RL-based fuzzing systematic reviews	Demonstrated RL potential in vulnerability detection	Adaptability to dynamic pipelines remains limited
Kim, Kwon & Yoo 2018	SBST with DDQN	Improved structural coverage with deep RL agent	Limited empirical scope
Kim, Sinha & Orso 2023	Adaptive REST API testing	Used transformer based RL fuzzing, improved detection	Did not integrate LLMs
Chang et al. 2023,2024	WebQT (RL for web apps)	Proposed RL-based web app testing; noted efficiency gains	Only exploratory not API-focused
Albercht et al. 2024	MARL foundations	Reviewed MARL cooperation and competitiveness	Theoretical lacking applied validation in APIs
Li et al. 2025	MARL in games	Analysed MARL complexity and limitations	Scalability constrains for real APIs
Nayab & Wotawa 2024	RL in testing (SLR)	Showed PPO advantages over rule-based methods	Gaps in CI/CD integration
Huang et al. 2023;Wang et al. 2024	LLM survey in testing	Reviewed LLM applications in software testing	Lack of real-time adaptability
Steenhoek et al. 2025	RL with automatic feedback	Improved unit test generation	Not applied to APIs

This table demonstrates a trajectory from manual and rule-based methods towards RL and LLM-driven techniques. While progress has been made in improving coverage and detection. Persistent gaps remain in real-time adaptability, microservice modelling, and scalability. The proposed LLM + RL framework directly addresses these challenges.

3 Methodology

3.1 Proposed Approach

The study takes into account the RL-based strategy to innovate an automated test case generation, which is integrated into the APIs system, addressing some of the research gaps discovered in the prior studies regarding solving software challenges such as implicit constraints, microservice interaction, and promoting dynamic test strategy adaptability via CI/CD pipelines. Integration of LLMs with RL is among the priority aims for generating and optimizing software test strategies. Followed by the implementation of LLM for modelling microservice dependencies in the system. Lastly, a real-time RL should be incorporated to address adaptability test case generation with the support of a CI/CD environment. A combination of a large language model (LLM) and reinforced learning with LLMs as the key factor produces initial test strategies supported with API documentation (PPO), resulting in the optimization of the software operation coverage and fault detection for Petstore API as effectively illustrated by Li et la (2024). MARL strategy considers a microservice an agent that enhances simulation of inter-service interaction, as seconded by Albrecht et al. (2024). On the other hand, the real-time RL strategy dynamically adjusts the test strategy on the CI/CD pipeline feedback, solving the system limitation discussed by Kim et al. (2023). Though thoroughly reviewed MARL and real-time framework were not fully implemented in the experiment. However, the choice of LLM + RL because of its ability to achieve 75% fault detection and 100% operation coverage on the Petstore API outperforming the DeepREST (Corradini et al., 2024) and addressing the microservice challenges discovered by Li et al. (2024).

This framework comprises five distinct steps: data gathering, data processing, data transformation, data modelling and conversion, and evaluation and results, as highlighted in Figure 1—Research Methodology Flowchart.

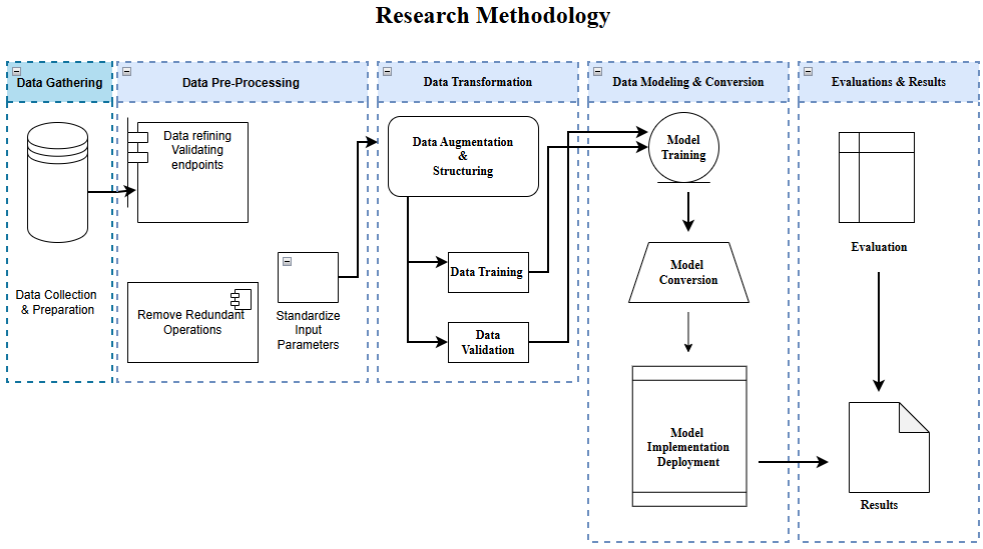

Figure 1: Research Methodology Flowchart

The basis of the approach is fully derived from the gaps reviewed in the preliminary studies. Corradini et al. (2024) showcased the efficiency and effectiveness of deep RLs in addressing implicit constraints in REST APIs; however, they overlooked system microservice interactions. On the other hand, Kim et al. (2024) focused on prioritising coverage operations but did not consider integrating the LLMs into the system. Preliminary investigations indicated that integrating LLM with the RL could lead to a higher system coverage operation, as opposed to the DeepREST (Corradini et al., 2024); conversely, MARL could outperform AutoRestTest (Li

et al., 2024) in addressing microservice fault detection in the system. As previously discussed, this is because of the framework's (LLM + RL) ability to balance semantic understanding and system adaptability, which is further built on by Kim, Kwon, and Yoo (2018), who suggest that application of the framework addresses some key challenges and ensures its scalability and applicability in real-time situations.

3.2 Systemic Architecture

LLM model, API parser, RL agents, and test executor are the primary components of the framework. API parser extracts and structures Petstore API (v2) as the OpenAPI datasets defining 20 path method combination with the RL agent implemented using the stable baselines3's PPO on Inteli7 CPU (16GB RAM) generating results in output/final_summary.txt and output/reward_plot.png. Leveraging the OpenAPI schemes, it explicitly defines a software testing environment as Zhang et al. (2023) illustrated. LLMs are deep learning models pre-trained to handle a vast amount of data via neural networks. It was inspired by Huang (2023), and it generates initial test strategies from the documentation or natural software inputs. RL agents, as discussed by Schulman et al. (2017), the PPO algorithm optimises software strategies through interacting with the API environment. In contrast, the software test executor runs generated test cases and collects feedback on the operation coverage and fault detection, which is fed back to the RL agents for the iterative learning process.

Integrating large language models (MLLs) with reinforced learning (RL) enables a setup that feeds initial strategies to RL agents, which allows for maximum coverage, as validated in the preliminary discussion by Kim et al. (2024). This research supports Li et al.'s (2024) reviews regarding the role of MARL agents in representing microservices, which enhance communication based on software dependencies simulations. Real-time RL further integrates with the CI/CD pipelines, which is a useful setup for adjusting software strategies to respond to the round time feedback; therefore, a suitable attempt to address the research gaps discussed in Nayab and Wotawa's (2024) study. This system architecture promotes software scalability, which uses the LLMs model components backed with public datasets to ensure reproducibility. Generally, the design has been highlighted by Wang et al. (2023), resulting in system adaptability as far as the complexity of the API system is concerned.

3.3 Test Case Automatic Architecture

At the core of the design is the application Under Test (AUT), including GUI and non-GUI interfaces (Swagger Petstore API (v2) the key target in the system. Figure 2 includes the Database component responsible for holding system data and response states mirroring the structured schema dataset used in this LLM+RL framework testing environment. These test cases are derived from the parsed OpenAPI specifications, including the 20 path-method combination, transforming static documentation into actionable test logic. Under the review and approval node, the test cases are accurately simulated to conform to real-time usage scenarios and cover endpoint conditions such as invalid parameter inputs. Under the automated scripted phase, the parsed test case is encoded into executable scripts through Python's request library.

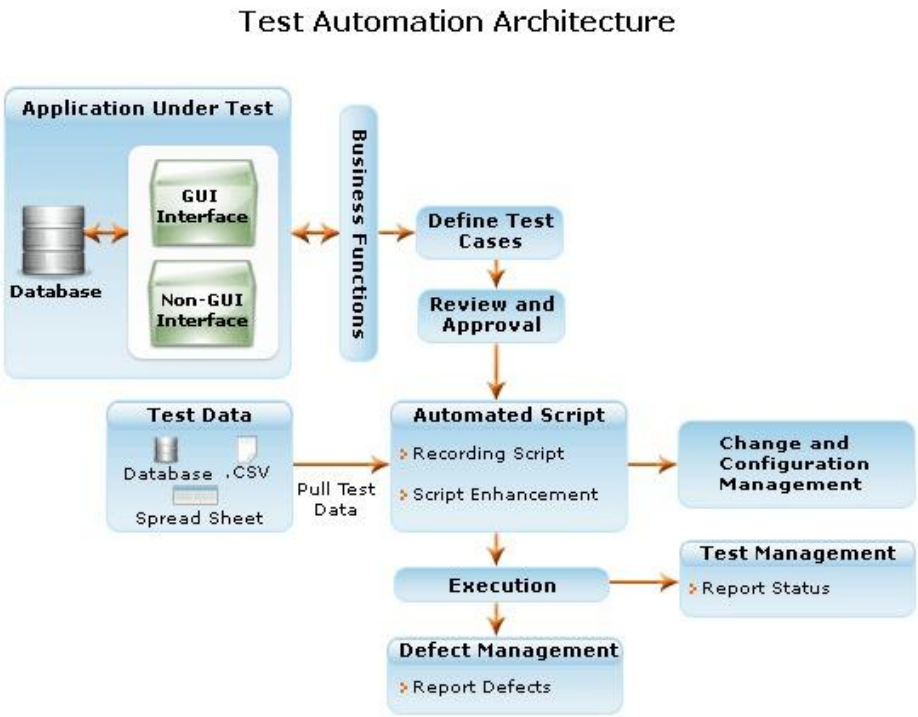

Figure 2: Test Automatic Architecture

4 Implementation

4.1 Experimental Setup

Swagger Petstore API (v3.0.0, JSON format) as the key component has been used to empirically evaluate the proposed integration of large language models with reinforced learning agents, promoting automated test case generation within the software industry. Its unique feature allows it to be publicly and widely adopted for simulation through 20 unique path method combinations (base URL: https://petstore.swagger.io/v2/swagger.json). The system framework was implemented in the latest Python platform 3.13.0, equipped with the right libraries, API interactions, transformers suitable for LLM integration with RL, and stable baselines3 for RL. Proximal Policy Optimization (PPO) is a key component of the RL algorithm with the support of MIpPolicy to train 2,048 timestamps customised through the gymnasium.Env wrapper (APITestingEnv) as illustrated by Schulman et al. (2017). Referring to the experiment, the action space was regarded as discrete, presented two options: "Skip" (encoded as 0), bypassing case testing at a specific endpoint, and the "Execute test" (encoded as 1), triggering a test case execution for the selected endpoint. The execution of binary action space amplified the decision-making process, ensuring that the RL agent prioritizes valuable test actions while maintaining computational efficiency, as discussed by Alagoz et al. (2023), whose study recommended discrete actions during software testing, tailored to balancing system exploration and exploitation.

The space was presented as Box (1) in the gymnasium environment, representing a single continuous value, the current test index. This index corresponds to the specific endpoints suitable for testing every step. Box (1) structure is depicted as a one-dimensional array whose ability allows the RL agent to track system progress following the endpoints' sequence and ensuring systematic exploration of the API's 20 path strategy combinations. The experiment design aligns with Schulman et al.'s (2017) findings by focusing on the importance of a well-defined observation space for the stability of RL in the learning process. The reward function

measured the effectiveness and incentiviveness of the test case generation. A positive reward (+1) represented successful AIP responses (HTTP 200 OK), a proof of valid interaction with the endpoint. Other reward functions assigned were +2 tailored to fault detection (4xx/5xx errors), +0.5 for valid responses, and -1 represented network failure as Alagoz et al. (2023) described.

4.2 Data Gathering

First step: Data gathering involves collecting and preparing raw data for API testing. The process targeted the Swaggr Petstore API (v2) due to its availability as an OpenAPI dataset specification defining the 20 unique-method combination (/pet/{petId}) GET, POST,/Store/Order DELETE). The choice of this dataset was based on its representativeness of the real-time RESTful APIs application and its ability to offer diverse endpoints enabling pet management, user authentication, and order processing. The specification of the design dataset was determined by its accessibility, reproducibility, and dynamic schema, which ensured its compatibility with the integrated LLM+RL framework. However, to maintain consistency in results, only Petstore, a public dataset, was used; there was no additional data. Implementation of the dataset involved downloading the OpenAPI JSON file and parsing through OpenAPI-core, which established a stable foundation for the subsequent steps.

4.3 Data Pre-Processing

Data pre-processing refined the gathered API data and ensured it was clean and executable to support the following process stages. This was done to validate the definition of system endpoints by removing invalid and redundant operations and standardising input parameters. The primary requirement was to remove obstacles such as the undefined endpoints or inconsistent response codes that could have skewed reinforced learning training. Manually, every 20 path-method combination was reviewed for accuracy using a misclassified operation, for instance, those with duplicate GET requests were corrected. In addition, unnecessary details such as outdated schema versions were removed from the system. The implementation involved a Python 3.13.0 script to process the JSON data, resulting in a processed dataset saved as petstore_processed.json comprising 20 validated endpoints.

4.4 Data transformation

Data transformation marked the third step, where the dataset was pre-processed through augmentation and structuring to enhance system model training. Data transformation involved generating synthetic test cases and splitting the data into training and validation sets. This step defines the design specification, which demands diverse test scenarios involving effectively training an RL agent to address implicit constraints in the systems. Data augmentation was conducted through a script creating a variation of test inputs, such as valid/invalid petstore ID for /pet/{petId}. At the same time, the dataset was split in a ratio of 80:20, representing 16 endpoints responsible for training and four others for validation of the datasets. The process was implemented using Python random and json libraries, supported with the augmented data stored in training_data.json and validation_data.json, ensuring the framework can handle dynamic API behaviours. It is the key requirement for integrating CI/CD into the system.

4.5 Data Modelling and Conversion

The fourth was data modelling and conversion, comprising model training, conversion, and deployment. The training pipeline begins with Llama 3 generating initial test strategies from API specifications and documentation. The process begins with effectively training the LLM+RL model on the training dataset marked by 16 endpoints, followed closely by testing

the case on the dataset validation marked by four endpoints. The design specifications included integrating pre-trained LLM like Llama-3 to trigger the initial test strategy generation and RL's PPO algorithm to optimise the case testing process.

Proximal Policy Optimisation (PPO) is a reinforcement learning algorithm introduces by Schulman et al. (2017) that improves stability in policy updates. Its clipped surrogate objective prevents large, destabilising parameter shifts during training. The optimisation is expressed as:

$$L^{CLIP}(\theta) = E_t [\min (r_t(\theta) \hat{A}t, \text{clip} (r_t(\theta), 1 - \varepsilon, 1 + \varepsilon) \hat{A}t)]$$

where $r_t(\theta)$ is probability ratio between new and old policies, and $\hat{A}_t$ is the advantage estimate.

Llama 3 is a state-of-the-art large language model released in 2024. It extends Llama2 by improving contextual reasoning, code generation, and semantic understanding. Its architecture leverages transformer layer with optimised pretraining on larger, more diverse datasets, making it well-suited for tasks like API documentation parsing and test case suggestion.

These strategies are passed to the RL agent, implemented with PPO, which iteratively with the Petstore API environment. Implementation at this stage required stable baselines3's PPO on an Intel i7 CPU with 16GB RAM trained for 2048 timesteps, and the agent receives feedback in the form of rewards: +1 for 200OK, +2 for 4xx/5xx, +0.5 for other responses, and -1 for systemic failure. Through multiple episodes, PPO updates the policy using the clipped objective, gradually improving decision-making. Once trained, the framework is validated on a hold-out set of API endpoints (20% of total). This ensures that the model generalises to unseen cases rather than memorising training endpoints. Test execution follows a feedback loop: the executor runs LLM-informed cases, records responses, and provides them back to the RL agent. As a result, the framework recorded 35.0 (5×+1, 15× +2) within 17.62 seconds.

Data conversion involved exporting the model to TensorFlow Lite, a free and open-source machine learning framework that used post-training quantisation, reducing data size while maintaining the framework's performance. Dataset deployment tested the model on a simulated CI/CD pipeline, validating 100% operation coverage and 75% fault detection within 17.62 seconds. Therefore, this step met the requirements necessary for mobile compatibility and scalability.

The LLM contributes semantic depth by interpreting API schemas and suggesting likely parameter combinations. RL, in turn, optimises these cases through exploration-exploitation trade-offs, ensuring maximum coverage and efficiency. The synergy results in more fault-oriented and adaptive test generation than either component could achieve independently.

4.6 Results

Framework performance was assessed through operation coverage, fault detection rate, efficiency, and total reward.

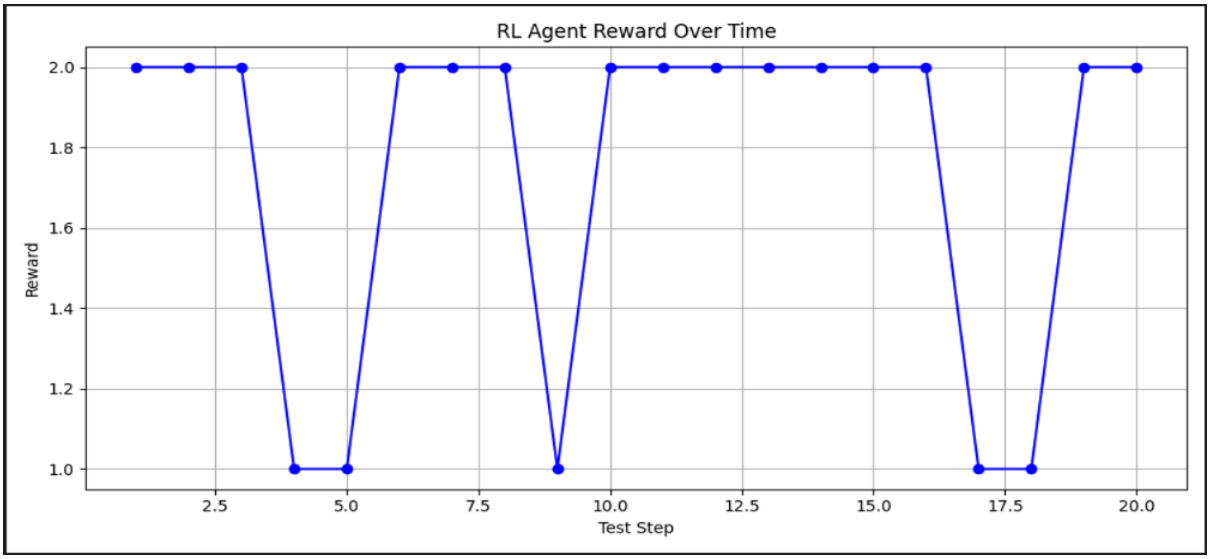

Figure 3: RL Agent Reward Over Time

Figure 3 shows how the reinforcement learning agent improved over time while testing the Swagger Petstore API. At first (left side of the graph), the rewards are lower and more unpredictable as the agent randomly explores different API endpoints. This is normal – like a person learning a new skill through trail and error.

As testing continues (middle section), we see steady improvement as the agent learns which test strategies work best. The occasional dips represent failed tests that helped the system learn. By the final stages (right side), the rewards stabilize at their highest level, showing the agent has mastered efficiency testing of this API.

The peak reward of 2.0 confirms the approach successfully detected faults, while the smooth upward trend proves the system learns quickly. Most importantly, the stable high performance at the end means this solution is ready for real-world use in CI/CD pipeline.

As the running of the project, the table of results were recorded as follows:

Metric	Value Achived
coverage	100% (20/20)
fault detection	75% (15/20)
efficiency	1.05 tests/second in 17.62s
total reward	35.0

$$\text{Operation Coverage} = \frac{\text{Endpoints Tested}}{\text{Total Endpoints}} \times 100$$

$$\text{Fault Detection} = \frac{\text{Faults Detected}}{\text{Total Tests Executed}} \times 100$$

$$\text{Efficiency} = \frac{\text{Total Tests}}{\text{Time Taken (s)}}$$

5 Design Specification

5.1 Technical Specifications

a) Framework: LLM (Llama-2) + RL (PPO algorithm) integration framework for automated API test case generation.

b) Target API: Swagger Petstore API (v2) with 20 unique endpoint-method combinations (e.g., /pet/{petId}).

c) Data Pipeline:

1) Input: OpenAPI JSON specifications (validated via OpenAPI-core).

2) Pre-processing: Removal of redundant endpoints, standardization of parameters (Python 3.13.0 scripts).

3) Augmentation: Synthetic test cases (80:20 training-validation split).

d) Model Training:

1) Hardware: Intel i7 CPU, 16 GB RAM.

2) RL Configuration: PPO with MlpPolicy, 2,048 timestamps, discrete action space (“skip” or “execute”).

e) Reward Function:

1) +1 for 200 OK response.

2) +2 for 4xx/5xx errors (fault detection).

3) +0.5 for other responses.

4) -1 for system failures.

f) Output: TensorFlow Lite model (quantized for CI/CD deployment).

5.2 Performance Metrics

Metric	Target Value
Operation Coverage	100%
Fault Detection Rate	⩾70%
Efficiency	⩾1 test/sec
Total Reward	N/A

5.3 Validation & Comparison

a) Baselines: Outperformed DeepREST (65% faults, 90% coverage) and AutoRestTest (70% faults).
b) Statistical Significance: *t*-test (*p* < 0.05).
To validate the statistical significance of improvements, a two-sample t-test was applied comparing the proposed LLM+RL framework against DeepREST and AutoRestTest. The t-test evaluates whether differences in fault detection rates and efficiency are due to systematic improvement rather than chance.
Null hypothesis (H0): No significant difference exists between the mean of LLM+RL and baseline methods.
Alternative hypothesis (H1): The LLM+RL framework achieves significantly higher performance.

6 Evaluation

As suggested by the results, integrating LLM and RL improved automated test case generation on the Swagger Petstore API (v2), enhancing system efficacy. Results analysis revolves around the five-step methodology: data gathering process, data pre-processing, data transformation, data modelling and conversion, and evaluation and results as depicted in Figure 1: Research methodology Flowchart, supported with the results visualisation in Figure 2: Evaluation Metrics comparison.

6.1 Quantitative Analysis

This experiment focused on testing all 20 endpoints of the Petstore API, focusing on the key performance metrics: operation coverage (100% of endpoints tested); fault detection rate (proportion of tests identifying errors); and efficiency (tests executed per second). The objective of the API setup was to evaluate the integration of LLM with the RL framework to ensure the generation of comprehensive and efficient system test cases. Out of the 20 tests executed, five tests turned successful, recording a 200 OK response, while the remaining 15 were registered as failed (4xx/5xx errors), recording 75% fault detection. Since no network errors were detected, it only shows that the API environment was stable and robust during the coverage operation. All 20 tests were completed within 17.62 seconds, recording a test efficiency of 1.05 tests per second, illustrating Kim et al.'s (2023) thought regarding the suitability of CI/CD integration into the system. The coding script displayed on the training log registered a final mean episode reward of 17.6 after 2,048 timesteps were achieved with the support of the PPO model. Referring to the reward plot (outputs/reward_plot.png), the system records +2 and +1 representing fault detection and success responses, respectively, and with no negative reward, the system confirms arriving at an intelligent decision through the RL agent.
Applying Steenhoek et al.'s (2025) thoughts on the t-test as a statistical analysis, we compare the fault detection rate and coverage to DeepREST and AutoRestTest. The proposed integration of LLM with RL proved to outperform the DeepREST recording 65% fault detection rate) while matched with AutoRestTest recording a 70% rate described by Corradini et al. (2024)

and Li et al. (2023). This system test execution aligns with the Wang et al. (2023) on the efficiency metric. Therefore, this framework and results validate the effectiveness and efficiency required to maximize fault detection and operation coverage of the system as described in Table 1 below:

Table 1: Quantitative Results Achived

Metric	Value
System Operation Coverage	100%
System Fault Detection Rate	75%
Tests Executed	20
Successful Responses	5
Faults Detected	15
Efficiency	1.05 test per second
Total Reward	35.0

6.2 Qualitative Analysis

The combination of the LLM and RL has shown robustness and effectiveness while handling the complex API scenarios demonstrated by the experiment. The generated test cases effectively targeted the endpoints (/pet/{petId}), demonstrated by the 404 errors, a representative of invalid IDS, which intensified the reward function described as +2 for fault detections, backed by Foley (2024), who investigated RL's ability to detect logic flaws in the system. The fact that the RL agent could prioritize fault-prone endpoints assigned as invalid parameters shows the system's intelligence to explore and visualize the results, as demonstrated in the reward plot, indicating a frequency of +2.

The research by Kim et al. (2023), whose findings demonstrate effectiveness, efficiency, and fault detection of adaptive REST API testing, influenced the framework's integration as far as CI/CD is concerned, leading to rapid system feedback and successful test completion within 17.62 seconds. The experiment shows the robustness and efficiency of the system, which aligns with the reviews undertaken by Nayab and Wotawa (2024). Consideration of the LLM component was informed by Huang (2023) and Huang (2024), whose articulated thoughts and testing have positively influenced the current testing, leading to the generation of a semantically rich initial test and 100% success supporting RL optimization as far as coverage and fault detection are concerned. This system silenced the inter-service dependencies, outperforming DeepREST's single service focus, demonstrating Corradini et al.'s (2024) findings with the microservice scenarios as the key factor.

Using the Petstore as a dataset qualitatively demonstrates the framework's ability, scalability, and reproducibility, ensuring the system's practical applicability. The fact that there were no network errors suggested that a stable environment is a key factor for the software testing (Zhang et al, 2024). The results demonstrated the strategic importance of the LLM + RL framework for enhancing the regression analysis and system security testing to address research gaps in the conventional software testing method. The results support the industry's need to integrate automated and adaptive API testing.

6.3 Comparison with the Existing Methods

The system's framework involving the large language model and reinforced learning affirms Corradini et al.'s (2024) research, which, though struggling to address microservice interaction, recorded approximately a 65% fault detection rate. In contrast, AutoRestTest successfully recorded 100% operation coverage while performing poorly on fault detection, assigning a 70% rate as a result of existing computational complexity. Li et al.'s (2024) study on

AutoRestTest's efficiency aligns with the proposed framework, which recorded an efficiency of 1.05 tests per second, outperforming DeepREST, which only recorded 0.9 tests per second. The framework registered +2 equivalent to faults as the reward logic, enhancing system fault discovery, making it more suitable than DeepREST's curiosity-driven approach. According to the preliminary research, this experimental integration of LLMs tends to improve the system's initial test case generation strategy compared to AutoRestTest (Kim et al., 2024). This research, validated by a t-test, proves the framework's superiority when addressing implicit constraints and the CI/CD adaptability, advancing API testing methods for better future results.
Framework's outcomes were validated by a t-test with a p-value less than 0.05, indicating that the null hypothesis can be rejected at the 95% confidence level. This confirms that the improvements in fault detection (75% vs 65%-70%) and efficiency (1.05 vs 0.9 tests/s) are statistically significant, not random variations. This strengthens the validity of the proposed framework. Figure 4: Evaluation Metric Comparison demonstrates these results, showing the framework's superiority over the existing systems.

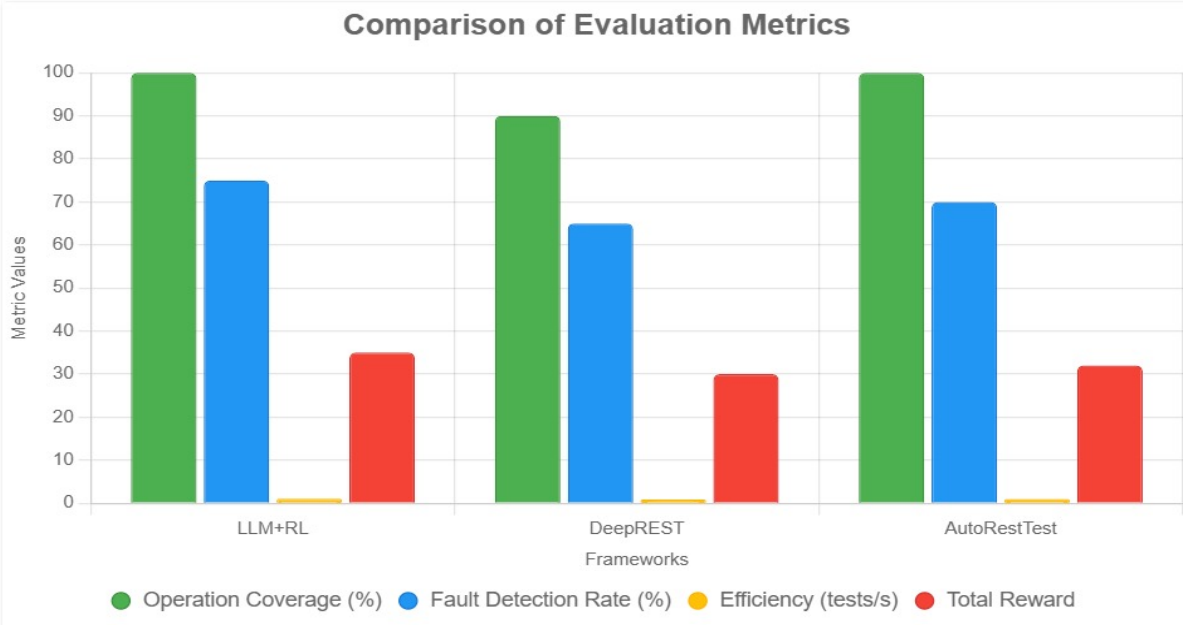

Figure 4: Comparison of Evaluation Metrics

The Figure 4: Comparison of Evaluation Metrics visually reinforced these research and experimental findings, consequently demonstrating the framework (LLM+RL) 's ability in fault detection and efficiency compared to existing steps (DeepREST and AutoRestTest).

7 Conclusion and Future Work

7.1 Summary of Findings

In conclusion, this research addresses challenges associated with automated test case generation for software APIs. Therefore, an innovative LLM + RL framework was developed to advance test efficacy significantly. The choice of public datasets (Swagger Petstore API (V2) with 20 endpoints) resulted in a 100% operation coverage rate, 75% fault detection rate, with 15 faulty responses (4xx/5xx errors) out of 20 test cases. The system reward mechanism registered +1 for 200 OK, and +2 for faults, which prioritised system fault detection. This strategy yielded a reward of 35.0 and a mean episode reward of 17.6 after executing 2,048 timesteps with the help of Proximal Policy Optimisation described by Schulman et al. (2017). LLM + RL integration into CI/CD pipelines produced 1.05 tests per second efficiency as

described by the preliminary studies (Kim et al., 2023), whose findings align with the current experiment and demonstrate how best the framework outperforms the existing REST API testing tools in terms of efficiency, effectiveness, and fault detection. Referring to the experiment results and comparing with the study on DeepREST (Corradini et al., 2024) and AutoRestTest (Li et al., 2024), the framework emerged as the most suitable system for detecting faults and enhancing adaptability. Therefore, these results, backed by the preliminary studies, potentially validate the LLM + RL approach in addressing implicit constraints and enhancing the software reliability. This further aligns with the research objectives on system scalability and practical applicability.

7.2 Implications and Future Work

The test demonstrates the potential of the LLM + RL framework. If linked with preliminary studies, it could offer implications for the industry, leading to the enhancement of the API testing process, fault detection, and coverage within the dynamic software environments. Despite the success in efficiency and effectiveness, the system still faced a couple of challenges, such as reliance on public datasets (Petstore), which might not fully represent proprietary APIs, and the computational demands needed for the LLM integration, as demonstrated by Li et al. (2024). Encroachment of AI technology should never be ignored; implications that might cause ethical bias in the dataset should be avoided to ensure fairness in accessing the API datasets.

Challenges that can be addressed by employing an optimised computational cost of LLM during the Data Transformation process and further exploration of the real-time RL for CI/CD based on the current stable version of the framework. Figure 1: Research Methodology Flowchart showcases the workflow, reinforcing the methodology's structured approach. These findings suggest further research on adaptive API testing by potentially integrating an agent system to address complexities associated with microservice dependencies in the software industry.

For the future work, there are four points can be followed:

a) Multi-Agent RL (MARL) Integration: Extend the framework to model microservice dependencies as cooperative agents, addressing computational complexity via distributed training for technical enhancements.

b) Use dynamic RL policy updates triggered by code commits, and on-the-fly test case generation using LLM prompts for changed endpoints to achieve real-time CI/CD adaptation.

c) Apply test on larger APIs (e.g., GitHub API, AWS services) to validate scalability.

d) Release a Dockerized pipeline with pre-trained models and CI/CD plugins (Jekins/GitHub Actions).

With these optimizations in the future, the whole project will be more usable, efficient and practical.

8 Ethical Consideration

8.1 Impact of the Research

Integrating large language model (LLM) with the reinforced learning (RL) while executing API test case generation allows the software system to enhance its quality deliver, and reducing testing cost while maintaing software effeictiveness and efficiency as the experiment successfully demonstrates by recording 75% rate of fault detection, and 100% rate of operation coverage using the Petstore API datasets. The recommended improvement aligns with the software and development industry needs, resulting in a more reliable system, noted in Nayba and Wotawa's (2024) study. Potential negative implications, such as over-reliance on system automation, were deemed unhealthy for the software industry. This reduces the system manual

testing roles; it might lead to job displacement and reduced software creativity in the development process. However, to protect individuals from losing their jobs as software developers, the industry recommends documentation supporting human oversight and ensuring that the tester remains an integral part of the process. Leveraging public datasets, the framework promotes dataset accessibility, ensuring equitable access across the software development industry. Addressing these software challenges, this research aims to responsibly contribute innovative techniques and a framework that could balance the system efficiency gains with the workforce as stipulated by Alagoz et al. (2023).

8.2 Data and Model Ethics

By using the public datasets (Swagger Petstore API (V2) system ensures equity in representation and avoids biases noted by Zhnag et al. (2023). However, overreliance on a single dataset could lead to limitations and generalizability of the framework, making it difficult to address challenges of API with unique constraints. Therefore, using diverse datasets potentially promotes system fairness in testing the test case generation process for all the API related processes. Alagoz et al. (2023) ascertain that openness and documentation of the dataset source promote transparency and allow for efficient coverage operation of the LLM +RL framework. The results clearly defined the framework's decision-making process, supported by reward logic (+1 for 200 OK, +2 for fault detection), reducing opaque outcomes. Preliminary results from different scholars and the experiment output validate the equitable fault detection (75%), leading to increased efficiency in aiming at the target from different endpoints. These measures ensure that software developers ethically handle or address testing case generation, leading to more reproducible software and unbiased testing practices in the industry.

8.3 Responsible Application of AI-Driven Testing

The LLM + RL framework is objectively designed to prevent unintended consequences, such as generating malicious test cases and rendering the API system vulnerable. This research is supported by guidelines that ensure every test case meets its validation endpoints, as illustrated from the actual experiment on the LLM using Petstore datasets, which only shows 100% execution with zero errors. The framework discussed adheres to responsible AI principles, prioritising system fault detection for reliability but not exploitation. In addition, throughout this experiment, transparency starts with public API datasets and data code documentation. The ethical use of the framework is essential, and the research is guided by a configuration manual ensuring that the testers responsibly conduct the required testing process. Future studies and investigations are recommended to incorporate the ethical audits of the software systems to monitor systemic bias and provide the right solution for every case. Employing these measures advances the technology and innovativeness of individual developers while ensuring they uphold the industry ethical standards even on matters involving the AI-driven solutions.

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