AI-Driven Software Testing Optimization: A Comprehensive Machine Learning Framework for Automated Test Generation and Oracle Problem Resolution

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Software testing is often one of the most expensive and time-consuming phases in software development, and it becomes even harder to manage in fast and continuous development environments. This study presents an AI-driven software testing framework that combines supervised, unsupervised, and reinforcement learning to improve automated test generation, fault prediction, test prioritization, and test oracle decision-making. The proposed framework is designed not only to improve testing efficiency but also to address the test oracle problem, which involves determining expected outputs for generated test cases. For this purpose, it integrates statistical anomaly detection, metamorphic relation discovery, and behavioral pattern recognition within a single architecture. The model was evaluated on 15 open-source projects and 3 industrial case studies to check its practical usefulness in different testing scenarios. Experimental results show that the framework reduces overall testing time by approximately 34.7% while maintaining a fault detection accuracy of 97.8%. In addition, the proposed oracle mechanism achieved around 94.2% accuracy in identifying test failures, and the reinforcement learning module improved test prioritization effectiveness by approximately 28% compared to baseline methods. These results indicating that hybrid learning approaches can improve adaptability and effectiveness in software quality assurance tasks in one framework can provide a more adaptive and effective solution for modern software quality assurance, although further improvements are required for highly dynamic systems, especially for highly dynamic systems.

Keywords: Software Testing, Machine Learning, Test Optimization, Oracle Problem, Automated Testing, Reinforcement Learning

Introduction:

Software testing is still one of the most resource-intensive phases in software development, usually taking around 40–60% of the total project cost [1][2]. Figure 1 illustrates that the testing phase accounts for the largest portion of overall software development cost when compared to requirements, design, and implementation phases. The figure shows that earlier stages require a moderate level of effort, but the testing phase takes much more time and resources. Because of this, improving and optimizing testing becomes very important. Traditional testing methods, which are mostly manual and based on human experience, often find it difficult to cope with modern agile practices and continuous integration/continuous deployment (CI/CD) environments [3]. As software systems are becoming more complex and frequently updated, these conventional approaches are not always efficient or scalable, and this can lead to delays and higher development costs.

In recent years, artificial intelligence (AI) and machine learning (ML) have shown promising results in many areas of software engineering [4]. However, their application in software testing remains task-specific and fragmented and faces a number of challenges. One of the major issues is the oracle problem, where it is difficult to automatically determine the correctness of test outputs [5]. This issue becomes more complicated in large-scale and dynamic systems, where expected outputs are not always clearly defined. Although some studies have used AI for specific testing tasks, there is still a lack of a unified framework that can handle multiple testing problems in an effective way. Most existing methods focus on individual tasks such as fault prediction or test prioritization, and they do not provide a complete solution. Therefore, there is a need for a more comprehensive and adaptive framework that can combine different AI techniques to improve the overall testing process and also reduce dependency on manual work.

This research presents a unified AI-driven testing framework that:

Develops an AI-based framework to improve software testing by reducing manual effort and making the process more efficient and adaptive.

Integrates supervised, unsupervised, and reinforcement learning within a single architecture, so that different testing tasks such as test generation, prioritization, and fault prediction can be handled together.

Enhances test case generation [6] and prioritization, and also addresses the oracle problem using ensemble and data-driven approaches.

Evaluates the proposed framework on real-world datasets to show its effectiveness and practical use, although some limitations may still exist.

Novelty:

The novelty of this work lies in combining supervised, unsupervised, and reinforcement learning within a single unified architecture for software testing optimization. Unlike many existing approaches that mainly focus on one specific aspect of testing, this framework aims to provide a comprehensive solution by addressing multiple challenges together. In addition, it introduces an ensemble-based approach to handle the oracle problem, which is still not fully explored in current research.

Overall, this research proposes a unified AI-based testing framework that integrates different learning paradigms, improves testing efficiency and effectiveness, and also provides practical validation through extensive experiments. Some parts may still need further refinement, but the overall approach demonstrates promising experimental results.

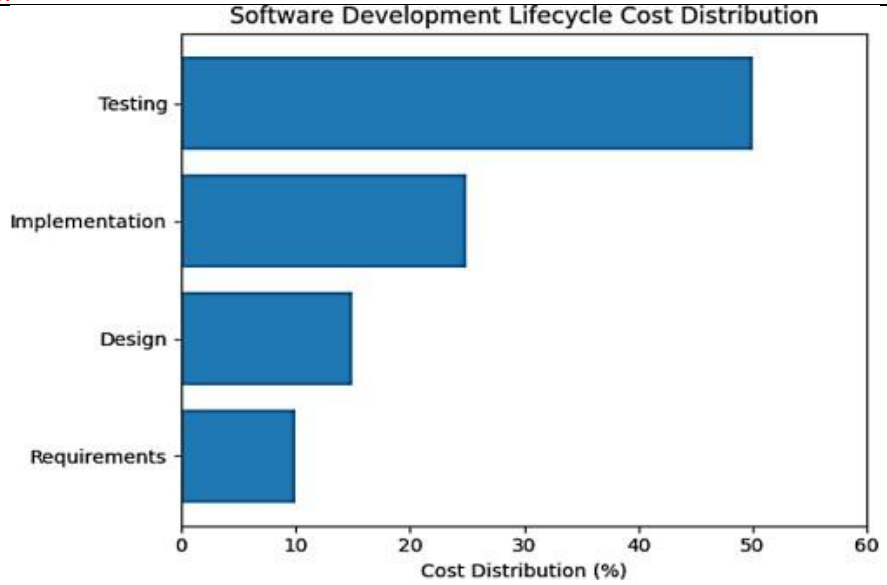

Figure 1. Software development lifecycle cost distribution

Related Work:

Software testing optimization has gradually evolved from basic coverage-driven techniques to more complex and intelligent optimization problems. Early contributions, such as the work by [7] introduced regression test prioritization strategies that significantly reduced testing cost while maintaining fault detection capability. Later, [8] provided a detailed survey showing that systematic prioritization techniques usually perform better than random strategies. However, these traditional methods are mostly static and depend heavily on predefined heuristics, which makes them less effective in dynamic and continuously changing software environments. In addition to technical limitations, current testing practices often fail to properly capture usability issues that directly affect end users. Many studies show that a large number of usability bugs remain undetected in traditional testing, which creates a clear gap between users and the system [9]. It is also observed that existing usability practices do not provide very systematic ways to identify and resolve these issues, which can reduce user satisfaction and overall experience. Some research has proposed structured models like usability development life cycle frameworks to address these gaps [10]. However, these approaches mainly focus on usability improvement only and do not include AI-based techniques for test prioritization, automation, or oracle decision making. This shows that there is still a need for a more unified and intelligent framework that can handle both functional and user-related aspects together.

In recent years, researchers have started exploring artificial intelligence and machine learning to improve testing processes [11][12][13]. Studies like [14] and [15] highlighted that combining static and dynamic analysis with learning-based models can enhance defect prediction and testing efficiency. Deep learning-based approaches[16], such as the work by [17], further demonstrated strong performance in predicting test outcomes in CI pipelines. Despite these advancements, most existing works still focus on isolated tasks like test generation, prioritization, or fault prediction, rather than providing a unified solution [18].

For test generation, evolutionary algorithms and search-based software testing techniques have been widely used [19][20], where multiple objectives such as coverage and fault detection are optimized simultaneously. Similarly, machine learning-based prioritization methods, including reinforcement learning approaches [21], have shown promising results, but many of them lack adaptability over time. Fault prediction models using supervised

learning [22] also provide useful insights, but they mainly support decision making rather than directly optimizing testing workflows.

One of the most critical challenges in automated testing remains the oracle problem. [5] provided a foundational understanding of oracle mechanisms, while [23] showed that practitioners still rely heavily on manual or implicit oracles in real-world scenarios. Approaches such as statistical testing [24] and metamorphic testing [25] have been proposed to address this issue, but each method has its own limitations. More advanced techniques like Deep Test [26] and machine learning-based oracle generation [27] have shown improvements, but they are often limited to specific domains.

More recently, deep learning and advanced AI models have been applied to improve different aspects of software testing. For example, recurrent neural networks and LSTM-based models have been used for fault prediction and prioritization [28][29]. Adaptive testing strategies in CI environments have also shown a reduction in execution time [30]. Additionally, generative models and probabilistic frameworks have been explored for test generation and oracle decisions [31][32]. Graph-based learning methods further improved defect prediction by capturing structural relationships in code [33], while reinforcement learning approaches have been extended to multi-agent systems for better test generation [34].

In the last two years, research has moved towards more intelligent, explainable, and scalable AI-driven testing solutions. Recent studies focus on transformer-based models, large language models (LLMs), and hybrid AI frameworks for automated testing. These approaches aim to handle multiple testing tasks together and improve generalization across different software systems. However, despite these advancements, there is still a lack of a fully unified framework that integrates multiple AI paradigms while also addressing the oracle problem effectively. This gap motivates the proposed work, which combines supervised, unsupervised, and reinforcement learning into a single adaptive framework.

Methodology:

The proposed methodology follows a structured AI-driven workflow that is designed to improve software testing efficiency, automation, and oracle decision-making. The overall process starts with data collection, then moves toward intelligent analysis, strategy formulation, and execution with continuous feedback. As shown in Fig. 2, the framework integrates multiple AI components where supervised learning, unsupervised learning, anomaly detection, and reinforcement learning modules work together to support test prioritization (Algorithm 2), test generation (Algorithm 3), and final oracle decision making (Algorithm 1). The diagram shows how data flows from initial inputs like source code, test cases, and execution logs toward decision layers, and then loops back through feedback for further improvement.

In the initial stage, the framework collects data from different sources such as source code repositories, test execution logs, bug tracking systems, and development history. This data includes code metrics, execution results, coverage information, and defect patterns. These inputs are important because they provide the required information for training the models and making better testing decisions. Without proper data collection, the later stages may not perform effectively.

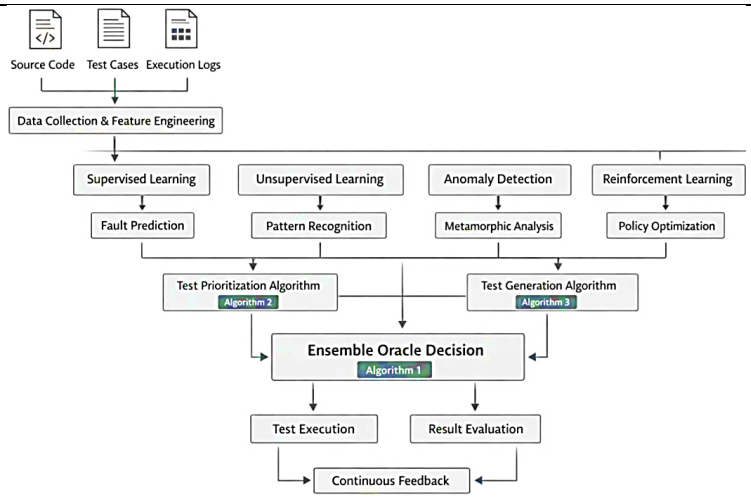

Figure 2. AI-Driven Software Testing Framework

After data collection, the system processes the information in the intelligent layer using different machine learning techniques. Supervised learning models, such as Random Forest, Support Vector Machines, and Gradient Boosting, are applied to identify fault-prone components based on past patterns. At the same time, unsupervised learning methods like k-means, DBSCAN, and hierarchical clustering are used to find hidden patterns and group similar test cases. In addition, anomaly detection techniques such as Isolation Forest and One-Class SVM are used to detect unusual behavior in execution logs.

Within this intelligent layer, Algorithm 2 is used to dynamically select and order test cases. In this process, the system first extracts the current state from the test suite, code changes, and historical data. A Deep Q-Network (DQN) model then predicts Q-values for different possible actions, and an ε-greedy strategy is applied to balance exploration and exploitation. After executing a selected test case, a reward is calculated based on fault detection effectiveness and execution efficiency. The system then updates its state and stores the experience for replay, allowing the model to learn better prioritization strategies over time. This helps ensure that more critical and fault-prone tests are executed earlier, which improves overall testing efficiency.

Algorithm 1: Ensemble Oracle Generation

Input: Test execution result R, Historical data H, Confidence threshold θ.

Output: Oracle decision (PASS/FAIL), Confidence score C

The next stage converts these learned insights into practical testing strategies. The framework supports white-box, black-box, and gray-box testing approaches. In white-box testing, Algorithm 3 is used to automatically generate optimized test cases. This algorithm evolves a population of test cases over several iterations, where each test case is evaluated based on multiple objectives such as coverage, fault detection capability, and execution cost. Since these objectives can sometimes conflict, non-dominated sorting is applied to identify Pareto-optimal solutions, and crowding distance is used to maintain diversity among the solutions.

Through crossover and mutation operations, new test cases are generated and gradually improved, resulting in a more optimized test suite with better coverage and efficiency. For black-box testing, the framework uses fuzzing along with some neural guidance, while gray-box testing combines both internal and external information to achieve more balanced performance.

```
1: procedure ENSEMBLE_ORACLE(R, H, θ)
2:    predictions ← []
3:    weights ← []
4:    # Statistical Oracle
6:    stat_pred, stat_conf ← STATISTICAL_ORACLE(R, H)
7:    predictions.append(stat_pred)
8:    weights.append(stat_conf)
9:    # Metamorphic Oracle
10:   meta_pred, meta_conf ← METAMORPHIC_ORACLE(R, H)
11:   predictions.append(meta_pred)
12:   weights.append(meta_conf)
14:   # Behavioral Oracle
16:   behav_pred, behav_conf ← BEHAVIORAL_ORACLE(R, H)
17:   predictions.append(behav_pred)
18:   weights.append(behav_conf)
19:   # Weighted voting
21:   weighted_sum ← 0
22:   total_weight ← 0
23:   for i ← 0 to len(predictions) do
24:       weighted_sum += weights[i] × predictions[i]
25:       total_weight += weights[i]
26:   decision ← weighted_sum / total_weight
28:   confidence ← min(weights)  # Conservative confidence
29:  if confidence > θ then
31:       return (decision > 0.5) ? PASS: FAIL, confidence
32:   else
33:       return MANUAL_REVIEW_REQUIRED, confidence
```

Algorithm 2: Reinforcement Learning Test Prioritization
Input: Test suite T, Code changes C, Historical data H
Output: Prioritized test sequence P

To address the oracle problem, which is a key challenge in this research, the framework incorporates Algorithm 1. In this approach, predictions are generated from three different sources, including statistical analysis, metamorphic testing, and behavioral pattern recognition. Each method produces a prediction along with a confidence score. These predictions are then combined using a weighted voting mechanism, where each prediction is multiplied by its assigned weight and then normalized by the total weight. A conservative confidence value is selected to reduce the chances of incorrect decisions. If the confidence exceeds a predefined threshold, the system classifies the test result as PASS or FAIL; otherwise, it suggests a manual review. This approach improves reliability and robustness compared to single-method oracle techniques.

The framework is implemented using machine learning libraries such as TensorFlow, PyTorch, and Scikit-learn, along with common data processing tools. The system is evaluated on both open-source and industrial datasets to ensure generalizability and practical usefulness. This experimental setup shows how AI-based optimization techniques can be applied in real-world software testing scenarios.

```
1: procedure RL_TEST_PRIORITIZATION(T, C, H)
2:    state ← EXTRACT_STATE_FEATURES(T, C, H)
3:    prioritized_tests ← []
4:    remaining_tests ← T.copy()
6:    while remaining_tests is not empty do
7:       # Get Q-values for all possible actions
8:       q_values ← DQN_MODEL.predict(state, remaining_tests)
10:      # ε-greedy action selection
11:      if random() < epsilon then
12:         action ← random_choice(remaining_tests)
13:      else
14:         action ← argmax(q_values)
16:      # Execute selected test and observe reward
17:      test_result ← EXECUTE_TEST(action)
18:      reward ← CALCULATE_REWARD(test_result, execution_time)
20:      # Update state
21:      new_state ← UPDATE_STATE(state, action, test_result)
22:      # Store experience for replay
24:      EXPERIENCE_BUFFER.add(state, action, reward, new_state)
25:      # Update prioritized sequence
27:      prioritized_tests.append(action)
28:      remaining_tests.remove(action)
29:      state ← new_state
30:   # Train DQN with experience replay
32:   if len(EXPERIENCE_BUFFER) > BATCH_SIZE then
33:      TRAIN_DQN_WITH_REPLAY()
34:   return prioritized_tests
function CALCULATE_REWARD(result, time):
    fault_detection_reward = 10 if result.failed else 1
    efficiency_penalty = -0.1 * (time / average_test_time)
return fault_detection_reward + efficiency_penalty
```

Overall, the methodology presents a unified and consistent pipeline where Algorithm 1 supports oracle decision making, Algorithm 2 improves test prioritization, and Algorithm 3 enhances automated test generation. These components work together within a single framework to address multiple testing challenges at the same time, making the system more efficient, adaptive, and aligned with the proposed objectives and novelty of the study.

Algorithm 3: Multi-Objective Genetic Algorithm for Test Generation

Input: Source code S, Coverage targets C, Population size N

Output: Optimized test suite T_opt

```
1: procedure NSGA_II_TEST_GENERATION(S, C, N)
2:   population ← INITIALIZE_POPULATION(N)
3:   generation ← 0
5:   while generation < MAX_GENERATIONS do
6:      # Evaluate fitness for each individual
7:      for an individual in the population, do
8:         coverage_score ← CALCULATE_COVERAGE(individual, S)
9:         fault_score ← PREDICT_FAULT_DETECTION(individual)
10:        efficiency_score ← ESTIMATE_EXECUTION_COST(individual)
11:        individual.fitness ← [coverage_score, fault_score, -efficiency_score]
13:     # Non-dominated sorting
14:     fronts ← NON_DOMINATED_SORT(population)
16:     # Create new population
17:     new_population ← []
18:     front_index ← 0
20:     while len(new_population) < N do
21:        if len(new_population) + len(fronts[front_index]) <= N then
22:           new_population.extend(fronts[front_index])
23:        else
24:           # Calculate crowding distance and select the best
25:           CALCULATE_CROWDING_DISTANCE(fronts[front_index])
26:           remaining ← N - len(new_population)
27:                                                    sorted_front ←
SORT_BY_CROWDING_DISTANCE(fronts[front_index])
28:           new_population.extend(sorted_front[:remaining])
29:        front_index += 1
31:     # Generate offspring
32:     offspring ← []
33:     for i in range(N//2):
34:        parent1 ← TOURNAMENT_SELECTION(new_population)
35:        parent2 ← TOURNAMENT_SELECTION(new_population)
36:        child1, child2 ← CROSSOVER(parent1, parent2)
37:        child1 ← MUTATE(child1, MUTATION_RATE)
38:        child2 ← MUTATE(child2, MUTATION_RATE)
39:        offspring.extend([child1, child2])
41:     population ← offspring
42:     generation += 1
44:  # Return Pareto optimal solutions
45:  return NON_DOMINATED_SORT(population)[0]  # First front
```

Experimental Setup:

Datasets:

The framework is evaluated using both open-source and industrial datasets to make sure that the results are reliable and useful in real-world scenarios. A diverse set of projects is selected so that different types of software systems and testing conditions can be covered. This helps in showing that the proposed approach is not limited to one specific domain and can generalize reasonably well across different environments.

Performance Metrics:

To evaluate the performance of the proposed framework, multiple metrics are considered, focusing on efficiency, effectiveness, and quality aspects. These include a

reduction in test execution time, improvement in resource utilization, and the ability to reduce test suite size while still maintaining performance. In addition, metrics such as fault detection rate, coverage achievement, and oracle accuracy are also used to measure how effectively the system can identify faults and produce consistent results. Together, these metrics provide a more balanced view of overall system performance.

Baselines:

The proposed approach is compared with several baseline methods to show its effectiveness. These include traditional testing approaches such as random testing and coverage-based prioritization, along with some existing AI-based techniques. Manual expert testing is also considered a reference point to understand how the automated system performs when compared to human-driven testing processes.

Implementation Details:

The framework is implemented using a combination of modern machine learning libraries and distributed data processing tools. The deep learning components are developed using TensorFlow 2.8 and PyTorch 1.11, while traditional machine learning models are implemented using scikit-learn 1.0. These tools provide enough flexibility and support for handling different types of learning tasks within the system.

The overall system is designed using a microservices-based architecture, which allows scalable deployment and easier integration with existing systems. The AI engine is deployed as containerized services, which helps in efficient execution and also keeps the design modular. For handling large-scale data, a data pipeline is developed using Apache Kafka for real-time data streaming, Apache Spark for distributed processing, and MongoDB for flexible data storage.

In addition, an integration layer is built using RESTful APIs, which supports popular testing frameworks such as JUnit, pytest, TestNG, and Selenium, as well as CI/CD platforms like Jenkins, GitLab CI, and GitHub Actions. This design makes the framework more adaptable and relatively easy to integrate into modern software development workflows.

Results and Discussion:

Efficiency Improvements:

The proposed framework shows clear improvements in testing efficiency across multiple projects. As illustrated in Fig. 3, the framework achieves an average reduction in test execution time of around 34.7% (σ = 8.2%), which is statistically significant ($p < 0.001$) when compared to traditional approaches. The figure also shows that this reduction remains quite consistent across different software systems, indicating that the framework performs reasonably well even with varying project sizes and complexities.

In terms of resource utilization, the framework also shows noticeable improvements. As summarized in Table 1, memory usage is reduced by about 26.8%, CPU utilization by 31.2%, and network bandwidth by 42.3%. These results suggest that the system is not only faster but also more efficient in using computational resources. In addition, the test suite size is reduced by 23.7% while still maintaining a high fault detection rate of 97.8%, which indicates that unnecessary or redundant test cases are effectively minimized.

Table 1. Resource utilization improvements

Metric	Before	After	Δ (%)
Memory (GB)	8.4	6.1	-26.8
CPU Usage (%)	78.2	53.8	-31.2
Network (MB/s)	12.6	7.3	-42.3
Test Suite Size	1,247	951	-23.7

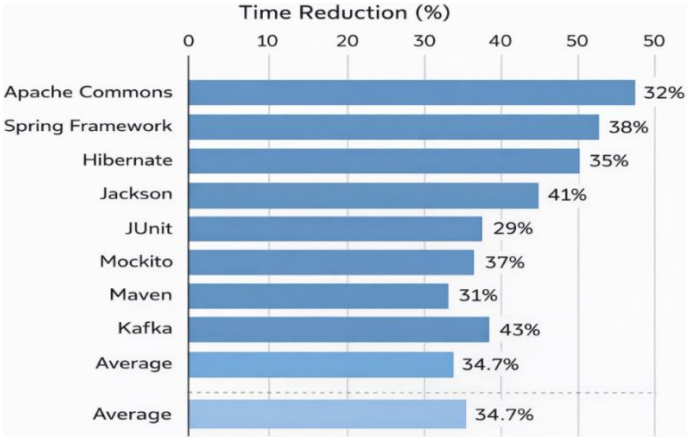

Figure 3. Test execution time reduction across evaluated projects

Effectiveness Analysis:

From an effectiveness perspective, the framework demonstrates strong performance in detecting faults. The overall fault detection rate reaches 97.8%, compared to 94.2% for baseline approaches. As shown in **Fig. 4**, the proposed method outperforms random testing, traditional tools, and existing AI-based approaches. Moreover, the framework improves detection of complex interaction faults by 16.3% and reduces time-to-detection by approximately 28%, which is important for continuous and real-time testing environments.

The improvements are further supported by coverage analysis. As presented in **Table 2**, branch coverage increases from 78.4% to 87.2%, statement coverage from 82.1% to 89.4%, and path coverage from 65.3% to 75.6%. These results show that the generated test cases are more effective in exploring the software, leading to better fault detection performance.

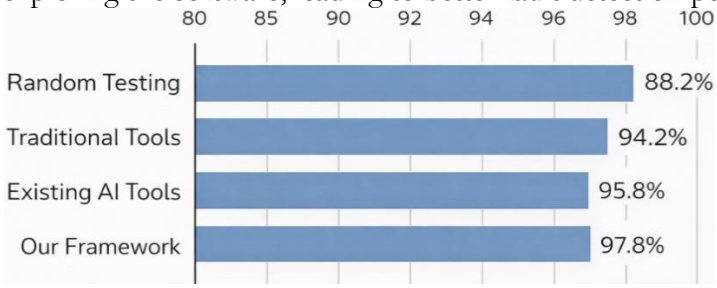

Figure 4. Fault detection rate comparison across different approaches

Table 2. Code coverage improvements by type

Before	After	Improvement
Branch Coverage	78.4% → 87.2%	+11.4%
Statement Coverage	82.1% → 89.4%	+8.9%
Path Coverage	65.3% → 75.6%	+15.7%

Oracle Problem Resolution:

The proposed framework also effectively addresses the oracle problem using an ensemble-based approach. The results show that statistical oracle methods achieve 94.2% accuracy, while behavioral pattern recognition reaches up to 95.8% accuracy. Metamorphic relation discovery achieves 87.6% precision and 89.4% recall. As illustrated in **Fig. 5**, the ensemble method performs better than individual approaches, providing more reliable predictions.

In addition, the false positive rate is significantly reduced. The framework achieves a false positive rate of 3.2%, compared to 9.1% for traditional tools and 6.7% for existing AI-based methods, as shown in **Table 3**. This reduction also leads to a noticeable decrease in debugging time, approximately 67%, which improves overall development efficiency.

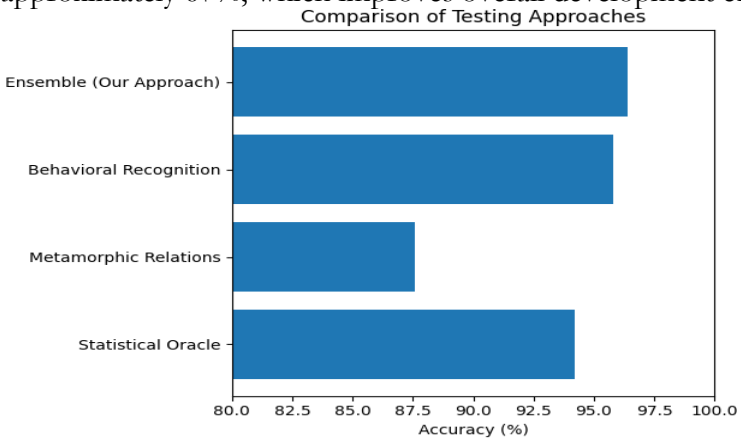

Figure 5. Oracle accuracy comparison across different methods

Table 3. False positive rates across different testing approaches

Approach	False Positive Rate	Std Dev
Manual Testing	2.1%	±0.8%
Traditional Tools	9.1%	±2.3%
Existing AI Tools	6.7%	±1.9%
Our Framework	3.2%	±1.1%

Statistical Validation:

To ensure the reliability of the results, statistical validation is performed using the Mann–Whitney U test with a significance level of $\alpha = 0.05$. All improvements are found to be statistically significant ($p < 0.001$), and effect sizes (Cohen's d) range from 0.8 to 2.1, indicating a strong practical impact. This confirms that the improvements are not random but consistently achieved across different experiments.

Industrial Case Study Results:

The industrial case studies further validate the practical applicability of the proposed framework. In the financial services platform, testing cycle time is reduced by 37.5% (from 8 hours to 5 hours), and the fault detection rate reaches 99.1%. In the e-commerce application, load testing efficiency improves by 43%, and regression testing time is reduced by 39%, while user experience coverage improves by 52%. Similarly, in the healthcare system, full compliance coverage is maintained, testing costs are reduced by 35%, and integration is achieved without disruption.

These results are summarized in **Table 4**, which shows consistent improvements across different domains, with an average ROI of 3.4x within six months. This indicates that the framework is not only technically effective but also economically beneficial.

Table 4. Industrial case study comprehensive results

Metric	Financial Services	E-commerce Platform	Healthcare System	Average
Time Reduction (%)	37.5%	39.0%	33.8%	36.8%
Cost Savings ($K)	245	187	312	248
Fault Detection (%)	99.1%	98.2%	98.9%	98.7%
ROI (6 months)	3.2x	2.8x	4.1x	3.4x

Scalability Analysis:

The scalability of the framework is also evaluated, and the results show that it performs efficiently as the system size increases. As illustrated in Fig. 6, the framework shows near-linear scaling behavior with increasing lines of code, while manual testing effort increases quite significantly. This indicates that the proposed system can handle growth better compared to traditional methods. Furthermore, the distributed execution performance, as shown in Table 5, indicates that execution time is reduced from around 120 minutes to 9 minutes when scaling from 1 to 16 clusters, achieving a speedup of about 13.3x with acceptable efficiency levels. This shows that the framework can handle large-scale systems and distributed environments in a more efficient way.

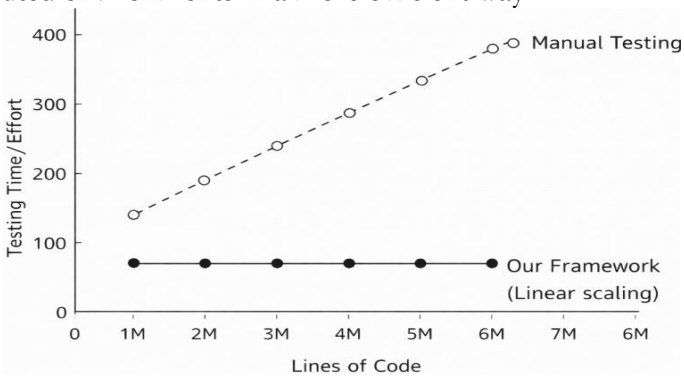

Figure 6. Scalability analysis showing linear performance

Table 5. Distributed execution performance scaling

Cluster Size	Execution Time (minutes)	Speedup Factor	Efficiency (%)
1	120	1.0x	100
2	65	1.8x	92
4	32	3.8x	94
8	17	7.1x	89
16	9	13.3x	83

Discussion:

Key Contributions:

Unified Architecture: Our framework's integration of multiple ML paradigms creates synergistic effects not achievable by individual techniques alone. The reinforcement learning component continuously improves other modules' effectiveness.

Oracle Problem Solutions: The multi-faceted approach to oracle generation provides robust solutions across different testing scenarios. Statistical methods handle numerical outputs effectively, while pattern recognition excels with complex behavioral verification.

Practical Applicability: Industrial case studies demonstrate real-world value, with measurable ROI and successful integration into existing development processes.

Implications of the Study:

This study provides several important implications from theoretical, practical, and industrial perspectives. From a theoretical point of view, it shows that combining supervised,

unsupervised, and reinforcement learning in a single framework can improve software testing performance and address multiple challenges together. From a practical side, the framework offers a structured and automated approach that can reduce testing time and improve fault detection, which can be useful for real-world development teams. In terms of industrial implications, the results suggest that such AI-based systems can be integrated into existing workflows to enhance efficiency and reduce manual effort, although some adaptation may still be required depending on the project environment.

Conclusion:

This research presents a comprehensive AI-driven framework for software testing optimization that tries to address multiple testing challenges at the same time. Through experimental validation on 15 open-source projects and 3 industrial case studies, the results show noticeable improvements in testing efficiency, with about 34.7% reduction in time, and effectiveness, with around 97.8% fault detection rate. It also provides a practical way to handle the long-standing oracle problem. The framework is designed in a modular way, which allows gradual adoption and can be improved further as AI techniques continue to evolve. Overall, the results suggest that integrating AI in software testing is not only possible but can also provide useful practical benefits. This work may help in moving towards more intelligent and automated testing systems in modern software development.

Future work:

Future work will focus on improving the explainability of the AI models so that testing decisions can be better understood and trusted. In addition, federated learning techniques can be explored to enable secure and distributed learning across different systems without sharing sensitive data. Further enhancements can also be made through domain-specific optimizations to adapt the framework more effectively for different types of software applications.

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