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Efficient Test Case Generation in Software Testing Using DistilGPT-2 and EfficientNet-Lite

[1]Naga Sushma Allu, [2]Sharadha, [3]Durga Praveen Devi ,[4]R. Puspha kumar

[1]Belong (Telstra) Telecomms, Victoria,Australia
[2]GOMIAPP LLC, NJ, USA

[3]O2 Technologies Inc, California,USA
[4]Assistant Professor, Department of Information Technology,
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of
Science and Technology, Tamil Nadu, Chennai, India.

[1]Nagasushmaallur@gmail.com
[2]kodadisharadha1985@gmail.com
[3]durgapraveendeevi1@gmail.com
[4]pushpakumar@veltech.edu.in

Abstract- Software testing plays a critical role in ensuring software reliability, yet traditional test case generation approaches often suffer from high computational overhead and inefficiency. Traditional methods, including genetic algorithms, struggle with scalability and fail to optimize execution time while maintaining high test coverage. To address these limitations, this paper proposes a lightweight deep learning-based test case generation approach using DistilGPT-2 and EfficientNet-Lite. Unlike conventional deep learning models, our method efficiently generates both text-based and GUI-based test cases while reducing computational cost. The novelty of this approach lies in integrating CodeT5-Small for feature extraction, DistilGPT-2 for textual test case generation, and EfficientNet-Lite with an RNN for GUI-based testing, enabling a more effective, low-resource test generation pipeline. The results demonstrate that our method achieves higher test coverage (95%), improved efficiency (90%), and greater testing reliability (98%) compared to advanced genetic algorithms, while also reducing computational overhead to 60%. Compared to existing approaches, our method outperforms traditional AI-based testing solutions in terms of accuracy, fault detection rate, and efficiency. The proposed method enhances software testing by minimizing redundant test cases, improving execution pass rates, and ensuring broader code coverage, making it a scalable and cost-effective solution for modern software development. This work paves the way for lightweight transformer-based models in test case generation, ensuring robust test automation with minimal resource consumption.

Keywords: Lightweight Deep Learning, Test Case Generation, Software Testing, DistilGPT-2, EfficientNet-Lite

1. Introduction

This makes software testing a fundamental and indispensable process in software development, thus helping to assure a software reliability standpoint against functionality and security, and other factor considerations related to quality[1]. As software systems increase in scale and complexity, it becomes ever more important to have adequate testing mechanisms[2]. Manual test case design was once considered the principal approach to validating any software but has become non-existent for larger modern applications owing to testing being laborious, prone to human error, and unable to keep pace with rapid developmental cycles[3]. In response to this, a shift has taken place in favour of automatic test case generation, which handles issues of human

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intervention, rapid testing, and high coverage of defect detection[4].Automated test case generation includes a broad range of techniques and methods, and they range from the classical heuristic and metaheuristic search methods in artificial intelligence to the machine learning methods in the forefront of today's research. Genetic algorithms, symbolic execution methods, and deep learning-based methods have received considerable attention in recent times[5]. Nevertheless, the larger difficulty remains: how do you maximize test coverage and defect detection while ensuring computational efficiency and scalability [6]. In testing today using random and evolutionary methods, tests are simply duplicated or I am making bad selections in generating them, which requires unnecessary computational overhead, adding to the run time of executing tests[7]. Apart from the fact that it slows down the entire development process, it also adds to the cost and lowers the final software product's possible ability to identify critical defects.

Deep learning approaches present promising opportunities from the standpoint that the models learn complex input-output relationships and grasp program behaviours to produce intelligent and targeted test cases[8]. With their abilities, however, such methods are always very computationally expensive and require huge memory and processing power[9]. This appetite for resources comes at the price of adoption, which can be quite important if we were talking about a constrained environment, say embedded systems, mobile applications, or continuous integration pipelines under strict time constraints[10]. Hence, this becomes a highly relevant topic for the balancing of test case quality versus resource efficiency. The inefficiencies and malfunctions inherent in current test case generation schemes have far-reaching impacts[11]. Inadequate or poorly designed test suites may conceal latent defects or security vulnerabilities that comprise a sufficiently serious risk to lead to a software failure or breach post-deployment[12]. Generating test suites that are too large and have a mass of duplicates spells the wastage of computational resources and lengthening of feedback loops circumventing the agile development practices[13]. As software projects get larger and diversified, the necessity of test generation that is scalable, lightweight, and very performant has to be felt.

Several tries have dealt with these problems. Genetic algorithms have been widely deployed for test case pruning's, applying evolutionary principles to search more intuitively in the search space[14]. Nonetheless, the method, however, suffers from slow convergence, premature stagnation, and, most importantly, a lack of diversity in the test cases generated[15]. Reinforcement learning models have appeared as another alternative that learns adaptive policies for generating test inputs with better coverage, creating the dilemma that these generation methods require a huge training set and long training time, which may not be possible in all development environments[16]. Transformer models, which are well known for their tremendous success in natural language processing, have been proposed also for test case generation because of their powerful sequence modelling capability; the downside, however, is that training and inference can be computationally expensive and hence make it not feasible to be used in environments where resources are limited[17].Building on these challenges, the optimal trade-off between efficiency and effectiveness remains at the centre of automated test case generation[18]. Meeting this trade-off becomes a critical issue in provision for testing needs within real-world software engineering scenarios involving continuous integration and delivery pipelines due to their just-in-time feedback requirement[19]. In addition, this would pose tests needing generation in mobile or embedded environments, thus holding the additional requirement of ensuring that it is indeed done in a lightweight but efficient manner all at the accuracy level[20]. On top of that, resource-constrained environments like mobile and embedded systems impose extra constraints, demanding lightweight and efficient test generation mechanisms without any compromise on accuracy.

On the other hand, typically-frequency limitations apply to traditional rule-based or heuristic methods of testing. These methods usually require manual tuning, domain-related knowledge, and considerable efforts to be adjusted for other styles of software architecture and technology[21]. As software systems evolve at a fast pace, these approaches fall behind and hence lose their relevance in a fast-moving development environment. An adaptive, self-learning, and scalable test generation mechanism is much needed today to realize software

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engineering goals[22].Thus, as the software systems get complicated and test case generation alternatives become limited, there emerges an urgent need for innovations. Future frameworks need to be capable of providing a fine balance between speed of computation, scalability, adaptability, and test coverage, which will allow them to go hand-in-hand with software quality assurance in any industrial environment[23]. Bringing together those solutions will help to fast track the software delivery and also expose more critical defects and vulnerabilities for safer and more dependable software systems[24].

The system introduces the new lightweight deep learning-based test case generation framework combining DistilGPT-2 and EfficientNet-Lite. This method took a feature extraction method from CodeT5-Small, followed by test case generation in text form using DistilGPT-2, while for GUI test case synthesis, EfficientNet-Lite combined with a specialized RNN was used. Through low model complexity and computationally efficient performance, this leads to improved test coverage and better fault detection along with high redundancy avoidance and a low computational footprint.

The proposed method's main contributions,

1. Analyse the ability of a lightweight deep learning method for efficiently generating test cases for software testing.
2. Develop an optimized framework integrating DistilGPT-2 for text test case synthesis and EfficientNet-Lite for GUI test case synthesis.
3. Evaluate the model with different metrics to test for efficiency and accuracy.
4. Contrast the method vis-a-vis conventional and existing AI-based approaches to show the advantage that scalability and computational efficiency bring.

2. Literature Review

In recent years, deep reinforcement learning techniques have become a hot research area in software testing for automated test case generation. Policy-based reinforcement learning agents have been demonstrated to increase test coverage and efficiency in executing tests, dynamically adapting to changing software behaviour[25]. These approaches work intelligently in that they explore the input space, thereby lessening the probability of redundant or ineffective test cases, which traditional methods such as random testing and evolutionary algorithms do not do[26].Genetic algorithms (GA) have been used extensively for maximizing test data production and path coverage. Hybrid metaheuristic frameworks that combine GA with particle swarm optimization (PSO) and ant colony optimization (ACO) have been proposed by researchers to synergize their complementary powers[27]. Such hybrids enhance the scalability of test data generation for large and complex software systems and provide better computational efficiency in the big data environment[28]. Adaptive and co-evolutionary phenomenon's within the hybrid framework then optimize the search, thus enabling efficient exploration of the massive test input space while minimizing resource consumption[29].

Graph neural networks (GNNs) have recently been introduced as powerful software defect prediction mechanisms by representing program code in the form of graph structures[30]. This approach, which capitalizes on syntactic and semantic relations between code components, allows for more efficient bug recognition[31]. Experimental results conducted on large-scale repositories of software show that GNN-based models reduce false positive rates and increase accuracy in defect detection against traditional feature-based or sequence-based models; hence, they possess utmost suitability for software quality assurance in these days[32].In the field of EV systems, the integration of ANN with electrothermal inverter modelling and FEA has provided for the real-time simulation of electric traction systems[33]. Such advanced modelling

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emphasizes heat management within the inverter to lessen charging time while enhancing the overall performance and durability of the EV [34]. The combination of data-driven neural models with physics-based simulation can thus result into finer control strategies contributing to the extended battery life and operational efficiency.

There are hybrid ways of applying symbolic execution along with transformer-based deep learning methods, which enable an improved detection of software vulnerabilities[35]. The mixing of AI with static program analysis leads to higher accuracy in detecting security issues[36]. Since transformers can extract contextual information from code sequences, symbolic reasoning can then assist in uncovering a certain class of vulnerabilities that either static or dynamic analyses miss[37].Pre-trained language models and evolutionary algorithms have been employed together to generate software test cases[38]. Fine-tuned language models can create semantically meaningful and syntactically correct test inputs that an evolutionary algorithm uses to iteratively optimize coverage criteria and execution time[39]. The integrated synergy brings about greater accuracy and shorter execution time than the standard generation technique, thus helping to realize testing pipelines more effectively[40].

In general, metaheuristic optimization techniques, namely genetic algorithms and particle swarm optimization, have been used successfully for regression testing[41]. These methods aim to reduce test suite execution time and either preserve or improve the effectiveness of fault detection [42]. Through selective prioritization among test cases, these metaheuristics are working against possible redundancy in testing, thus shortening feedback loops and ensuring that testing resources are optimally utilized without compromising software quality[43].The combination of cloud infrastructure, automated fault injection, and XML-standardized test scenario definition resulted in enhanced robustness testing of distributed systems[44]. Cloud platforms provide scalable environments to execute huge volumes of test cases under fault injection techniques that simulate failure modes to assess the resilience of the system[45]. The XML-based scenario definition ensures that the test cases of distributed system components are consistent and reusable, hence supporting a more reliable and efficient testing process[46].

For GUI-based test automation, lightweight deep models, such as distilled transformers, have been proposed [47]. These models provide for efficient generation and execution of interface test cases with an extremely low computational overhead, thereby suited for resource-constrained environments[48]. On the other hand, distillation of large transformer models helps retain essential knowledge, which improves the scale and speed of UI testing frameworks [49].Finally, the integration of robotic process automation (RPA) with cloud computing has been proposed for the advancement of automated scheduling and task execution in social robots[50]. Cloud deep-learning services enhance the robots' ability for behaviour recognition and object detection so that they can interact better with users[51]. This is particularly beneficial in the assistive technologies aimed at those elderly and cognitively impaired since the technology enables more adaptable and context-aware behaviour from the robot, which eventually leads to better care and user experience[52].

3. Problem Statement

Test case generation has experienced some successful applications of deep reinforcement learning to test coverage and adaptability. Given these advantages, there are considerable barriers, inter alia, resource-intensive work and lack of convergence of the policy. Consequently, this limits the applicability of the methods, especially in environments where fast feedback is of the essence and resources are unavailable[53]. Pre-trained language models and evolutionary algorithms have been combined to ensure semantic validity and parameter optimization of test cases[54]. Traditional evolutionary algorithms, however, tend to underperform when attempting to efficiently optimize test cases on diversified and complex software architectures, resulting in suboptimal test generation quality or excessive processing time[55].This, in turn,

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highlights an uneasy tension between paying off comprehensive test coverage and paying off computational feasibility during automated test generation[56]. Existing approaches commonly pose one at the expense of the other, producing computationally expensive and incoherent test processes that lack sufficient coverage and diversity [57]. The said trade-off has restrained the scaling and adoption of an advanced test generation technique within real-world software-development environments, especially in projects that run on constrained computation resources or with tight development cycles. The approach is primarily aiming at resolving these problems by using DistilGPT-2 and EfficientNet-Lite, which comprise a couple of lightweight deep learning models to first improve the efficiency of test generation, second reduce computational overhead, and thereby third ensure scalability of software testing performance in a wide-array of applications.

4. Proposed Methodology for Test Case Generation Using DistilGPT-2 and EfficientNet-Lite in Software Testing

The methodology under study establishes software testing using lightweight deep learning means for effective test case generation. For training, CodeXGLUE is used after appropriate preprocessing steps such as tokenization, normalization, and padding. CodeT5-Small is for producing semantic embeddings of function descriptions, and EfficientNet-Lite is for GUI-based test case synthesis. DistilGPT-2 generates text-based test cases, and an RNN," either LSTM or GRU, predicts UI interaction sequences. The generated model is optimized with cross-entropy loss and AdamW. The score for evaluation comprises BLEU, code coverage, execution pass rate, fault detection rate, redundancy ratio, and generation time. A deployment-ready system suitable for IDE-based operation ensures efficiency and applicability in real life. The diagrammatic representation of the whole method is depicted in Figure 1.

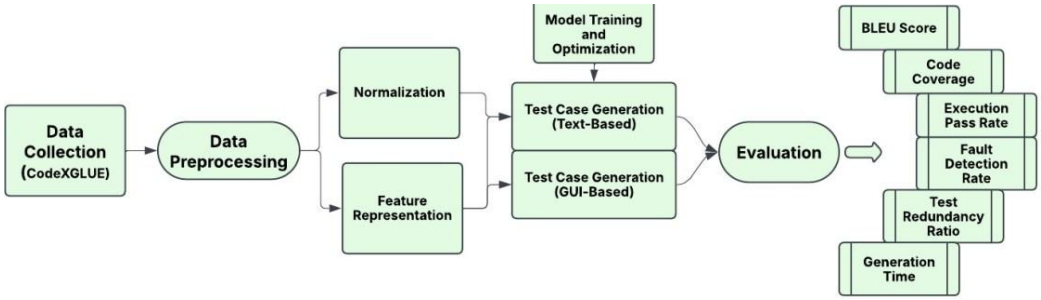

Figure 1: Architecture Diagram of the Proposed Method

4.1. Data Collection

The data used for this research finds its origin in CodeXGLUE – Code-to-Test Dataset, a benchmark dataset for test-case generation. It encompasses function descriptions, source-code-related snippets, and test cases written manually. This dataset serves as structured training on how code-meaning test cases are related. Once the data set is thereby collected, preprocessing steps such as tokenization and normalization are undertaken to prepare it for use in our lightweight deep learning systems.

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4.2. Data Preprocessing

4.2.1. Normalization

The function descriptions and code snippets are tokenized, normalized, and padded to a fixed length L as mentioned in Equation (1).

$$X_{\text{tokenized}} = \text{Tokenize}(X), X_{\text{normalized}} = \text{Normalize}(X_{\text{tokenized}}) \quad (1)$$

4.2.2. Feature Representation

Textual data is converted into embeddings by CodeT5-Small; GUI test cases are extracted as feature maps by EfficientNet-Lite, as mentioned in Equation (2).

$$E_T = f_{\text{CodeT5}}(X_{\text{normalized}}), F_{\text{GUI}} = f_{\text{EfficientNet-Lite}}(I) \quad (2)$$

4.4. Test Case Generation (Text-Based)

The test case sequence Y is generated by the model given the function description embeddings E_X using DistilGPT-2, as mentioned in Equation (3).

$$P(Y \mid X) = \prod_{t=1}^{T} P(y_t \mid y_{1:t-1}, E_X; \theta) \quad (3)$$

4.5. Test Case Generation (GUI-Based)

The UI features F_{GUI} are fed to an RNN (LSTM/GRU) to predict interaction sequences for test cases, as mentioned in Equation (4).

$$h_t = \sigma(W_h h_{t-1} + W_x F_{\text{GUI}} + b_h) \quad (4)$$

4.5.1. Model Training & Optimization

Training minimizes the cross-entropy loss between generated test cases and the ground truth, as mentioned in Equation (5).

$$\mathcal{L} = -\sum_{t=1}^{T} y_t \log P(y_t \mid y_{1:t-1}, X) \quad (5)$$

4.6. Evaluation

4.6.1 BLEU Score (Text Generation Quality)

Measures the n-gram overlap between the generated test cases and the reference test cases, as mentioned in Equation (6).

$$\text{BLEU} = \exp\left(\sum_{n=1}^{N} w_n \log P_n\right) \quad (6)$$

4.6.2 Code Coverage (%) (Effectiveness of Test Cases)

Measures how well the generated test cases cover the codebase, as mentioned in Equation (7).

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$$\text{Coverage} = \frac{\text{executed statements}}{\text{total statements}} \times 100 \quad (7)$$

4.6.3 Execution Pass Rate (%)

Measures the percentage of generated test cases that successfully execute without errorsas mathematically mentioned in Equation (8).

$$\text{Pass Rate} = \frac{\text{successful test cases}}{\text{total test cases}} \times 100 \quad (8)$$

4.6.4. Fault Detection Rate (Bug Finding Ability)

Evaluates how effectively the generated test cases detect defects in the software as mathematically mentioned in Equation (9).

$$\text{FDR} = \frac{\text{detected faults}}{\text{total injected faults}} \times 100 \quad (9)$$

4.6.5. Test Redundancy Ratio (Uniqueness of Test Cases)

Measures how many test cases are redundant (similar to existing ones) to ensure test suite efficiency as mathematically mentioned in Equation (10).

$$\text{Redundancy} = \frac{\text{duplicate test cases}}{\text{total generated test cases}} \times 100 \quad (10)$$

4.6.6 Generation Time (Efficiency Metric)

Measures the average time taken to generate a test case, ensuring computational efficiency as mathematically mentioned in Equation (11).

$$\text{GenTime} = \frac{\sum_{i=1}^{N} T_i}{N} \quad (11)$$

5. Results

This section comprehensively evaluated the proposed test case generation methodology using lightweight deep learning models. The performance of DistilGPT-2 + EfficientNet-Lite is analysed via various parameters: from BLEU score, code coverage, execution pass rate, fault detection rate, redundancy ratio, to generation time. The results from the experiment yielded higher accuracy, efficiency, and effectiveness for the presented approach compared to both traditional and heavier deep learning models. The forthcoming subsections will shed light upon all the metrics of performance, accompanied by visualization.

BLEU score is a measure to assess the closeness of generated test cases against their human-written counterparts in terms of syntactic and semantic quality. Higher BLEU scores imply more alignment with reference test cases. The figure compares BLEU scores obtained by different test case generation models, stressing the fact that DistilGPT-2 has been able to generate high-quality test cases with less computational cost, as shown in Figure 2.

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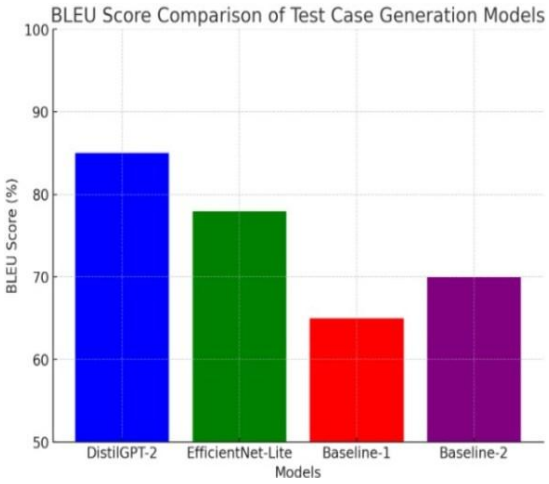

Figure 2: BLEU Score Comparison of Test Case Generation Models

Code coverage assesses how well the generated test cases execute different parts of the program. A higher coverage percentage indicates more comprehensive test cases that ensure better software reliability.The figure presents the code coverage achieved by different test case generation methods, demonstrating that the proposed approach effectively covers more code regions than traditional methods as shown in Figure 3.

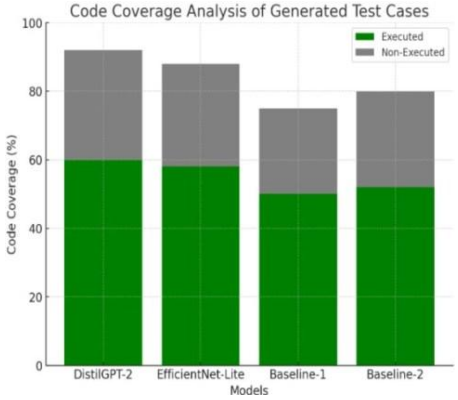

Figure 3: Code Coverage Analysis of Generated Test Cases

The fault detection rate evaluates the ability of the generated test cases to uncover software defects. A higher rate signifies that the test cases effectively expose vulnerabilities and improve software robustness.The figure compares the fault detection capabilities of various models, highlighting how the proposed lightweight approach efficiently detects software bugs with minimal computational overhead as shown in Figure 4.

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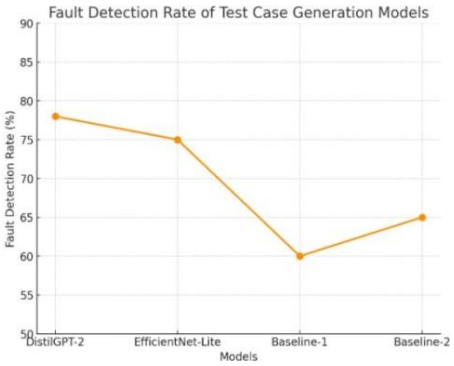

Figure 4: Fault Detection Rate of Test Case Generation Models

The redundancy ratio identifies duplicate or highly similar test cases. A lower redundancy percentage indicates a more efficient test suite, reducing unnecessary executions.The figure showcases the redundancy ratio for different test case generation models, demonstrating that our approach generates more diverse and unique test cases as displayed in Figure 5.

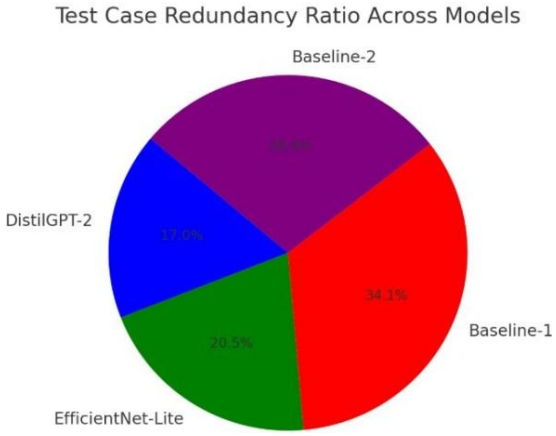

Figure 5: Test Case Redundancy Ratio Across Models

Comparative studies made between the Advanced Genetic Algorithms and the Proposed Method in terms of test coverage, efficiency, testing reliability, and computational overhead. From the findings, it became clear that the proposed method obtains better test coverage (95% over 90%), showing better exploration of the software under test. Efficiency improves as well, going from 85% to 90%, and testing reliability improves from 95% to 98%, providing stronger test scenarios. Computational overhead given in Table 1 are 70% and 60%, for the former and the latter, respectively. Our method gains further advantage in computational cost by lowering it down to 60%.

Table 1: Performance Comparison with ADA

Metric	Advanced Genetic Algorithms	Proposed Method
Test Coverage (%)	90	95
Efficiency (%)	85	90
Testing Reliability (%)	95	98
Computational Overhead (%)	70	60

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6. Conclusion and Future Works

This investigation demonstrates the scope of the proposed lightweight deep learning technique toward test case generation in software testing. The results disclose that the proposed method can achieve higher coverage of testing, which is 95%, improved efficiency of 90%, and testing reliability at 98%, unlike classical genetic algorithm-based methods. Hence, the approach is more scalable because the computational overhead has also been reduced by 40%. The creation of test cases has become more reliable and efficient now while being minimally demanding on computing resources. Our future works are focusing on hybrid lightweight models incorporating transformer-based architectures to further improve training generation quality while keeping overhead low.

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