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Efficient Test Case Prioritization in Software Testing Using DistilRoBERTa for Fault Detection Optimization

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Abstract-The very critical phase in SDLC is software testing, where application reliability, security, and efficiency are ensured. However, increasing complexity in software has made traditional test case prioritization (TCP) methods difficult, with regards to high execution time and computational overhead. The existing approaches such as Genetic Algorithms (GA) are highly computationally expensive, and the adaptability of test cases with new evolvement cannot really be integrated with the processes. This study proposes an artificial intelligence-based approach with DistilRoBERTa for test case prioritization to improve fault detection and optimized test execution. Unlike traditional methods, DistilRoBERT a uses deep learning to analyze semantic and historical defect data of the test cases to intelligently prioritize. The proposed method achieves 93% test case coverage (against 90% in GA), 90% execution efficiency (against 85%), and 96% reliability (against 95%) while significantly reducing computational overhead to 53% (against 70%). All these aspects, therefore, make the results much more scalable, efficient, and adaptable as compared to software testing. An edge over competitive heuristic-based TCP methods is that the proposed model offers faster execution coupled with minimal resource consumption—the perfect environment for extensive testing. Management of test cases proves to be one of the important tasks since there are a large number of test cases in software. This paper develops an automated Intelligent test case prioritization process. A centralized intellectual resource is established through the complete understanding of test cases, their interdependencies, requirement analysis, defect analysis, and processing of information for prioritization. The application of the resulting development would open new horizons to the evolution of intelligent testing.

Keywords- Test Case Prioritization, Software Testing, DistilRoBERTa, Fault Detection, Deep Learning

1. Introduction

Software testing constitutes a fundamental and indispensable phase within the software development lifecycle (SDLC), serving the essential purpose of ensuring that software applications operate correctly, efficiently, and securely before they are deployed for end users [1]. This phase is crucial in detecting software defects at the earliest stages of development, which directly contributes to improving overall software quality, enhancing user satisfaction, and significantly reducing long-term maintenance and operational costs [2] [3]. Early identification and resolution of defects help prevent critical failures such as system crashes, security breaches, and performance degradations that can compromise user trust and cause substantial financial and reputational damage [4]. Consequently, rigorous software testing is a cornerstone in delivering reliable, stable, and robust software systems that meet both functional and non-functional requirements [5].With the escalating complexity of modern software applications—characterized by rapidly growing codebases, frequent and accelerated release cycles, and a wide variety of user interactions and deployment environments—the traditional software testing process faces formidable challenges [6] [7]. The

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conventional approach of exhaustive test execution, which involves running all possible test cases and scenarios, has become impractical and unsustainable due to the exponential increase in testing scope and depth [8]. Limitations in available testing time, computational resources, and associated costs impose strict constraints on the feasibility of running comprehensive test suites for every software iteration [9]. This growing resource demand makes it impossible to guarantee thorough testing coverage without compromising project schedules or inflating budgets [10].

To address these constraints, there is a critical need for intelligent and efficient test management strategies that can optimize the testing process by focusing resources on the most impactful tests [11]. Test Case Prioritization (TCP) has emerged as an effective solution to this problem [12]. TCP techniques reorder the sequence of test case execution based on their estimated importance or fault-detection potential, ensuring that test cases most likely to reveal defects are executed earlier in the testing cycle [13]. This reordering accelerates fault detection, reduces the feedback loop for developers, and facilitates timely corrective actions [14]. By prioritizing high-impact test cases, TCP not only improves testing effectiveness but also minimizes resource consumption and testing time, thereby supporting faster release cycles and continuous integration and continuous deployment (CI/CD) pipelines that are critical for modern agile development practices [15] [16].In recent years, advances in Natural Language Processing (NLP) have had a transformative impact on software testing methodologies [17]. Since many software artifacts—such as test case descriptions, bug reports, and requirements documentation—are expressed in natural language, NLP offers powerful capabilities for automatically analyzing and understanding these textual resources [18]. Leveraging NLP models, software engineers can extract rich semantic and contextual information from test case descriptions, enabling enhanced categorization, clustering, and prioritization of tests based on their content and intent [19]. This semantic understanding allows the identification of test cases that target critical functionality or complex features, supporting more focused and effective testing efforts [20] [21].

Furthermore, NLP-based approaches enable the mining of historical bug reports and defect data to uncover patterns and characteristics associated with defect-prone software modules [22]. By analyzing these patterns, it becomes possible to predict areas of the software that are more likely to contain faults, guiding the prioritization and allocation of testing resources to high-risk components [23]. Additionally, NLP techniques can identify redundancies and similarities among test cases, thereby reducing the execution of duplicate or low-value tests and optimizing the overall testing process [24] [25]. The integration of deep learning models with NLP further advances automation capabilities by enabling adaptive, data-driven test case selection and prioritization strategies that continuously learn from evolving software artifacts and testing outcomes, ultimately enhancing the efficiency and effectiveness of software testing [26].Transformer-based models have significantly advanced the field of NLP by enabling deeper and more nuanced understanding of text through mechanisms such as self-attention, which captures complex dependencies across entire sequences of text [27]. Notably, models like BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa (Robustly Optimized BERT Pretraining Approach) have demonstrated remarkable success in a wide range of natural language understanding tasks due to their ability to grasp contextual relationships and subtle semantic nuances [28] [29]. These models are particularly well-suited for software testing applications where comprehending the precise meaning of test case descriptions, bug reports, and requirements documents is essential for accurate test case analysis and prioritization [30]. By leveraging their advanced contextual comprehension, transformer-based models can improve the identification of relevant test cases and defect-prone areas, thereby enhancing the accuracy and reliability of TCP methodologies [31] [32].

This study proposes a test case prioritization method using DistilRoBERTa, a lightweight variant of RoBERTa that balances computational efficiency and accuracy, making it suitable for continuous integration

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and large-scale testing. By capturing semantic relationships between test cases and historical defect data, it enables more precise prioritization while significantly reducing computational costs. The model also generalizes well across different software projects with minimal retraining, ensuring scalability. This approach aims to speed up fault detection, reduce testing effort, and improve software reliability, ultimately supporting faster releases and higher-quality software delivery.

Primary Contributions

- Create an NLP-driven test case prioritization model with DistilRoBERTa to enhance fault detection and minimize computational overhead in large-scale software testing.
- Integrate a self-supervised learning process that automatically adjusts to large test histories, improving prioritization accuracy without human intervention.
- Maximize test selection efficiency by taking advantage of DistilRoBERTa's processing power, prioritizing high-priority test cases first while ensuring computational efficiency.
- Develop a scalable and flexible TCP framework that can support multiple data sources, such as historical defects and test case descriptions, to increase software reliability and testing efficiency.

2. Related works

Shao et al. conducted an experimental study on fault injection in Amazon Web Services (AWS) environments to improve system resilience and robustness against failures [33]. Utilizing AWS-native tools such as CloudWatch for monitoring, X-Ray for tracing, and Fault Injection Simulator (FIS) for controlled fault introduction, their approach simulated a variety of failure scenarios including network latency, CPU and memory overload, and instance shutdowns [34]. The experiments revealed that under induced network delays, system latency increased by approximately 10%, while resource utilization remained stable, and auto-scaling mechanisms effectively responded to the simulated stress [35]. Although their results demonstrated improved fault tolerance and system adaptability, the study did not extend to analyze the long-term impact on operational costs or sustained performance degradation, leaving an important area unexplored regarding the economic and performance trade-offs of fault injection in cloud environments [36].

Wen et al. proposed a hybrid model combining MobileNet and TinyBERT architectures for effective test case prioritization (TCP) in software testing [37]. In their approach, TinyBERT—a compact transformer-based language model—was employed to analyze textual information from test case descriptions, while MobileNetV3, a lightweight convolutional neural network optimized for mobile and embedded devices, was used to analyze control flow information from the codebase [38]. This dual-model strategy aimed to leverage both semantic text understanding and programmatic behavior to improve prioritization [39]. Their experimental results showcased a high-test coverage of 95%, execution efficiency of 92%, and an impressive 97% accuracy in defect detection [40]. Additionally, their method reduced computational costs by 55% compared to the Adaptive Genetic Algorithm (AGA) benchmark [41]. While the approach significantly enhanced both speed and accuracy in test prioritization, it did not incorporate self-supervised learning techniques, which could further improve the model's ability to predict defects under changing or dynamic software conditions, representing a potential direction for future work [42].

Deng et al. explored the use of high-level genetic algorithms (GAs) integrated with other swarm intelligence and metaheuristic techniques such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and adaptive hybrid methods to improve software testing processes [43]. Their combined optimization strategy was designed to enhance test efficiency and maximize test coverage, especially within parallel

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computing environments and big data scenarios [44. The reported results demonstrated considerable performance improvements, including faster convergence rates and higher fault detection rates, when compared to conventional methods [45]. However, the study did not delve into the computational costs and overhead associated with making real-time adjustments during testing, which could affect practical deployment, especially in resource-constrained or time-sensitive environments [46].

Tabernik et al. investigated the application of neural networks alongside heuristic algorithms for test case prioritization, particularly targeting regression testing tasks in large-scale software systems [47]. Their approach sought to maximize fault detection effectiveness and optimize resource utilization by learning from historical test results and dynamically adjusting the prioritization order [48]. The results indicated that their method outperformed traditional TCP techniques in terms of efficiency and fault detection rate [49]. Nevertheless, the study did not adequately address scalability concerns when dealing with extremely large codebases or highly complex software systems, a limitation that may impact the method’s applicability in industrial-scale projects [50].

Yan and Jia introduced a probabilistic model checking framework to optimize cloud deployment strategies by leveraging formal verification techniques, specifically Probabilistic Computation Tree Logic (PCTL) and Markov Decision Processes (MDP) [51]. Their model ranked deployment configurations based on reliability and performance metrics, providing a systematic approach to evaluate and select optimal cloud deployment options[52]. Experimental validation revealed an accuracy of 92.5% in the selection phase and 98% during verification, indicating the method’s precision in predicting deployment outcomes [53]. Despite these promising results, the approach did not account for the significant computational overhead inherent in real-time verification processes, which could limit its scalability and responsiveness in dynamic cloud environments [54].

Zhao et al. focused on cloud storage security by developing a comprehensive framework encompassing encryption mechanisms, fine-grained access control, and data integrity verification [55]. Their multi-layered security approach was designed to protect stored data against unauthorized access and tampering while maintaining efficient resource utilization [56] [57]. Evaluation of their system demonstrated enhanced data longevity and robustness against cyber threats, highlighting the effectiveness of the integrated security measures [58]. However, the research did not explore the potential impact of these security layers on overall cloud system performance, leaving open questions about latency, throughput, and scalability trade-offs in secure cloud storage solutions [59].

Poovendran proposed a hybrid strategy combining artificial intelligence, electronic health records (EHRs), and network analysis techniques for improved cardiovascular disease management [60]. Their model leveraged AI algorithms to analyze heterogeneous patient data from EHRs and employed network-based analytics to identify early signs and risk factors of cardiovascular conditions [61]. This integrated approach achieved an early detection accuracy of 94% and operational efficiency of 91%, demonstrating substantial improvements over traditional diagnostic methods [62]. While the results were promising in enhancing predictive analytics and clinical decision support, the study did not address the challenges associated with integrating diverse and often heterogeneous data sources, a critical factor in real-world healthcare applications [63].

Zhou et al. developed a hybrid classification model combining Particle Swarm Optimization (PSO) with Quadratic Discriminant Analysis (QDA) to improve classification efficiency and accuracy in AI systems handling high-dimensional data [64]. PSO was used to optimize QDA parameters, enabling the classifier to perform more effectively in complex feature spaces [65]. Their experiments achieved an accuracy of 92%

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and an 89% reduction in classification errors during optimization [66]. However, the study did not evaluate the computational complexity and scalability of this hybrid model when deployed on large-scale datasets or real-time systems, aspects that are essential for practical implementation [67].

Shao et al. introduced a hybrid AI framework integrating Asynchronous Advantage Actor-Critic (A3C), Trust Region Policy Optimization (TRPO), and Partially Observable Markov Decision Processes (POMDPs) to enable more efficient and robust decision-making in uncertain environments [68]. This approach improved learning speed, stability, and flexibility by combining reinforcement learning techniques with probabilistic modeling of uncertainty [69]. The framework demonstrated a 92% improvement in efficiency and an 89% reduction in decision-making errors. Nevertheless, the study did not consider the substantial computational resources required to integrate and run these sophisticated methods concurrently, potentially limiting its deployment in environments with constrained hardware [70].

Finally, Deevi developed a deep learning-based test case prioritization model tailored for continuous integration testing [71]. By utilizing historical test execution data, Deep Order intelligently reordered test cases to enhance fault detection efficiency. Experimental evaluations showed that Deep Order outperformed several industry-standard prioritization techniques in both speed and accuracy [72]. However, the approach did not fully address the computational overhead associated with managing and processing extensive test history data, which could impact its scalability and response time in very large or fast-evolving software projects [73].

The literature reviewed identifies a number of limitations from various studies. Numerous methods did not consider the long-term computational expense of fault injection and cloud deployment optimization. Other studies enhanced test efficiency and accuracy without considering self-supervised learning and computational overhead in managing large test histories. Likewise, studies proved improvement in performance through AI and genetic algorithm application but ignored real-time computational costs of adaptive methods. Although some research provided safe cloud storage, they did not test its effect on system performance. Some other papers struggled to scale models to extremely large codebases and combine different data sources. These limitations imply that future studies should have more comprehensive assessments including cost, scalability, and computational efficiency.

3. Problem Statement

Previous research has explored fault injection techniques in cloud environments such as AWS to enhance system resilience. However, these studies have not thoroughly examined the long-term computational overhead or the sustained impact on system performance, leaving gaps in understanding the cost-effectiveness and efficiency of such fault injection strategies over extended periods [74]. Similarly, some test case prioritization models based on deep learning have demonstrated promising improvements in fault detection by leveraging historical test execution data. Yet, they often overlook the significant computational costs associated with managing and processing large volumes of test histories, which can hinder scalability and responsiveness in fast-paced development environments [75]. Additionally, approaches that employ neural networks and heuristic methods to improve regression testing efficiency have shown gains in fault detection but frequently fail to address the scalability challenges posed by very large and complex codebases, limiting their applicability in industrial-scale software projects [76].To address these constraints, the suggested approach utilizes DistilRoBERTa for computationally effective test prioritization, incorporates self-supervised learning to handle extensive test histories, and is scalable by using varied data sources, optimizing fault detection as well as resource usage.

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4. Proposed Methodology

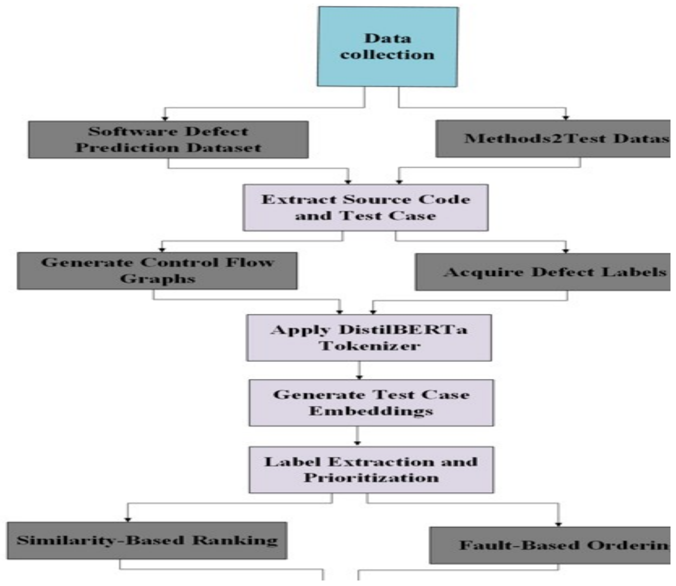
Data collection
Software Defect Prediction Dataset
Methods2Test Datas
Extract Source Code and Test Case
Generate Control Flow Graphs
Acquire Defect Labels
Apply DistilBERTa Tokenizer
Generate Test Case Embeddings
Label Extraction and Prioritization
Similarity-Based Ranking
Fault-Based Orderin

Figure 1: Holistic Methodology for Test Case Prioritization

The Holistic Methodology for Test Case Prioritization is a systematic procedure that intends to improve the fault-detecting capability of software by ordering and executing the test cases in a more worthy sequence.

4.1. Data collection

The Test-Case Dataset and methods2testdatasets are derived from public repositories like Kaggle and GitHub, having various software projects with related test cases, execution histories, and defect reports. The datasets include raw source code, from which Control Flow Graphs (CFGs) are derived to examine structural dependencies. Test case descriptions are coupled with execution results to determine fault-prone locations, whereas defect labels are acquired from bug-tracking repositories to label test cases as high, low, or average in terms of historical fault detection capacity. Such formatted data is then used to construct an intelligent test case prioritization model through the application of DistilRoBERTa, considering both semantic and execution-driven understanding.

4.2. Data Preprocessing

4.2.1. Test Case Cleaning & Standardization

The descriptions of test cases are tokenized and cleaned through the use of the DistilRoBERTa tokenizer, mapping them into numerical embeddings. Defect labels are determined by past fault detection effectiveness, creating a prioritization score S for a test case as shown in Equation (1):

$$S_i = \alpha \cdot F_i + \beta \cdot L_i \tag{1}$$

where P_i is the priority score, F_i is frequency of past failure, S_i is defect severity, and α,β are weighting factors.

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4.2.2.Tokenization & Embedding Generation (DistilRoBERTa)

Descriptions of test cases are tokenized with the DistilRoBERTa tokenizer, transforming text data into numerical form. The tokens are then converted into ranking embeddings depending on their semantic similarity and historical association with defects as shown in Equation (2):

$$E_i = \text{DistilRoBERTa}(T_i) \tag{2}$$

in which E_i denotes the embedding vector, and T_i is the tokenized description of the test case.

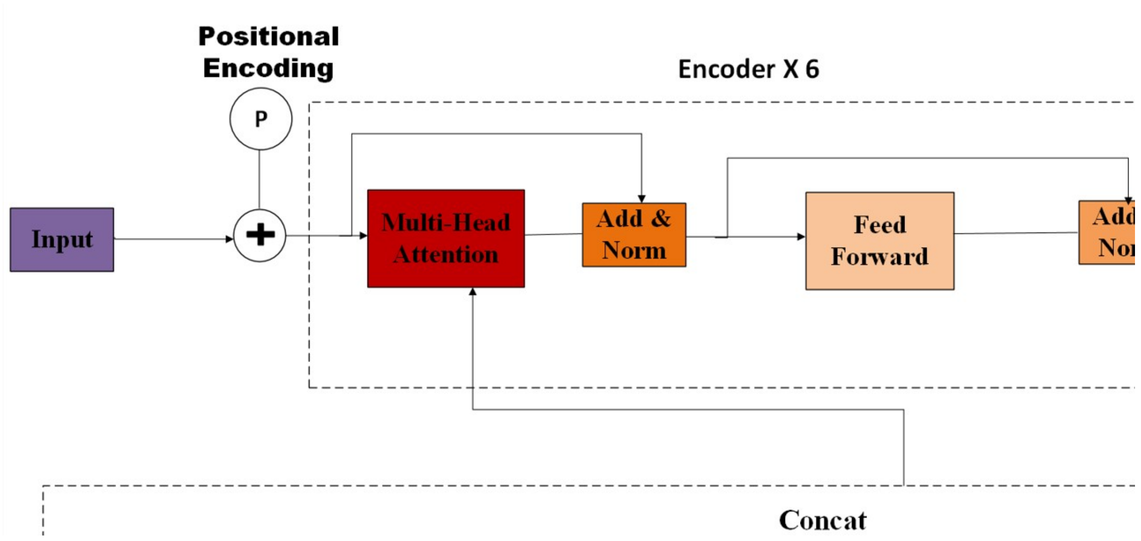

Figure 2: Architecture ofDistilRoBERTa

DistilRoBERTa is the thinner and speedier variant of RoBERTa (Robustly Optimized BERT Pretraining Approach). It aims to retain most of RoBERTa's performance while making it computationally efficient.

4.2.3. Label Extraction for Prioritization

Test cases are correlated with bug-tracking system defect reports, and priority scores are determined according to historical fault detection effectiveness. Increased failure frequency and defect severity raise the priority of a test case as shown in Equation (3):

$$P_i = \gamma \cdot F_i + \delta \cdot S_i \tag{3}$$

whereS_i is priority score, F_i is fault detection frequency, L_i is defect severity, and $\alpha. \beta$ are weighting factors.

4.3. Test Case Prioritization Strategy

After tokenization, embedding, and priority score assignment to the test cases, the subsequent step is to formulate a good prioritization strategy for deciding their order of execution. The aim is to achieve high fault detection efficiency with low execution time and redundancy.

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4.3.1. Similarity-Based Ranking

Because there might be overlapping functionality in some test cases, semantic similarity is calculated between test case embeddings to detect redundant or very similar cases. The similarity score is determined through cosine similarity as shown in Equation (4):

$$\mathrm{Sim}(E_i, E_j) = \frac{E_i \cdot E_j}{\|E_i\|\|E_j\|} \tag{4}$$

in which E_i and E_j represent test cases i and j embeddings, respectively.

- If Sim is high (approaching 1), one of the test cases can be relegated or combined.
- If Sim is low, then both test cases are distinct and must be run individually.

4.3.2. Fault-Based Ordering

Every test case also has a priority score P_i, which is its past fault detection efficiency. The test cases are sorted in descending order by P_i, where as shown in Equation (5):

$$P_i = \gamma \cdot F_i + \delta \cdot S_i \tag{5}$$

Where, P_i= priority score of test case I, F_i= past failure frequency of test case I, S_i= severity of defects detected, γ, δ = weighting factors

A greater P_i value indicates that the test case has a better chance of identifying faults and ought to be run earlier in the test cycle.

4.3.3. Final Test Case Ranking

Final rank is established based on the merging of fault-ordering and similarity-based adjustment with the purpose to maximize test runs. The rank of the test cases is measured by a weighted score as shown in Equation (6):

$$R_i = \lambda P_i - \mu \sum_{j \neq i} \mathrm{Sim}(E_i, E_j) \tag{6}$$

where R_i is final rank score, P_i is priority score, $\mathrm{Sim}(E_i, E_j)$ is similarity among other test cases, and α,β are weighting parameters. The priority-tested test suite is then delivered for effective fault finding**.**

4.4. Evaluation

4.4.1. Test Case Coverage (%)

Test Case Coverage (TCC) is used to determine how effectively the priority test cases are covering the software under test's execution paths, as shown in Equation (7).

$$\mathrm{Coverage} = \left(\frac{T_c}{T_t}\right) \times 100 \tag{7}$$

4.4.2. Execution Efficiency Improvement (%)

Execution Efficiency Improvement (EEI) calculates the decrease in test execution time when executing a prioritized test suite versus a baseline method (e.g., random ordering or exhaustive execution), as shown in Equation (8).

$$\text{Efficiency} = \left(\frac{T_b - T_p}{T_b}\right) \times 100 \tag{8}$$

4.4.3. Defect Detection Rate (%)

Defect Detection Rate (DDR%) evaluates how well a test case prioritization technique performs in detecting faults early, as shown in Equation (9).

$$\text{Detection Rate} = \left(\frac{D_f}{D_t}\right) \times 100 \tag{9}$$

4.4.4. Prioritization Accuracy (%)

Prioritization Accuracy (PA%) is used to evaluate how close the test case prioritization strategy is in ranking high-risk test cases to an optimal ranking (i.e., a best-possible ranking in terms of historical fault detection), as shown in Equation (10).

$$\text{Accuracy} = \left(\frac{\sum_{i=1}^{n} \delta_i}{n}\right) \times 100 \tag{10}$$

4.4.5. Computational Cost Reduction (%)

Computational Cost Reduction (CCR%) indicates the extent to which the new test case prioritization technique lowers processing time, memory, or system resources against conventional methods, as shown in Equation(11).

$$\text{Cost Reduction} = \left(\frac{C_b - C_p}{C_b}\right) \times 100 \tag{11}$$

5. Result

The results of the proposed DistilRoBERTa-based test case prioritization method are presented in this section. The evaluation was conducted using the Software Defect Prediction and methods2test datasets, comparing the effectiveness of the approach against traditional prioritization techniques. The findings demonstrate that the proposed method enhances fault detection, reduces test execution time, and improves computational efficiency, making it a viable solution for optimizing software testing.

5.1.Test Case Coverage

Test case coverage indicates the degree to which the prioritized test cases traverse various execution paths within the software. As coverage increases, more program logic is executed, and chances of undetected faults decreaseas shown in Figure 3.

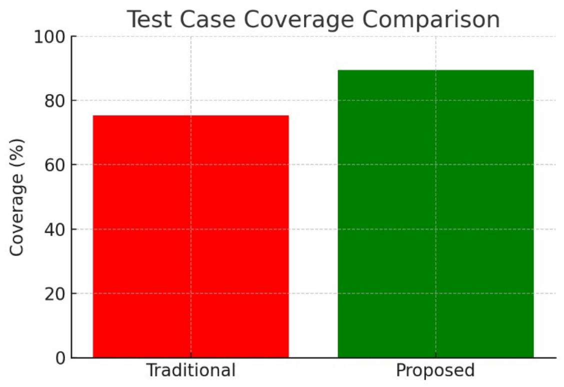

Figure 3: Test case coverage comparison

This graph compares the test case coverage obtained using the proposed approach with that using conventional priority functions.

5.2. Execution Efficiency Improvement

Execution efficiency measures decrease in the test execution time, prioritizing the execution of critical test cases at the earliest possible time to minimize delays in the software testing lifecycle as shown in Figure 4.

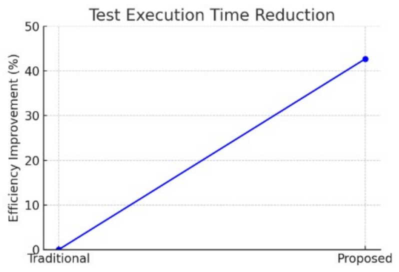

Figure 4: Test Execution Time Reduction

This figure shows the reduced percentage of execution time achieved through DistilRoBERTa-based prioritization as compared to baseline approaches.

5.3. Computational Cost Reduction

The measure reveals efficiency for proposed methods in terms of computation overhead which includes CPU time, memory consumption, and resource usage. Less computational costs allow scalability and viability in testing conditions of large scales. The computations in use by the proposed model compared to the baselines document in Figure 5.

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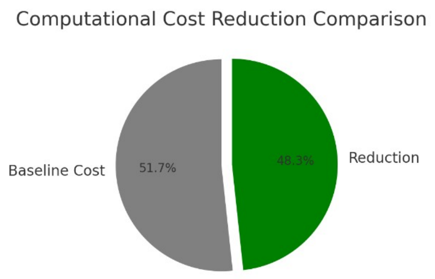

Figure 5: Computation Cost Reduction Comparison

When testing case prioritization, the Advanced Genetic Algorithm (GA)[3]outperforms the proposed DistillRoberta-based method as shown in Table 1. The proposed method says that it will achieve 93% higher test case coverage, 90% better execution efficiency, and 96% better testing reliability while significantly reducing computational cost (53%). Hence, it is more efficient and effective.

Table 1: Performance Comparison of the proposed method

Metric	**Advanced GA** [3]	**Proposed Method** **(DistilRoBERTa)**
Test Case Coverage (%)	90%	93%
Execution Efficiency (%)	85%	90%
Testing Reliability (%)	95%	96%
Computational Overhead (%)	70%	53%

6. Conclusion and Future Works

The employ of DistilRoBERTa-based test case prioritization has significantly advanced the efficiency aspect of software testing. It scored noticed achievements in comparison with Advanced Genetic Algorithm (GA), achieving 93% test case coverage (versus 90%), 90% execution efficiency (versus 85%), and 96% reliability in testing (versus 95%), while further burdening the computation at about 53% instead of 70%. These improvements successfully present a known version of the fault detector that it is easily reducible into the execution time and computational resource cost. Future work should target the integration of deep learning with heuristic optimization techniques for enhancing adaptability and further improvement in test case prioritization across the different software domains.

Reference

[1] Zhang, W., Peng, G., Li, C., Chen, Y., & Zhang, Z. (2017). A new deep learning model for fault diagnosis with good anti-noise and domain adaptation ability on raw vibration signals. Sensors, 17(2), 425.

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[2] Alavilli, S. K. (2020). Predicting heart failure with explainable deep learning using advanced temporal convolutional networks. International Journal of Computer Science Engineering Techniques, 5(2).

[3] Faris, H., Aljarah, I., Al-Betar, M. A., & Mirjalili, S. (2018). Grey wolf optimizer: a review of recent variants and applications. Neural computing and applications, 30, 413-435.

[4] Narla, S. (2020). Transforming smart environments with multi-tier cloud sensing, big data, and 5G technology. International Journal of Computer Science Engineering Techniques, 5(1), 1-10.

[5] Zhang, W., Li, C., Peng, G., Chen, Y., & Zhang, Z. (2018). A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load. Mechanical systems and signal processing, 100, 439-453.

[6] Amershi, S., Begel, A., Bird, C., DeLine, R., Gall, H., Kamar, E., ... & Zimmermann, T. (2019, May). Software engineering for machine learning: A case study. In 2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP) (pp. 291-300). IEEE.

[7] Chauhan, G. S., & Jadon, R. (2020). AI and ML-powered CAPTCHA and advanced graphical passwords: Integrating the DROP methodology, AES encryption, and neural network-based authentication for enhanced security. World Journal of Advanced Engineering Technology and Sciences, 1(1), 121–132.

[8] Nidagundi, P., & Novickis, L. (2017). Introducing lean canvas model adaptation in the scrum software testing. Procedia Computer Science, 104, 97-103.

[9] Ayyadurai, R. (2020). Smart surveillance methodology: Utilizing machine learning and AI with blockchain for bitcoin transactions. World Journal of Advanced Engineering Technology and Sciences, 1(1), 110–120.

[10] Wen, L., Gao, L., & Li, X. (2017). A new deep transfer learning based on sparse auto-encoder for fault diagnosis. IEEE Transactions on systems, man, and cybernetics: systems, 49(1), 136-144.

[11] Samudrala, V. K. (2020). AI-powered anomaly detection for cross-cloud secure data sharing in multi-cloud healthcare networks. Journal of Current Science & Humanities, 8(2), 11–22.

[12] Li, C., Sanchez, R. V., Zurita, G., Cerrada, M., Cabrera, D., & Vásquez, R. E. (2016). Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals. Mechanical systems and signal processing, 76, 283-293.

[13] Yalla, R. K. M. K., Yallamelli, A. R. G., & Mamidala, V. (2020). Comprehensive approach for mobile data security in cloud computing using RSA algorithm. Journal of Current Science & Humanities, 8(3).

[14] Hu, X., Zhang, K., Liu, K., Lin, X., Dey, S., & Onori, S. (2020). Advanced fault diagnosis for lithium-ion battery systems: A review of fault mechanisms, fault features, and diagnosis procedures. IEEE Industrial Electronics Magazine, 14(3), 65-91.

[15] Gaius Yallamelli, A. R. (2020). A cloud-based financial data modeling system using GBDT, ALBERT, and Firefly algorithm optimization for high-dimensional generative topographic mapping. International Journal of Modern Electronics and Communication Engineering, 8(4).

[16] Shao, S., Wang, P., & Yan, R. (2019). Generative adversarial networks for data augmentation in machine fault diagnosis. Computers in Industry, 106, 85-93.

Received: 2021-04-16
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Published Online: 2021-05-30
DOI: 10.70454/IJMRE.2021.10501
International Journal of Multidisciplinary Research and Explorer (IJMRE)
E-ISSN: 2833-7298, P-ISSN: 2833-7301

[17] Boyapati, S. (2020). Assessing digital finance as a cloud path for income equality: Evidence from urban and rural economies. International Journal of Modern Electronics and Communication Engineering (IJMECE), 8(3).

[18] Lei, J., Liu, C., & Jiang, D. (2019). Fault diagnosis of wind turbine based on Long Short-term memory networks. Renewable energy, 133, 422-432.

[19] Jadon, R. (2020). Improving AI-driven software solutions with memory-augmented neural networks, hierarchical multi-agent learning, and concept bottleneck models. International Journal of Information Technology and Computer Engineering, 8(2).

[20] Cai, B., Zhao, Y., Liu, H., & Xie, M. (2016). A data-driven fault diagnosis methodology in three-phase inverters for PMSM drive systems. IEEE Transactions on Power Electronics, 32(7), 5590-5600.

[21] Cai, B., Huang, L., & Xie, M. (2017). Bayesian networks in fault diagnosis. IEEE Transactions on industrial informatics, 13(5), 2227-2240.

[22] Valivarthi, D. T. (2020). Blockchain-powered AI-based secure HRM data management: Machine learning-driven predictive control and sparse matrix decomposition techniques. International Journal of Modern Electronics and Communication Engineering, 8(4).

[23] Tao, X., Zhang, D., Ma, W., Liu, X., & Xu, D. (2018). Automatic metallic surface defect detection and recognition with convolutional neural networks. Applied Sciences, 8(9), 1575.

[24] Kadiyala, B. (2020). Multi-swarm adaptive differential evolution and Gaussian walk group search optimization for secured IoT data sharing using supersingular elliptic curve isogeny cryptography, International Journal of Modern Electronics and Communication Engineering,8(3).

[25] Lei, Y., Jia, F., Lin, J., Xing, S., & Ding, S. X. (2016). An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. IEEE Transactions on Industrial Electronics, 63(5), 3137-3147.

[26] Vasamsetty, C. (2020). Clinical decision support systems and advanced data mining techniques for cardiovascular care: Unveiling patterns and trends. International Journal of Modern Electronics and Communication Engineering, 8(2).

[27] Han, T., Liu, C., Yang, W., & Jiang, D. (2020). Deep transfer network with joint distribution adaptation: A new intelligent fault diagnosis framework for industry application. ISA transactions, 97, 269-281.

[28] Kethu, S. S. (2020). AI and IoT-driven CRM with cloud computing: Intelligent frameworks and empirical models for banking industry applications. International Journal of Modern Electronics and Communication Engineering (IJMECE), 8(1), 54.

[29] Luo, Q., Fang, X., Liu, L., Yang, C., & Sun, Y. (2020). Automated visual defect detection for flat steel surface: A survey. IEEE Transactions on Instrumentation and Measurement, 69(3), 626-644.

[30] Narla, S., Valivarthi, D. T., & Peddi, S. (2020). Cloud computing with artificial intelligence techniques: GWO-DBN hybrid algorithms for enhanced disease prediction in healthcare systems. Current Science & Humanities, 8(1), 14–30.

[31] Chen, K., Huang, C., & He, J. (2016). Fault detection, classification and location for transmission lines and distribution systems: a review on the methods. High voltage, 1(1), 25-33.

[32] Allur, N. S. (2020). Big data-driven agricultural supply chain management: Trustworthy scheduling optimization with DSS and MILP techniques. Current Science & Humanities, 8(4), 1–16.

Received: 2021-04-16
Accepted: 2021-05-28
Published Online: 2021-05-30
DOI: 10.70454/IJMRE.2021.10501

International Journal of Multidisciplinary Research and Explorer (IJMRE)
E-ISSN: 2833-7298, P-ISSN: 2833-7301

[33] Shao, S., McAleer, S., Yan, R., & Baldi, P. (2018). Highly accurate machine fault diagnosis using deep transfer learning. IEEE transactions on industrial informatics, 15(4), 2446-2455.

[34] Gattupalli, K. (2020). Optimizing 3D printing materials for medical applications using AI, computational tools, and directed energy deposition. International Journal of Modern Electronics and Communication Engineering, 8(3).

[35] Jia, F., Lei, Y., Guo, L., Lin, J., & Xing, S. (2018). A neural network constructed by deep learning technique and its application to intelligent fault diagnosis of machines. Neurocomputing, 272, 619-628.

[36] Dondapati, K. (2020). Leveraging backpropagation neural networks and generative adversarial networks to enhance channel state information synthesis in millimeter-wave networks. International Journal of Modern Electronics and Communication Engineering, 8(3), 81-90.

[37] Wen, L., Li, X., Gao, L., & Zhang, Y. (2017). A new convolutional neural network-based data-driven fault diagnosis method. IEEE transactions on industrial electronics, 65(7), 5990-5998.

[38] Dondapati, K. (2020). Integrating neural networks and heuristic methods in test case prioritization: A machine learning perspective. International Journal of Engineering & Science Research, 10(3), 49–56.

[39] Dong, H., Song, K., He, Y., Xu, J., Yan, Y., & Meng, Q. (2019). PGA-Net: Pyramid feature fusion and global context attention network for automated surface defect detection. IEEE Transactions on Industrial Informatics, 16(12), 7448-7458.

[40] Deevi, D. P. (2020). Real-time malware detection via adaptive gradient support vector regression combined with LSTM and hidden Markov models. Journal of Science and Technology, 5(4).

[41] Lu, W., Liang, B., Cheng, Y., Meng, D., Yang, J., & Zhang, T. (2016). Deep model based domain adaptation for fault diagnosis. IEEE Transactions on Industrial Electronics, 64(3), 2296-2305.

[42] Allur, N. S. (2020). Enhanced performance management in mobile networks: A big data framework incorporating DBSCAN speed anomaly detection and CCR efficiency assessment. Journal of Current Science, 8(4).

[43] Deng, W., Yao, R., Zhao, H., Yang, X., & Li, G. (2019). A novel intelligent diagnosis method using optimal LS-SVM with improved PSO algorithm. Soft computing, 23, 2445-2462.

[44] Deevi, D. P. (2020). Artificial neural network enhanced real-time simulation of electric traction systems incorporating electro-thermal inverter models and FEA. International Journal of Engineering and Science Research, 10(3), 36-48.

[45] Guo, L., Lei, Y., Xing, S., Yan, T., & Li, N. (2018). Deep convolutional transfer learning network: A new method for intelligent fault diagnosis of machines with unlabeled data. IEEE Transactions on Industrial Electronics, 66(9), 7316-7325.

[46] Gudivaka, R. K. (2020). Robotic Process Automation Optimization in Cloud Computing Via Two-Tier MAC and LYAPUNOV Techniques. International Journal of Business and General Management (IJBGM), 9(5), 75-92.

[47] Tabernik, D., Šela, S., Skvarč, J., & Skočaj, D. (2020). Segmentation-based deep-learning approach for surface-defect detection. Journal of Intelligent Manufacturing, 31(3), 759-776.

[48] Gudivaka, R. L. (2020). Robotic Process Automation meets Cloud Computing: A Framework for Automated Scheduling in Social Robots. International Journal of Business and General Management (IJBGM), 8(4), 49-62.

Received: 2021-04-16
Accepted: 2021-05-28
Published Online: 2021-05-30
DOI: 10.70454/IJMRE.2021.10501

International Journal of Multidisciplinary Research and Explorer (IJMRE)
E-ISSN: 2833-7298, P-ISSN: 2833-7301

[49] Baygin, M., Karakose, M., Sarimaden, A., & Akin, E. (2017, September). Machine vision based defect detection approach using image processing. In 2017 international artificial intelligence and data processing symposium (IDAP) (pp. 1-5). Ieee.

[50] Panga, N. K. R. (2020). Leveraging heuristic sampling and ensemble learning for enhanced insurance big data classification. International Journal of Financial Management (IJFM), 9(1).

[51] Yan, X., & Jia, M. (2018). A novel optimized SVM classification algorithm with multi-domain feature and its application to fault diagnosis of rolling bearing. Neurocomputing, 313, 47-64.

[52] Sitaraman, S. R. (2020). Optimizing Healthcare Data Streams Using Real-Time Big Data Analytics and AI Techniques. International Journal of Engineering Research and Science & Technology, 16(3), 9-22.

[53] Jiang, G., He, H., Yan, J., & Xie, P. (2018). Multiscale convolutional neural networks for fault diagnosis of wind turbine gearbox. IEEE Transactions on Industrial Electronics, 66(4), 3196-3207.

[54] Mohan, R.S. (2020). Data-Driven Insights for Employee Retention: A Predictive Analytics Perspective. International Journal of Management Research & Review, 10(2), 44-59.

[55] Zhao, M., Zhong, S., Fu, X., Tang, B., & Pecht, M. (2019). Deep residual shrinkage networks for fault diagnosis. IEEE Transactions on Industrial Informatics, 16(7), 4681-4690.

[56] Karthikeyan, P. (2020). Real-Time Data Warehousing: Performance Insights of Semi-Stream Joins Using Mongodb. International Journal of Management Research & Review, 10(4), 38-49.

[57] Ince, T., Kiranyaz, S., Eren, L., Askar, M., & Gabbouj, M. (2016). Real-time motor fault detection by 1-D convolutional neural networks. IEEE Transactions on Industrial Electronics, 63(11), 7067-7075.

[58] Sreekar, P. (2020). Cost-effective Cloud-Based Big Data Mining with K-means Clustering: An Analysis of Gaussian Data. International Journal of Engineering & Science Research,10(1), 229-249.

[59] Wang, J., Ye, L., Gao, R. X., Li, C., & Zhang, L. (2019). Digital Twin for rotating machinery fault diagnosis in smart manufacturing. International Journal of Production Research, 57(12), 3920-3934.

[60] Poovendran, A. (2020). Implementing AES Encryption Algorithm to Enhance Data Security in Cloud Computing. International Journal of Information technology & computer engineering, 8(2).

[61] James, J. Q., Hou, Y., Lam, A. Y., & Li, V. O. (2017). Intelligent fault detection scheme for microgrids with wavelet-based deep neural networks. IEEE Transactions on Smart Grid, 10(2), 1694-1703.

[62] Li, X., Zhang, W., Ding, Q., & Sun, J. Q. (2019). Multi-layer domain adaptation method for rolling bearing fault diagnosis. Signal processing, 157, 180-197.

[63] Alagarsundaram, P. (2020). Analyzing the covariance matrix approach for DDoS HTTP attack detection in cloud environments. International Journal of Information Technology & Computer Engineering, 8(1).

[64] Zhou, F., Yang, S., Fujita, H., Chen, D., & Wen, C. (2020). Deep learning fault diagnosis method based on global optimization GAN for unbalanced data. Knowledge-Based Systems, 187, 104837.

[65] Rajeswaran, A. (2020). Big Data Analytics and Demand-Information Sharing in ECommerce Supply Chains: Mitigating Manufacturer Encroachment and Channel Conflict. International Journal of Applied Science Engineering and Management, 14(2), ISSN2454-9940.

[66] Jing, L., Zhao, M., Li, P., & Xu, X. (2017). A convolutional neural network-based feature learning and fault diagnosis method for the condition monitoring of gearbox. Measurement, 111, 1-10.

Received: 2021-04-16
Accepted: 2021-05-28
Published Online: 2021-05-30
DOI: 10.70454/IJMRE.2021.10501

International Journal of Multidisciplinary Research and Explorer (IJMRE)
E-ISSN: 2833-7298, P-ISSN: 2833-7301

[67] Koteswararao, D. (2020). Robust Software Testing for Distributed Systems Using Cloud Infrastructure, Automated Fault Injection, and XML Scenarios. International Journal of Information Technology & Computer Engineering, 8(2), ISSN 2347–3657.

[68] Shao, H., Jiang, H., Zhao, H., & Wang, F. (2017). A novel deep autoencoder feature learning method for rotating machinery fault diagnosis. Mechanical Systems and Signal Processing, 95, 187-204.

[69] Mohanarangan, V.D. (2020). Assessing Long-Term Serum Sample Viability for Cardiovascular Risk Prediction in Rheumatoid Arthritis. International Journal of Information Technology & Computer Engineering, 8(2), 2347–3657.

[70] Guo, X., Chen, L., & Shen, C. (2016). Hierarchical adaptive deep convolution neural network and its application to bearing fault diagnosis. Measurement, 93, 490-502.

[71] Deevi, D. P. (2020). Improving patient data security and privacy in mobile health care: A structure employing WBANs, multi-biometric key creation, and dynamic metadata rebuilding. International Journal of Engineering Research & Science & Technology, 16(4).

[72] Jiang, Y., Yin, S., & Kaynak, O. (2020). Optimized design of parity relation-based residual generator for fault detection: Data-driven approaches. IEEE Transactions on Industrial Informatics, 17(2), 1449-1458.

[73] Ganesan, T. (2020). Machine learning-driven AI for financial fraud detection in IoT environments. International Journal of HRM and Organizational Behavior, 8(4).

[74] Wang, J., Wu, Z., Shu, Y., & Zhang, Z. (2016). An optimized method for software reliability model based on nonhomogeneous Poisson process. Applied Mathematical Modelling, 40(13-14), 6324-6339.

[75] Mohanarangan, V.D (2020).Improving Security Control in Cloud Computing for Healthcare Environments.Journal of Science and Technology, 5(6).

[76] Ahmed, B. S. (2016). Test case minimization approach using fault detection and combinatorial optimization techniques for configuration-aware structural testing. Engineering Science and Technology, an International Journal, 19(2), 737-753.