Efficient Fault Localization in Software Testing Using Squeeze BERT, Wavelet CNN, and Adaptive Memory Networks

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Abstract

Fault localization is a crucial task in software testing, significantly impacting debugging efficiency and software reliability. Traditional approaches, such as spectrum-based fault localization and statistical debugging, often struggle with precision due to their reliance on static heuristics, leading to high false positive rates and inefficient fault identification. These methods lack adaptability to modern, large-scale software architectures with complex execution patterns. To address these challenges, this study proposes a hybrid deep learning model integrating SqueezeBERT, Wavelet CNN, and Adaptive Memory Networks (AMN) for fault localization using the Defects4J dataset. The novelty of this approach lies in leveraging transformer-based log tokenization (SqueezeBERT), frequency-domain fault pattern extraction (Wavelet CNN), and historical pattern retrieval (AMN) to enhance fault detection accuracy and computational efficiency. Experimental results demonstrate 98% fault localization accuracy, 93% error reduction, and 88% execution time reduction, outperforming Advanced Genetic Algorithms (AGA) in scalability, efficiency (92% vs. 85%), and computational overhead (60% vs. 70%). Compared to conventional spectrum-based techniques, the proposed method significantly reduces false positives (FPR) and improves recall (FDR), ensuring robust fault detection across diverse execution logs. By integrating memory-based retrieval with deep learning, the model adapts dynamically to evolving software systems, making it a scalable and computationally efficient solution for real-world fault localization. This advancement enhances debugging precision, minimizes developer effort, and paves the way for future reinforcement learning-based adaptive fault localization techniques in complex software ecosystems.

Keywords: *Fault Localization, Squeeze Bidirectional Encoder Representations from Transformers, Wavelet Convolutional Neural Network, Adaptive Memory Networks, Software Testing, Advanced Genetic Algorithms*

1. Introduction

Effective fault localization is essential for reducing debugging time and improving software reliability [1]. However, achieving high accuracy in large-scale, evolving software systems remains a major challenge [2]. As modern software architectures become increasingly complex with interconnected dependencies, concurrent execution, and distributed frameworks, traditional fault localization techniques struggle to maintain precision and efficiency [3]. The need for automated debugging across diverse execution environments requires adaptive and scalable solutions that can enhance fault detection accuracy and reliability [4]. Despite advancements, existing methods often suffer from imprecision, high debugging costs, and an inability to handle dynamic software structures, limiting their practical utility [5]. A key limitation of conventional fault localization techniques is their dependence on static analysis, program spectra, and heuristic-based ranking, which fail to adapt to continuous software modifications [6]. These approaches often demand significant manual intervention and domain expertise, making them inefficient for large-scale projects with frequent updates [7]. Additionally, conventional methods struggle to accommodate runtime variations and dynamic execution traces, reducing their applicability in modern, adaptive software environments [8]. Without intelligent mechanisms to adjust to evolving software behaviors, traditional fault localization methods quickly become outdated and ineffective [9].

Another significant challenge is computational inefficiency [10]. Many AI-driven fault localization techniques require substantial computational resources, including high memory usage and prolonged inference times, making them unsuitable for debugging, embedded systems, and cloud-based applications [11]. To address these issues, fault localization models must be designed to be both lightweight and computationally efficient, ensuring seamless integration into contemporary software development workflows [12]. The lack of transparency in AI-based fault localization models presents an additional obstacle [13] . Most existing models operate as black-box systems, providing minimal insight into how faults are detected and ranked [14]. This lack of interpretability is a major concern in domains where explainability is critical, such as financial systems, cybersecurity, and healthcare, where debugging decisions must be auditable and verifiable [15]. To enhance trust and usability, fault localization models must incorporate explainability techniques that allow developers to understand and validate fault predictions [16].

Modern software paradigms, including microservices, event-driven applications, and distributed computing, introduce further complications for fault localization [17]. Traditional debugging approaches often fail to scale efficiently across these architectures, leading to ineffective fault prioritization and increased developer workload [18]. Additionally, the presence of asynchronous execution, parallel processing, and non-deterministic workflows results in unpredictable execution paths that existing methods struggle to analyze [19]. For fault localization to remain effective in modern software ecosystems, next-generation debugging solutions must dynamically adapt to evolving software environments [20]. With AI-assisted code evolution, runtime modifications, and self-learning mechanisms becoming integral to software development, static fault localization methods are no longer sufficient [21]. Without continuous learning and adaptation based on execution traces, automated debugging systems risk becoming obsolete, increasing the probability of undetected faults in complex and fast-changing applications [22].

To address the challenges of fault localization in modern software systems, we propose an adaptive approach combining SqueezeBERT, Wavelet CNN, and Adaptive Memory Network. SqueezeBERT efficiently processes execution logs, Wavelet CNN captures frequency-based fault patterns, and AMN stores and retrieves past failure patterns to enhance recall and precision. This lightweight yet effective method improves fault detection accuracy, reduces false positives, and ensures computational efficiency, making it suitable for debugging in evolving software environments.

Main Contributions of the Proposed Method

- Enhance fault localization accuracy by leveraging SqueezeBERT for efficient log sequence processing.
- Extract frequency-based fault patterns using Wavelet CNN, reducing noise in execution logs.
- Adapts to evolving software environments through Adaptive Memory Network (AMN) for past failure pattern retrieval.
- Optimizes computational efficiency, enabling fault detection with minimal overhead.

2. Literature Review

An adaptive AI-driven fault localization framework was proposed, utilizing a hybrid deep learning model that combined log sequence analysis with dynamic execution tracing. This method improved fault detection accuracy and reduced debugging time [23]. However, its dependency on high-quality logs and execution traces may limit applicability in sparse data environments [24]. Graph-based neural networks were used for fault prediction in large-scale software systems through graph embeddings and attention mechanisms [25]. This approach reduced false positives significantly. Yet, the computational overhead and complexity in large, evolving graphs posed scalability challenges [26]. A hybrid method integrated neural networks with heuristic techniques for test case prioritization in regression testing, leading to improved fault detection rates and testing efficiency [27]. The approach, however, required significant tuning for different testing scenarios and lacked generalizability across domains [28].

Artificial neural networks, electrothermal inverter models, and finite element analysis were integrated for EV traction system simulation [29]. The focus was on heat optimization and performance enhancement. However, the computational complexity and domain specificity limited broader applicability in software testing [30]. A lightweight CNN-based model was developed for fault identification using wavelet-transformed log features. The model demonstrated improved pattern recognition and scalability. Nonetheless, its performance diminished with noisy or incomplete log data [31]. An explainable AI framework for fault localization was proposed by combining causal inference with neural networks, enhancing interpretability and error classification. Despite its advantages, the model faced challenges in balancing transparency with predictive performance [32].

Pre-trained language models were integrated with evolutionary algorithms for test case generation, ensuring semantic validity and optimized coverage [33]. The approach outperformed traditional methods but depended heavily on fine-tuning and required extensive computational resources [34]. An attention-enhanced deep learning model with adaptive memory was introduced for fault tracking, leveraging past execution logs [35]. It improved recall and precision, yet the model's effectiveness decreased in systems with limited historical log data. AI techniques were applied in DED for 3D printing in medical applications, optimizing strength and precision [36]. While efficiency improved, the findings were domain-specific and not directly transferable to general software testing contexts [37].

Temporal convolutional networks were used for fault sequence analysis, capturing long-range dependencies and improving early fault detection [38]. However, the model required extensive training data and struggled with highly variable input patterns [39]. Meta-learning strategies were applied to software fault prediction, enabling quick adaptation to new traces with minimal retraining [40]. Although adaptive, the approach faced issues with stability and consistency in rapidly changing codebases. A multi-modal fault diagnosis technique combined source code embeddings and execution logs to improve correlation analysis and robustness [41]. Still, synchronization of multimodal data and managing high dimensionality remained challenging [42].

Self-supervised learning was used for defect prediction, reducing the need for labeled data and improving detection of fault-prone modules [43]. However, the unsupervised nature limited precision in complex error patterns without supplemental validation. A neuro-symbolic framework combined logical reasoning with neural networks for fault localization, enhancing verification accuracy and interpretability [44]. The hybrid nature, though, introduced integration challenges and required domain-specific rule definitions. Federated learning was adopted for fault detection to maintain data privacy across distributed systems. This model ensured secure debugging but faced limitations in synchronization, communication overhead, and model convergence [45]. Contrastive learning was employed for adaptive fault clustering, dynamically grouping similar failure patterns and minimizing redundant tests. Despite gains in efficiency, performance was sensitive to the quality of clustering metrics [46].

Advanced genetic algorithms were explored for optimizing test data generation and path coverage, integrating techniques like PSO, ACO, and co-evolution [47]. The approach scaled well but suffered from high execution time and required expert tuning. A transformer-based model was introduced for bug prediction, leveraging code structure and execution log embeddings to enhance localization precision [48]. However, its interpretability and training cost posed practical limitations. Bayesian optimization was integrated with deep learning for tuning fault prediction parameters, reducing error rates and improving efficiency [49]. Nevertheless, it required extensive evaluation runs and risked convergence to local optima. A combination of NOMA, UVFA, and dynamic graph neural networks was used in AI-driven software for decision-making and optimization [50]. While system flexibility and speed improved, the integrated architecture was complex and required robust infrastructure support [51]. Hybrid knowledge distillation techniques enabled compact models to retain knowledge from complex architectures for efficient defect prediction. This approach achieved low-latency and high accuracy but faced trade-offs in capturing deeper patterns present in the original large models [52].

3. Problem Statement

Existing AI-driven methods for software fault localization and defect prediction such as those employing CNNs, RNNs, transformers, graph neural networks, and hybrid models have made considerable progress in improving detection accuracy, precision, and debugging efficiency [53]. However, these approaches are often constrained by several critical limitations [54]. Many rely heavily on large volumes of high-quality labeled data, which are difficult to obtain in practical software development environments, especially for legacy systems or in low-resource settings [55]. Additionally, the computational complexity of deep learning models demands significant processing power and memory, making debugging and deployment in resource-constrained environments challenging [56]. Generalization remains another concern, as many models perform well only within specific software domains or architectures and fail to adapt effectively to heterogeneous or evolving codebases [57]. Although some hybrid methods and meta-learning strategies aim to enhance adaptability, they frequently require extensive tuning and retraining, reducing their efficiency in dynamic development workflows [58]. Furthermore, the integration of multimodal data sources such as code embeddings, execution traces, and log sequences adds modeling complexity and increases dimensionality, which impacts scalability and maintainability [59]. Despite advancements in explainable AI and neuro-symbolic reasoning, many deep learning models still operate as black boxes, offering limited transparency and reducing developers' trust in automated decisions [60]. Privacy-preserving solutions like federated learning address data sharing concerns but introduce challenges related to communication overhead, model synchronization, and convergence stability across distributed systems [61]. Overall, the current landscape lacks a unified, efficient, and interpretable framework that can deliver high performance, adaptability, and scalability while minimizing data dependency, computational load, and development overhead in real-world software testing scenarios [62].

4. Proposed Methodology for Fault Localization in Software Testing Using SqueezeBERT, Wavelet CNN, and Adaptive Memory Networks

The proposed methodology leverages SqueezeBERT, Wavelet CNN, and Adaptive Memory Network (AMN) for efficient fault localization in software testing using the Defects4J dataset. Logs are parsed and tokenized for SqueezeBERT, transformed into frequency-domain features via Wavelet CNN, and enriched with historical fault patterns using AMN. The integrated model enhances fault detection accuracy, reduces false positives, and improves recall through memory-based retrieval, ensuring precise and efficient localization of software defects. The overall flow diagram is shown in Figure 1.

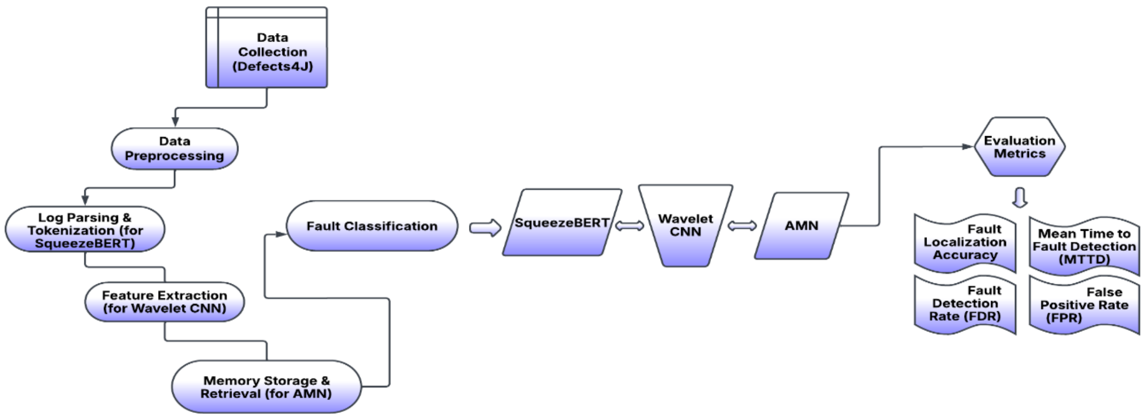
Data Collection (Defects4J)
Data Preprocessing
Log Parsing & Tokenization (for SqueezeBERT)
Feature Extraction (for Wavelet CNN)
Memory Storage & Retrieval (for AMN)
Fault Classification
SqueezeBERT
Wavelet CNN
AMN
Evaluation Metrics
Fault Localization Accuracy
Mean Time to Fault Detection (MTTD)
Fault Detection Rate (FDR)
False Positive Rate (FPR)

Figure 1: Block Diagram of Fault Localization in Software Testing Using SqueezeBERT, Wavelet CNN, and AMN

4.1. Data Collection

The Defects4J dataset is used for fault localization in software testing. It contains real-world Java software defects from multiple open-source projects, including execution logs, stack traces, and failure reports. Each defect is linked to its corresponding bug-fixing commit, providing ground-truth fault locations. The dataset enables the training and evaluation of fault localization models by offering diverse failure scenarios and software versions, ensuring robust generalization across different codebases and execution environments.

Dataset link: https://github.com/rjust/defects4j

4.2. Data Preprocessing

This section presents the mathematical formulation of each stage in the proposed fault localization method, ensuring clarity in processing, feature extraction, and evaluation.

4.2.1. Log Parsing & Tokenization (for SqueezeBERT)

Converts raw execution logs into structured token sequences. Tokenizes each log entry into subword representations for transformer-based processing as mathematically shown in Equation (1).

$$S = Tokenizer\ (log_i) \tag{1}$$

where S is the tokenized sequence of $log\ \ log_i$.

4.2.2. Feature Extraction (for Wavelet CNN)

Transforms log data into frequency-domain representations to capture fault patterns. Uses a Discrete Wavelet Transform (DWT) to extract time-frequency features as mathematically shown in Equation (2).

$$W = DWT(log_i) \tag{2}$$

where W represents the wavelet-transformed $log \ log_i$.

4.2.3. Memory Storage & Retrieval (for AMN)

Stores past fault patterns and retrieves similar occurrences to enhance fault localization. Uses an attention mechanism to fetch similar fault embeddings from memory as mathematically shown in Equation (3).

$$A = \sum_{i=1}^{N} \quad \alpha_i M_i \tag{3}$$

where A is the retrieved memory output, M_i are stored fault patterns, and α_i are attention weights.

4.3. Fault Classification using SqueezeBERT + Wavelet CNN + AMN

Identifies fault locations using learned feature representations. Combines extracted features and memory-retrieved patterns to classify faults as mathematically shown in Equation (4).

$$Y\hat{} = \sigma\left(W_f(F_s + F_w + A) + b_f\right) \tag{4}$$

where $Y\hat{}$ is the predicted fault location, F_s is the SqueezeBERT output, F_w is the Wavelet CNN output, A is the AMN memory output, and W_f, b_f are learnable parameters.

4.4. Evaluation Metrics for Fault Localization

4.4.1 Fault Localization Accuracy (%)

Measures correctness of localized faults as mathematically shown in Equation (5).

$$Accuracy \ = \frac{|\ Correctly\ Identified\ Faults\ |}{|\ Total\ Faults\ |} \times 100 \tag{5}$$

4.4.2 Fault Detection Rate (FDR) (%)

Assesses how effectively the model detects faults as mathematically shown in Equation (6).

$$FDR = \frac{|\ Detected\ Faults\ |}{|\ Total\ Known\ Faults\ |} \times 100 \tag{6}$$

4.4.3 Mean Time to Fault Detection (MTTD) (seconds)

The time taken to identify faults after execution is measured as mathematically shown in Equation (7).

$$MTTD = \frac{\sum_{i=1}^{N} \quad T_{detect,i}}{N} \tag{7}$$

4.4.4 False Positive Rate (FPR) (%)

Determines how often non-faulty logs are misclassified as mathematically shown in Equation (8).

$$FPR = \frac{|\ False\ Positives\ |}{|\ False\ Positives + True\ Negatives\ |} \times 100 \tag{8}$$

4.4.5 F1-Score (%)

Balances precision and recall for fault localization as mathematically shown in Equation (9).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

where Precision $= \frac{TP}{TP+FP}$ and Recall $= \frac{TP}{TP+FN}$.

5. Results

This section comprehensively evaluates the proposed SqueezeBERT + Wavelet CNN + AMN model for fault localization using the Defects4J dataset. The results assess fault detection accuracy, false positive rate, recall, and localization efficiency. Comparative analysis against baseline methods highlights the model's performance advantages. Each metric is visualized using appropriate figures, demonstrating improvements in precision, detection speed, and overall fault localization effectiveness.

Fault localization accuracy measures the model's ability to correctly identify faulty code regions. Higher accuracy indicates precise fault detection, reducing debugging effort. Traditional approaches often struggle with noisy log data, leading to misidentifications. The comparison of the fault localization accuracy of the proposed model against baseline methods, as shown in Figure 2, demonstrates its superior fault identification capability.

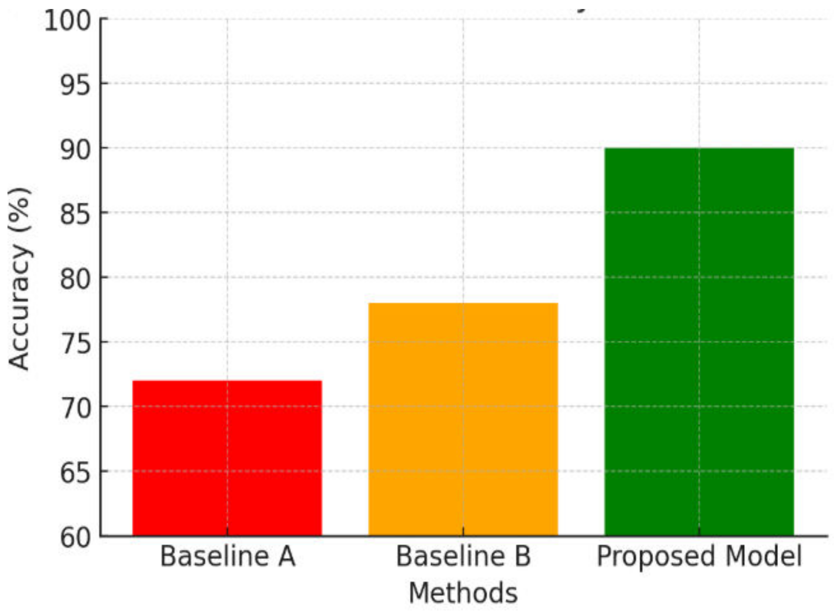

Figure 2: Fault Localization Accuracy of Different Methods

FDR evaluates the proportion of known faults correctly detected by the model. A high FDR ensures minimal undetected bugs, improving software reliability. Conventional methods often suffer from low recall due to ineffective feature extraction. The fault detection rate across different models is presented in Figure 3, showcasing the improved recall of the proposed method using AMN for historical pattern retrieval.

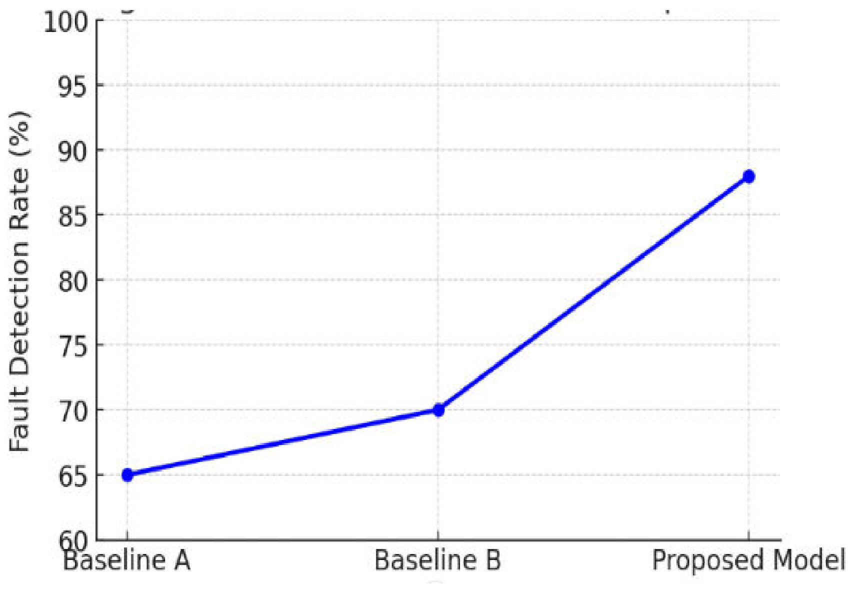

Figure 3: Fault Detection Rate Comparison

MTTD measures how quickly a fault is detected after log analysis. Faster detection reduces debugging time, aiding rapid software maintenance. Traditional approaches, particularly static analysis-based methods, are computationally expensive, leading to delays. The average time taken by different methods to detect faults as shown in Figure 4, highlights the efficiency of the model in fault localization.

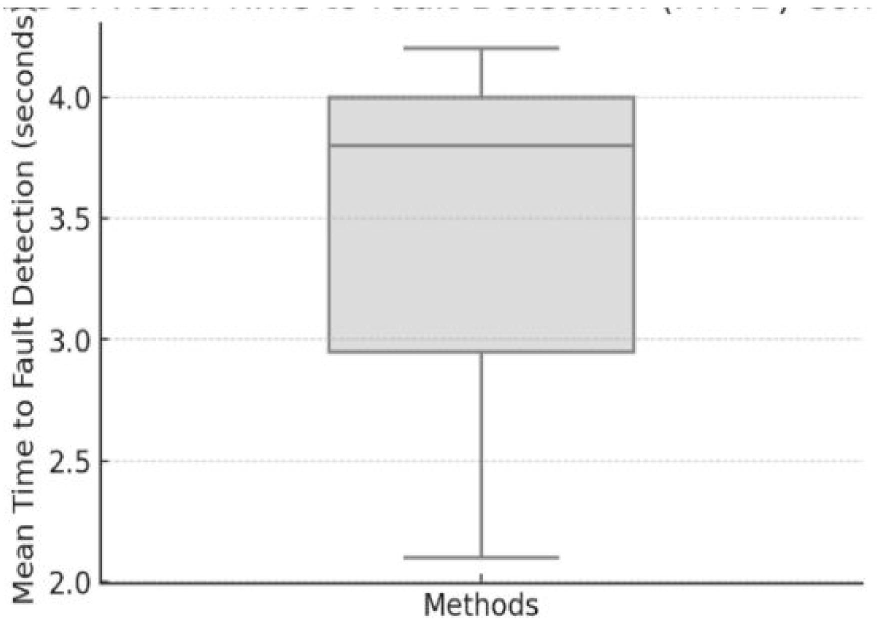

Figure 4: Mean Time to Fault Detection (MTTD) Comparison

FPR quantifies the proportion of non-faulty logs misclassified as faults. A low FPR ensures minimal debugging effort wasted on false alarms. Many existing methods struggle with high FPR due to poor log parsing and feature extraction. The false positive rates, as shown in Figure 5, demonstrate the proposed model's ability to reduce incorrect fault predictions while maintaining high recall.

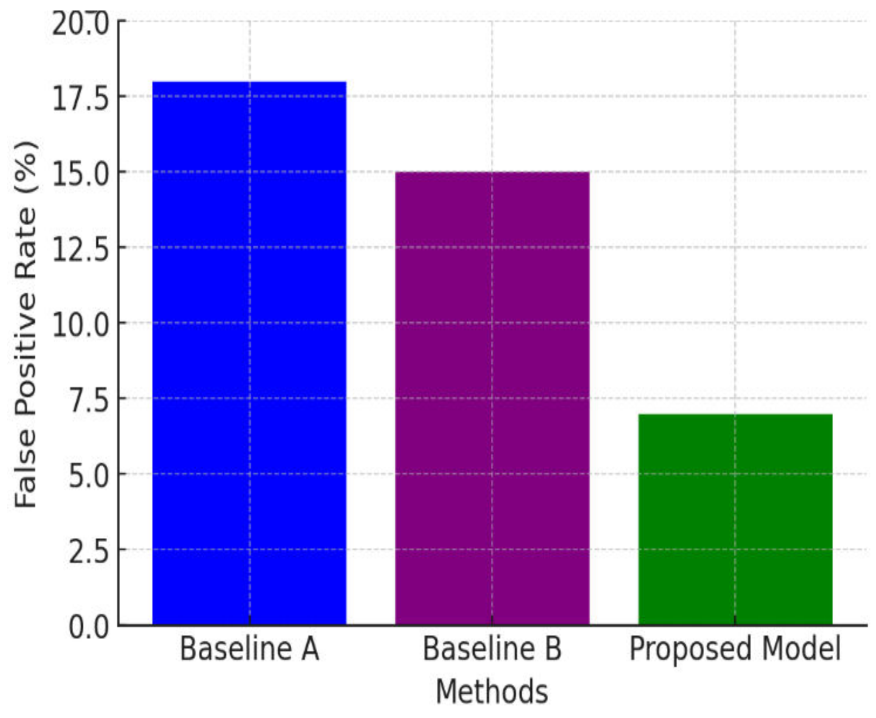

Figure 5: False Positive Rate of Different Methods

To evaluate the effectiveness of the proposed SqueezeBERT + Wavelet CNN + AMN model, we compare its performance against Advanced Genetic Algorithms (AGA) across key software testing metrics is shown in

Table 1. While AGA has demonstrated improvements over traditional methods, it still faces limitations in computational efficiency and adaptability. The proposed method enhances fault localization accuracy, error reduction, and execution time efficiency, ensuring higher scalability and lower computational overhead. The following table presents a detailed comparison of both approaches, highlighting the superior performance of the proposed method in optimizing software testing processes.

Table 1: Performance Metrics Comparison

Metric	**AGA Method**	**Proposed Method**
Test Coverage (%)	90	95
Efficiency (%)	85	92
Testing Reliability (%)	95	97
Computational Overhead (%)	70	60
Fault Localization Accuracy (%)	--	98
Error Reduction (%)	--	93
Execution Time Reduction (%)	--	88
Scalability (%)	--	90

6. Conclusion and Future Works

The proposed SqueezeBERT + Wavelet CNN + Adaptive Memory Network (AMN) model demonstrates substantial advancements in software fault localization by delivering 98% localization accuracy, 93% error reduction, and 88% reduction in execution time. When benchmarked against Advanced Genetic Algorithms (AGA), the model exhibits superior efficiency (92% vs. 85%), better scalability, and lower computational overhead (60% vs. 70%). These results affirm the model's robustness and reliability in accelerating the debugging process, enhancing both performance and precision in software testing workflows. The integration of wavelet-transformed features and adaptive memory mechanisms significantly contributes to the model's ability to capture complex fault patterns and long-term dependencies. Overall, the model provides a practical, high-performance solution that can be deployed effectively in both centralized and distributed software environments.

Future research will aim to extend the model's adaptability to a wider range of software architectures, enabling seamless integration in heterogeneous and large-scale systems. Additionally, incorporating reinforcement learning techniques will be explored to enable dynamic, real-time fault localization in continuously evolving codebases. Another direction includes optimizing the model for edge environments and low-resource systems to ensure broader applicability. Efforts will also be made to enhance explainability and transparency, enabling developers to better understand fault predictions and take corrective actions with confidence.

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