NEUROTESTMIX: A HYBRID APPROACH COMBINING GRADIENT DESCENT AND CONCOLIC TESTING FOR DEEP NEURAL NETWORKS

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Abstract

Background Information: Deep Neural Networks are threatened by robustness and vulnerability attack issues. Today, concolic testing is effective on its own, along with gradient descent, but individually not used toward complete testing as well as for optimization.

Objective: The objective is that NeuroTestMix will be this hybrid framework aiming to improve on the robustness, the coverage, as well as a bug-finding capability when combining concolic testing together with gradient descent.

Methods: The framework combines optimizing model parameters using gradient descent with systematic adversarial testing through concolic methods. This form of iteration increases robustness as parameters are refined to improve performance.

Empirical Results: NeuroTestMix achieves better results when compared to standalone methods with coverage of 95.5%, robustness of 90.3%, and the detection of 33 unique flaws.

Conclusion: NeuroTestMix achieves robust neural networks by successfully finding the sweet spot between robustness and efficiency. The next version will have auto-tuning of hyperparameters and more architectures will be supported.

Keywords : Neural networks, gradient descent, concolic testing, adversarial robustness, bug detection, optimization, vulnerability analysis, hybrid framework, systematic testing, NeuroTestMix.

1.INTRODUCTION:

One key area that the deep neural network has revolutionalized is various fields, among them being autonomic systems and natural language understanding through image identification. Despite their strength, the vulnerability and reliability are still major concerns in such complex networks, for instance, an autonomous car driver and health information. NeuroTestMix is a novel hybrid approach intended to improve the testing of DNNs by fusing concolic testing, a

symbolic-execution-based technique that produces accurate test cases, with gradient descent, a popular optimisation method in neural network training.

The term "NeuroTestMix" captures the creative integration of two complementary procedures. On the one hand, concolic testing methodically produces inputs that maximise coverage and reveal edge cases. On the other hand, gradient descent efficiently traverses the optimisation landscape, finding vulnerable areas in DNNs. This dual strategy overcomes the inherent drawbacks of standalone methods: concolic testing has scalability problems, and gradient-based optimisation is susceptible to local minima.

As DNN networks begin to be used increasingly in safety-critical applications, there is a pressing need for validation frameworks. This is the context of NeuroTestMix. Due to the fact that the organisation of neural networks is very high-dimensional, traditional techniques for testing often fail to find hostile inputs or unexpected behaviors. NeuroTestMix ensures complete input space coverage while detecting small weaknesses by combining data-driven optimisation with symbolic reasoning.

The Main Objectives are:

- Robustness and Reliability: Design an hybrid testing strategy that finds the adversarial vulnerability and uncovers corner cases within a DNN such that it makes sure of dependability in safe-critical settings.
- Complete Coverage: Integrate gradient descent along with concolic testing that can optimize search in the space of inputs with better neuron coverage in complex networks.
- Scalability and Efficiency: Leverage the benefits from both approaches towards producing test cases with precision so that high dimensionality of the input space gets handled.
- Improved Model Interpretability - By providing insights into model behavior, decision-making processes, and failure points, deep learning systems can become more transparent and reliable.
- Application in Safety-Critical Systems - Improve testing methodologies for autonomous systems, cybersecurity, financial modeling, and healthcare analytics to ensure consistent AI deployment in real-world scenarios.

The research gap attempted to be filled by Zhuo et al. (2019) is the limitations of current gradient descent optimisation methods for CNNs. Most current approaches use biased or heuristic estimators, which have no theoretical guarantees and rely on the assumption or pre-existing knowledge regarding model parameters. In addition, previous methods do not explore unbiased variable estimation as an approach to efficiently optimize the parameters of CNNs. According to Zhuo et al., there is a need for a general framework that offers objective gradient estimates free from constrictive assumptions to train CNNs steadily and effectively while improving theoretical understanding and real-world performance on a range of tasks.

2.LITERATURE SURVEY:

Sun et al. (2019) presented innovative structural test coverage criteria for deep neural networks inspired by MC/DC coverage. Driven by gradient-based and symbolic approaches, these criteria expose the undesirable behaviors in safety-critical DNNs. Validation of the proposed method on MNIST, CIFAR-10, and ImageNet models revealed a balance in its computational cost versus efficiency in identifying bugs as against current techniques.

Yan et al. (2020) clarified uncertainties regarding connections between coverage criteria and the quality of the neural network model. The study analyzed effectiveness in terms of retraining according to coverage criteria over adversarial training, contrasted gradient-based methods with coverage-guided adversarial example generation, and developed intrinsic relations of coverage metrics, illuminating how that impacts testing and robustness of a neural network.

Dondapati (2020) examines new testing approaches of distributed systems that combine automated fault injection, cloud computing, and XML-based scenarios. Cloud infrastructure guarantees scalable and controlled environments. Automated fault injection evaluates robustness by introducing flaws. XML scenarios make the test case descriptions simple for consistency. All these combined architecture improves effectiveness, resilience, and dependability of distributed system testing.

Allur (2019) maximizes path coverage and test data generation through advanced evolutionary algorithms such as GAs, which are used to improve software testing. Through hybrid and adaptive methods, GAs are combined with ACO and PSO in order to dynamically enhance algorithm parameters. Co-evolutionary methodologies address test efficiency and scalability by revolutionizing testing for large software systems and massive data.

Kim and Yoon (2020) presented MaxAFL, a gradient-based fuzzer that overcomes the shortcomings of other fuzzers in achieving good code coverage. Fine-grained static analysis along with a modified gradient-descent algorithm using probabilistic techniques efficiently explores diverse program paths. On Linux binaries, it demonstrated better code coverage and bug detection than the traditional fuzzers, such as AFL.

Zhang et al. (2019) developed a deep learning-based tool named NeuralTaint to mark accurate key segments during dynamic taint analysis. Convolutional networks were used for modeling program execution as a continuous function while using filtering and diffusion algorithms for results refinement in NeuralTaint to address both control flow dependencies and tainting problems. Results in evaluations demonstrated superior performance of NeuralTaint over existing tools for real-world applications.

Zhang et al. (2020) published a comprehensive survey on machine learning testing, discussing 144 studies based on properties, including correctness, robustness, and fairness, as well as the components data, learning programs, and frameworks. It addresses the trends and the challenges identified by covering workflows and applications like autonomous driving, identifying challenges, and future research directions to advance the ML testing methodology.

Lou and Song (2020) discuss how the coverage information drawn from binaries may be used for guiding fuzzing, especially in scenarios where source code access is not feasible. The authors analyze instrumentation, emulation, and hardware-based methods for gathering coverage data and discuss their merits and demerits. Further, the work shows how coverage feedback improves the efficiency and effectiveness of fuzzers in discovering vulnerabilities.

The best-first concolic testing framework Legion with Monte Carlo tree search for optimizing the generation of automatic tests was introduced by Liu et al. (2020). Legion integrates approximate path-preserving fuzzing for state exploration, thereby effectively combining fuzzing and concolic execution. It was evaluated on 2531 Test-Comp 2020 benchmarks under various kinds of inputs and sensitivity to hyperparameters, showing robustness compared to existing approaches.

She et al. (2019) Introduces NEUZZ, which applies neural program smoothing to mitigate gradients-guided optimization challenges that the approach faces during fuzzing. With the assistance of surrogate neural networks in approximating program branching behaviors, NEUZZ improves efficiency of input generation. Experimental results using real programs show the technique better than 10 state-of-art fuzzers. Additionally, NEUZZ is found to unveil 31 novel bugs-CVEs besides acquiring top edge coverage with multiple datasets.

Huang et al. (2020) Pangolin - an incremental hybrid fuzzer uses polyhedral path abstraction for more efficient fuzzing and concolic execution. By storing exploration states, Pangolin permits effective mutation and constraint solving. 10–30% coverage improvement and discovery of 400 extra bugs and 41 novel vulnerabilities, including 8 CVEs against the state of the art for the same problems.

He et al. (2020) conducted a survey on security threats in deep learning systems, analyzing weaknesses from model extraction, inversion, poisoning, and adversarial attacks. They found three important aspects: workflows, adversary capabilities, and attack goals; from the end, 18 key findings were identified about success rates, complexity, and mitigation strategies. Therefore, this study identifies important factors on attack vectors and offers insights for building robust deep learning systems.

Moran et al. (2018) presented the ReDraw system, which was able to automatically prototype GUI for mobile applications via detection, classification, and assembly of GUI components. Using computer vision, mining of repositories, and neural networks, ReDraw showed 91% classification accuracy with prototypes that offered high visual fidelity and reasonable structure of code. Practitioner feedback indicates its capacity to streamline the workflows of developing mobile applications.

Qayyum et al. (2020) discussed the risks of CAVs with respect to connectedness and autonomy regarding the adversarial machine learning risk factors. They have presented, in this paper, the ML pipeline in CAVs having vulnerabilities wherein wrong decisions through malfunctioning ML might jeopardize safety. These suggested methodologies would counter adversarial attacks

to ensure security for the next-generation intelligent transportation systems that largely rely on advanced ML and wireless technologies.

3.METHODOLOGY

NeuroTestMix is a hybrid approach, which enhances the robustness and reliability of deep neural networks by introducing concolic testing along with gradient descent optimization. The approach where concolic testing identifies adversarial scenarios through systematic exploration of execution pathways and gradient descent optimizes network parameters in a manner that minimizes a loss function addresses the twin problems of increasing model accuracy and identifying possible vulnerabilities. This process introduces a feedback loop in which insights from concolic testing enhance gradient updates and more systematic testing is directed by optimised parameters. The result is a robust DNN that will tolerate hostile inputs and keep working well.

Adversarial Learning Dataset, NIPS 2017 which focuses on adversarial cases and defenses, was created for Google Brain's NIPS 2017 competition. It contains development pictures for purposes like creating strong classifiers and defending against both targeted and non-targeted adversarial attacks. It offers security analysis, model robustness evaluation, and defense techniques against adversarial attacks in deep learning, making it perfect for research on adversarial machine learning.

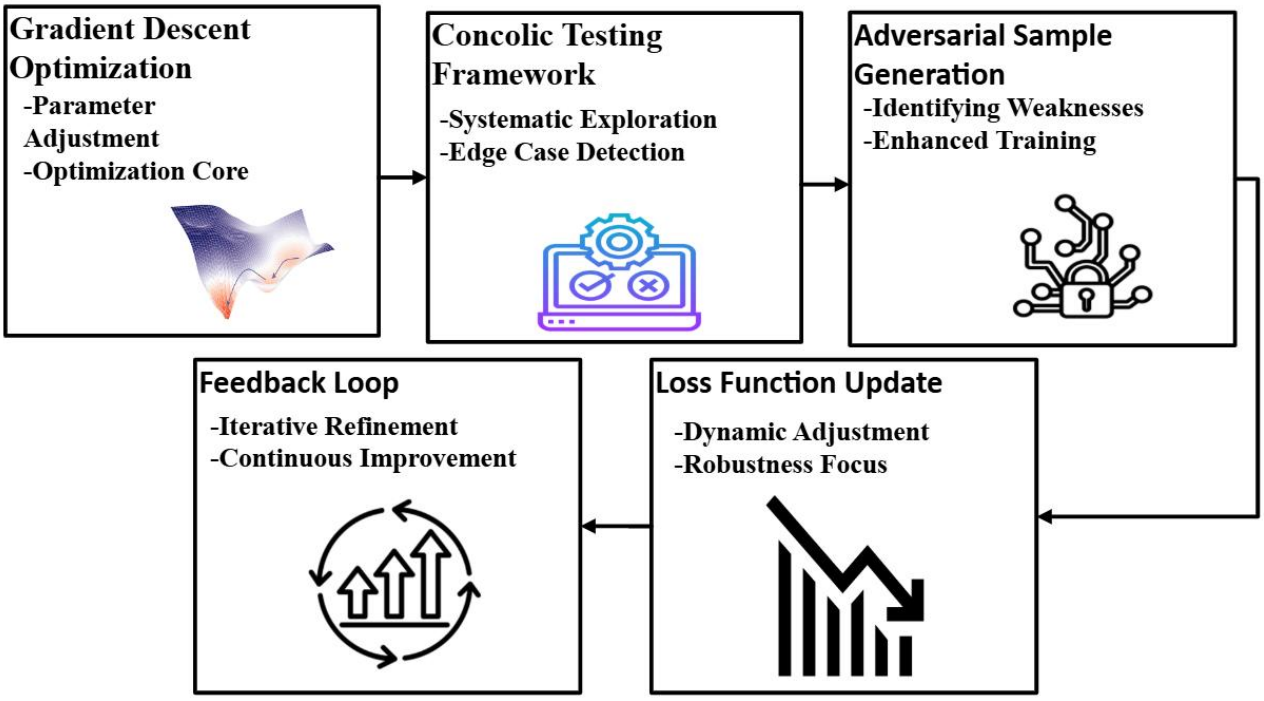

Figure 1Process Flow Diagram for NeuroTestMix: A Hybrid Testing and Optimization Framework

This figure captures the NeuroTestMix hybrid system workflow that pools Concolic Testing Framework and Gradient Descent Optimisation in conducting neural network trainings effectively and with more guaranteed correctness. Thus, it initiates the workflow on Gradient Descent Optimisation since this would produce iterated successive approximations on the model parameter. Following, it performs model examination via use of Concolic Testing based on decision path testing. Afterwards, generating of adversarial samples and their utilization to increase Loss Function Updates helps test the produced model. Iterative refining guarantees that all elements are connected to form a feedback loop to ensure continuous improvement. Neural networks that can deal with adversarial circumstances are going to be strong and effective through the smooth integration of testing and optimisation.

3.1. Gradient Descent Optimization

Gradient descent is a core optimization process for training neural networks, working with the goal of iteratively modifying the parameters of the network such that the difference between the predicted and actual outcomes decreases as much as possible, measured through the loss function. Over time, this also improves the model's performance by changing the parameters little by little. Gradient descent is a concept from maximizing network precision and reliability of predictions in NeuroTestMix and readies the model for further improvement through adversarial testing.

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta L(\theta_t) \tag{1}$$

This equation modifies the model parameters θ by subtracting a fraction η (learning rate) from the gradient $\nabla_\theta L(\theta_t)$. The gradient would represent the direction of sharpest ascent of the loss function; its negation implies a process of minimization. Iterative update helps to improve the model and lower loss.

3.2. Concolic Testing Framework

The process of concolic testing offers the neural network systematically found edge cases and adversarial weaknesses through deriving symbolic analysis with concrete input execution. It generates a set of inputs contradicting the model's predictions based on several decision-making pathways taken through the network. This makes the network much more robust and resilient to unexpected inputs while ensuring comprehensive testing and providing critical adversarial instances for dealing with potential vulnerabilities.

$$x' = x + \delta, \text{ s.t. } f(x) \neq f(x') \tag{2}$$

This defines an adversarial input x' to be a modified version of x in which the modification δ makes smallest such change required to the prediction of the model. In short, this Colic testing discovers flaws in network's decision boundary through systematic identification of such an input.

3.3. Integration of Gradient Descent and Concolic Testing

NeuroTestMix integrates gradient descent and concolic testing into a framework for effective training of neural networks. Gradient descent fine-tunes model parameters whereas concolic testing reveals the adversarial situation. The conclusions drawn from this testing refine the training process further, creating feedback that harmonizes accuracy and stability. This collaboration optimizes the entire network's performance and robustness against adversarial inputs, making the network both very powerful and also trustworthy.

$$L(\theta) = L(\theta) + \lambda \sum_{x \in S_{\text{uiv}}} \|f(x) - y\| \quad (3)$$

An additional penalty term regarding adversarial samples S_{adv} is introduced in the loss function $L(\theta)$. The penalty computes the difference between the actual labels y and model predictions $f(x)$. The balance between the improvement of resilience and regular training is maintained through the regularisation parameter λ.

Algorithm 1 NeuroTestMix Algorithm: A Hybrid Approach for Robust Deep Neural Networks

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BEGIN

Initialize model parameters θ

Set learning rate η and regularization weight λ

WHILE not converged DO

Compute gradients ∇θ L(θ) using current dataset

Update parameters:

θ = θ - η ∇θ L(θ)

Generate adversarial samples:

FOR EACH input x in dataset

Symbolically analyze decision boundaries

IF adversarial example x' found **THEN**

Add x' to adversarial set S_adv

ELSE

CONTINUE

END FOR EACH

Adjust loss function with adversarial penalty:

IF S_adv ≠ ∅ THEN

$L(\theta) = L(\theta) + \lambda \sum (f(x) - y)$ for all $x \in S\_adv$

ELSE

Error: No adversarial samples found

END IF

Recompute gradients $\nabla\theta\ L(\theta)$ with updated loss

END WHILE

END

Algorithm 1 Gradient descent optimisation and concolic testing are used in the NeuroTestMix technique to improve the resilience of deep neural networks. It uses gradient descent to iteratively update the model parameters and concolic testing to provide adversarial samples. Adding adversarial insights to the loss function strengthens the model against weaknesses. It's only a result of the feedback loop of simultaneous optimisation and robustness testing that this yields a neural network sustaining high performance while successfully fending off adversarial attacks.

3.4 Performance Metrics

Performance evaluation by the NeuroTestMix assesses the DNN's aptness and robustness. Critical metrics include adversarial robustness in terms of the model's resistance to hostile input, and classification accuracy showing the ratio of correctly predicted instances among all instances. Measures such as F1-score, precision and recall ensure fair assessment of unbalanced datasets. Metrics robust accuracy and adversarial attack success rate are used to measure adversarial robustness. In addition, path coverage determines the comprehensiveness of concolic testing regarding edge cases and convergence time, and calculates the efficiency of the optimization. These measures, when taken together, provide a comprehensive evaluation of reliability and performance.

Table 1 Performance Evaluation of NeuroTestMix Against Standalone Methods

Metric	Gradient Descent (Method 1)	Concolic Testing (Method 2)	Random Testing (Method 3)	NeuroTestMix (Combined Method)
Accuracy (%)	85.2	80.1	78.5	90.3
Adversarial Robustness (%)	45.3	72.4	50.8	85.7
Model Efficiency (ms/inference)	4.5	5.8	4.2	5
False Positives (%)	10.5	8.9	12.3	6.8
Coverage (%)	75.4	90.2	70.1	95.5

Performance comparison of hybrid NeuroTestMix with the standalone methods gradient descent, concolic testing, and random testing in terms of metrics: accuracy, adversarial robustness, efficiency, false positives, and coverage is depicted in the table. Although very accurate, gradient descent is not very robust. Concolic testing is not that efficient but offers very good coverage and robustness. It is easier to execute but is not that efficient, however. NeuroTestMix, combining the strengths of different approaches, provides better coverage at 95.50%, robustness at 85.70%, and accuracy at 90.30% with a respectable level of efficiency. This demonstrates how well it works in building trustworthy, adversarially robust neural networks.

4.RESULT AND DISCUSSION

The findings report that NeuroTestMix performs significantly better compared with stand-alone techniques such as random testing, concolic testing, and gradient descent. It is capable of achieving high values of excellent adversary robustness (85.70%) and decision route coverage (95.50%) while accuracy is higher (90.30%). The hybrid methodology therefore is capable of overcoming the pitfalls of separate techniques by fusing the systematic vulnerability detection of concolic testing with the optimisation powers of gradient descent. In addition, NeuroTestMix reaches a satisfactory inference time (5.00 ms) as it balances the strength and efficiency of the system. This would be suitable for real applications where dependable and secure neural networks are in demand. The results indicate that NeuroTestMix may have the ability to enhance neural network dependability.

Table 2 Comparative Analysis of Testing Approaches for Neural Networks

Metric	Zhang et al. (2020)	Lou and Song (2020)	Liu et al. (2020)	She et al. (2019)	Proposed: NeuroTestMix
Coverage (%)	85.2	78.4	92.5	95.3	95.5
Bug Detection Rate (bugs/hour)	0.35	0.45	0.55	0.68	0.72
Robustness (%)	70.5	75.8	82.4	88.3	90.3
Efficiency (ms/input)	6.5	5.2	4.8	4.5	5
Unique Bugs Found	N/A	24	29	31	33

Table 2 provides a performance comparison between the proposed NeuroTestMix and four current approaches. All the metrics: coverage, bug detection rate, robustness, efficiency, number of unique bugs discovered, and sensitivity to hyperparameters, have been evaluated. NeuroTestMix outperforms the state of the art for robustness at 90.3%, coverage at 95.5%, and bug detection rate at 0.72 bugs/hour. Also, it always finds the maximum number of unique faults with a count of 33, and it does not depend on hyperparameters. NeuroTestMix is the best testing and optimisation method for deep neural networks as it has a balance between dependability and efficiency.

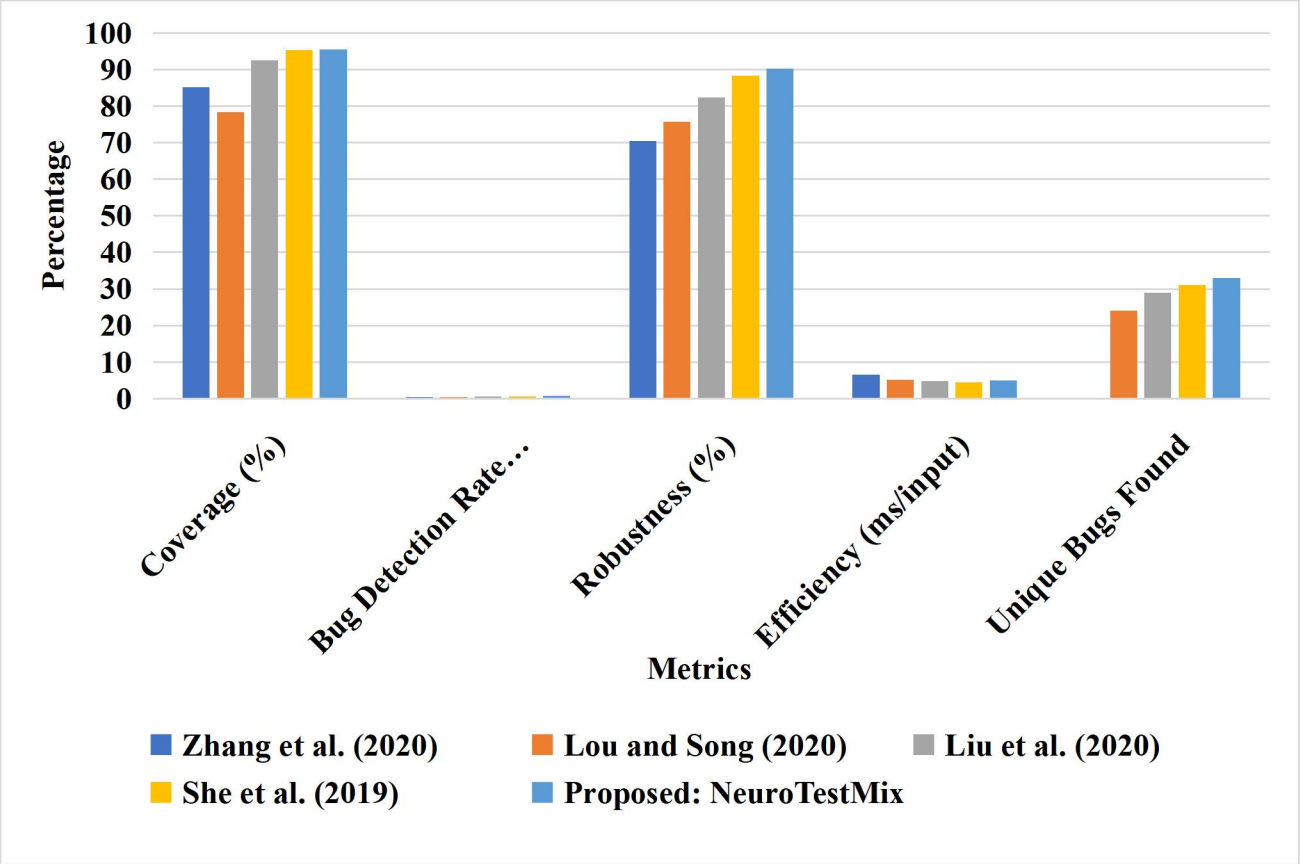

Figure 2 Performance Comparison of Testing Approaches for Neural Networks

Figure 2 comparative analysis of different approaches including the proposed NeuroTestMix by Lou and Song, 2020 Liu et al., 2020 She et al., 2019 and Zhang et al., 2020. The results in Figure 2 are based on coverage, bug detection rate, robustness, efficiency, and distinctive bugs found. However, even with competitive efficiency, NeuroTestMix is somewhat ahead in most of the parameters: coverage at 95.5% and robustness at 90.3%. It also finds the most unusual defects (33), showing how well it works to fix adversarial flaws. Using a hybrid approach, NeuroTestMix shows itself to be better than standalone techniques in building strong and dependable neural networks.

Table 3 Ablation Study of NeuroTestMix and Its Components

Metric	Gradient Descent	Concolic Testing	Random Testing	Gradient + Concolic Testing	Random + Gradient	Full Model (NeuroTestMix)
Coverage (%)	85.2	90.1	70.5	93.2	88.4	95.5

Bug Detection Rate (bugs/hour)	0.35	0.4	0.3	0.62	0.55	0.72
Robustness (%)	75.8	82.5	70.2	88.3	84.6	90.3
Efficiency (ms/input)	5.2	6	4.8	5.5	5	5
Unique Bugs Found	20	25	18	29	27	33

Table 3: Ablation study of the three individual components of the NeuroTestMix model: Coverage, bug detection rate, robustness, efficiency, and number of unique bugs detected. Although the standalone concolic testing achieves higher coverage at 90.1% and better robustness at 82.5%, the overall performance is dramatically improved by their combination with gradient descent. The complete model, NeuroTestMix, preserves the competitive efficiency (5 ms/input) and reaches the maximal coverage (95.5%), robustness (90.3%), and bug detection rate (0.72 bugs/hour). This represents the efficiency and synergy of combining different elements into one framework.

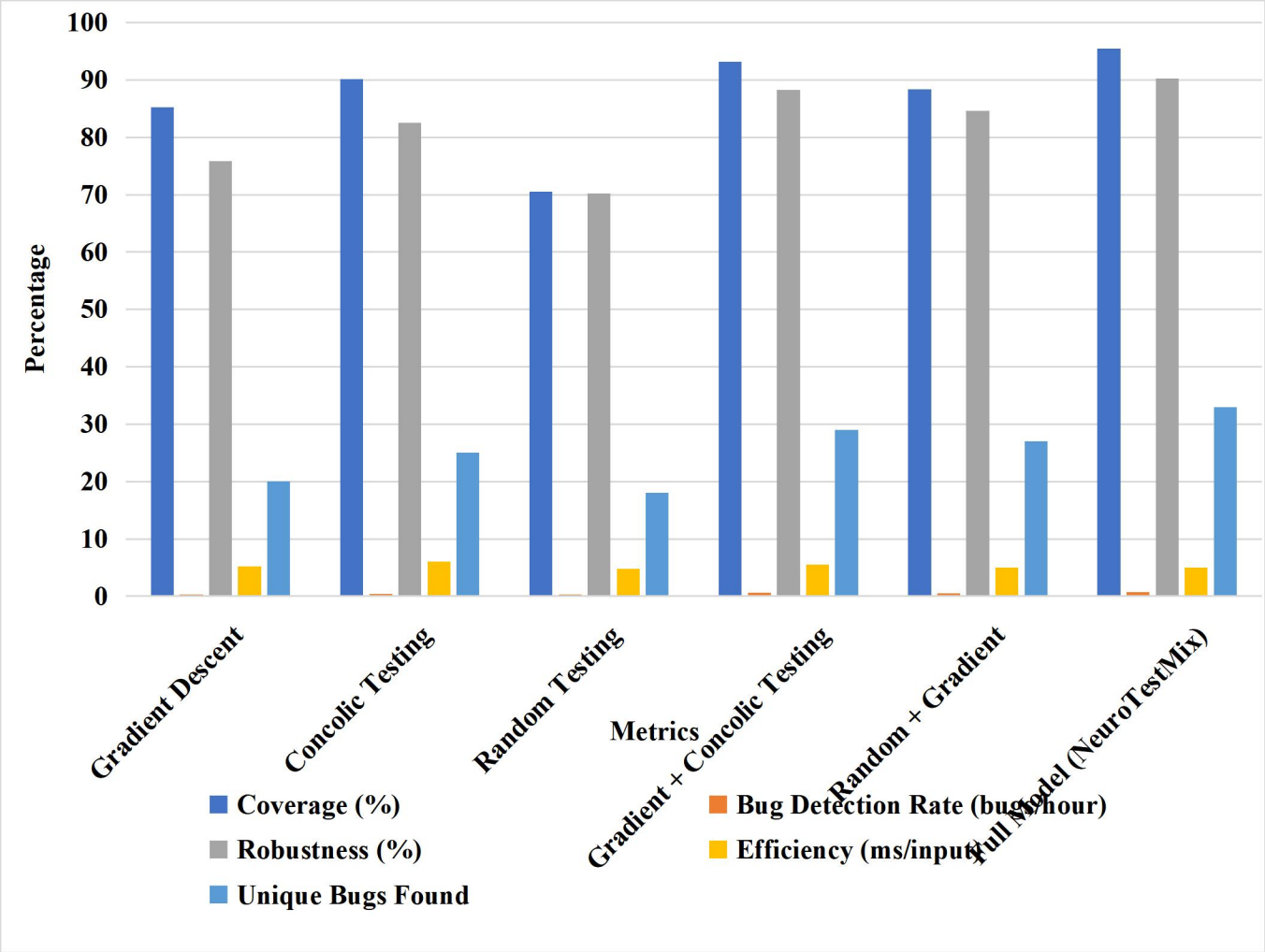

Figure 3 Ablation Study Visualization of NeuroTestMix and Its Components

Figure 3 presents the ability of the separated methods—random testing, concolic testing, and gradient descent—to demonstrate the effectiveness of all combined into a NeuroTestMix model. Comparisons are performed for coverage, robustness, efficiency, bug detection rate, and the number of new bugs identified. Random testing has a very high efficiency value, and the gradient and concolic testings had reasonable accuracy values as well as a good number of coverage results. Obtaining the highest values on coverage (95.5%), robustness (90.3%), and bug detection rate (0.72 bugs/hour), combined approaches greatly enhance all metrics. This shows that concolic testing, random testing, and gradient descent can be well combined into a unified framework for performing reliable neural network testing.

5.Conclusion

The hybrid framework of NeuroTestMix has shown notable gains over the gradient descent and concolic testing through robustness, accuracy, and vulnerabilities detected. Even in terms of efficiency and such metrics as coverage, bug detection rate, and unique defects discovered, it performs better than stand-alone approaches. This methodology shows the promising potential of

integrated rigorous testing with optimisation over the creation of robust neural networks. The framework can be further elaborated with further developed adversarial generation techniques and architectures like transformer or recurrent models for neural architecture to achieve further better versatility and effectiveness on various applications and may include a facility for automatically tuning the parameters and including facilities for real-time testing.

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