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Genetic Algorithm Based Neural Network Architecture Search with DQN (GANAS with DQN) for Enhancing Detection of Zero Day Attacks in Cyber Threat Prone Environment

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In cyber threat prone environments, the detection of zeroday attacks remains a paramount challenge due to their unprecedented nature. Traditional detection methods often falter in identifying such threats, necessitating innovative approaches. In this study, we propose a novel strategy that amalgamates Genetic Algorithm for Neural Network Architecture Search (GANAS) with Deep QNetworks (DQN) to bolster the detection of zeroday attacks. GANAS optimizes the architecture of neural networks for intrusion detection, while DQN facilitates dynamic learning and adaptation to evolving attack patterns. Through experimentation in simulated cyberthreat environments, our approach demonstrates superior accuracy and resilience in zeroday attack detection compared to conventional methods. Specifically, our approach achieves an average detection accuracy of 95% on a diverse set of zeroday attack scenarios, outperforming baseline methods by 15%. Additionally, the false positive rate is reduced by 20%, indicating improved robustness against false alarms. This research contributes to the advancement of cybersecurity defenses in confronting emerging threats in volatile environments.

Keywords: Zeroday attacks, Genetic Algorithm, Neural Network Architecture Search, Deep QNetworks, Cybersecurity, Threat Detection.

1. Introduction

Cybersecurity is a critical concern in today's digital age, with organizations facing an

everincreasing number of cyber threats. Among these threats, zeroday attacks stand out as particularly challenging. Zeroday attacks exploit vulnerabilities that are previously unknown to security experts or software vendors, making them difficult to detect and mitigate effectively [1]. Traditional cybersecurity measures, such as signature based intrusion detection systems (IDS), are often insufficient in detecting zeroday attacks due to their reliance on known patterns and signatures [2].

1.1 Machine Learning in Cybersecurity

In recent years, machine learning techniques have emerged as promising tools for augmenting traditional cybersecurity measures. These techniques, particularly those based on deep learning, have demonstrated the ability to learn complex patterns and features directly from data, enabling more effective detection of cyber threats [3]. However, designing optimal neural network architecture for intrusion detection remains a challenging task, requiring careful consideration of various factors such as network topology, layer sizes, and activation functions [4].

1.2 The Rising Threat of ZeroDay Attacks

In today's hyperconnected world, where digital infrastructure underpins critical aspects of society, cybersecurity has emerged as a paramount concern. Among the myriad of cyber threats, zeroday attacks pose a particularly menacing challenge. Zeroday attacks exploit vulnerabilities in software or hardware that are unknown to the vendor or have not yet been patched. These attacks are especially insidious as they can occur without warning, leaving organizations vulnerable to significant breaches and data exfiltration [1].

1.3 The Imperative for Advanced Detection Techniques

Traditional signature-based detection systems struggle to cope with zeroday attacks due to their reliance on known patterns. Consequently, there has been a growing interest in developing advanced detection mechanisms that can proactively identify and mitigate these threats. Machine learning (ML) techniques, particularly neural networks, have shown promise in this regard by enabling the detection of anomalous patterns indicative of zeroday attacks [2].

1.4 Challenges in Neural Network Architecture Design

While neural networks offer a powerful framework for detecting zeroday attacks, designing an optimal architecture remains a nontrivial task. The performance of a neural network is highly dependent on its architecture, including the number of layers, the type of activation functions, and the connectivity patterns. However, manual design of neural network architectures is timeconsuming and often suboptimal. Additionally, the vast search space of possible architectures presents a formidable challenge for automated methods [3].

1.5 Genetic-Based Neural Network Architecture Search

To address the limitations of manual and exhaustive search methods, genetic algorithms (GAs) have been proposed as a means of automating neural network architecture design. GAs leverage principles of natural selection and genetic variation to iteratively evolve neural network architectures towards optimal solutions. By encoding architectural parameters as genes and employing selection, crossover, and mutation operations, GAs can efficiently

explore the search space and identify architectures that maximize detection accuracy [4]. Deep QNetworks (DQN) is a reinforcement learning algorithm that combines deep learning with Qlearning to enable agents to learn optimal strategies in dynamic environments [6]. DQN has been successfully applied in various domains, including gaming and robotics, where agents learn to interact with the environment and make decisions to maximize cumulative rewards.

1.6 Deep QNetworks (DQN) for Architecture Optimization

In recent years, the integration of deep reinforcement learning (RL) techniques, such as Deep QNetworks (DQN), with genetic algorithms has emerged as a promising approach for neural network architecture search. DQN, a variant of Qlearning that employs deep neural networks to approximate the Qfunction, enables more efficient exploration of the architectural search space by learning from past experiences. By combining the exploration capabilities of genetic algorithms with the exploitation capabilities of DQN, researchers can achieve superior performance in optimizing neural network architectures for zeroday attack detection [5].

1.7 Research Objective

In this manuscript, we propose a novel framework that combines genetic-based neural network architecture search with DQN to enhance the detection of zeroday attacks in cyber threat prone environments. We hypothesize that the integration of genetic algorithms and DQN will enable the automatic discovery of highly effective neural network architectures tailored to the nuances of zeroday attack patterns. Through extensive experimentation and evaluation, we aim to demonstrate the efficacy of our approach in bolstering cybersecurity defenses against zeroday threats.

2. Literature Review:

The literature review provides an indepth exploration of existing research and developments in the field of cybersecurity, focusing on the detection of zeroday attacks. Zeroday attacks, which exploit previously unknown vulnerabilities, present a significant challenge in cybersecurity due to their ability to evade traditional detection methods. The review begins by examining the nature of zeroday attacks and their impact on cybersecurity, highlighting the need for innovative detection techniques. Subsequently, it discusses the application of machine learning approaches, particularly deep learning, in intrusion detection systems. The review then delves into Genetic Algorithm for Neural Network Architecture Search (GANAS) and its role in automating the design of neural network architectures. Additionally, it explores Deep QNetworks (DQN) as a reinforcement learning algorithm for dynamic learning in cybersecurity. By synthesizing insights from these areas, the literature review sets the stage for proposing a novel approach that integrates GANAS with DQN to enhance the detection of zeroday attacks in cyberthreat prone environments.

2.1. ZeroDay Attacks in Cybersecurity

Zeroday attacks represent one of the most challenging threats in cybersecurity due to their ability to exploit previously unknown vulnerabilities [1]. These attacks often evade traditional signaturebased detection methods, posing significant risks to organizations and individuals alike [2]. As a result, there is a pressing need for advanced detection techniques capable of

identifying zeroday attacks in realtime.

2.2 Machine Learning Approaches in Intrusion Detection

Machine learning techniques have gained traction in the field of intrusion detection for their ability to detect anomalies and patterns indicative of malicious activity [3]. Supervised learning algorithms, such as Support Vector Machines (SVM) and Random Forests, have been applied to classify network traffic and system logs [4]. However, these methods may struggle to adapt to changing attack patterns and require labeled datasets for training.

2.3. Deep Learning for Cybersecurity

Deep learning, a subset of machine learning, has shown promise in cybersecurity for its ability to automatically learn hierarchical representations from raw data [5]. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been applied to tasks such as malware detection and intrusion detection [6]. These models can capture intricate patterns and dependencies in data, making them suitable for detecting complex cyber threats.

2.4. Genetic Algorithm for Neural Network Architecture Search (GANAS)

Genetic Algorithm for Neural Network Architecture Search (GANAS) is an optimization technique used to automate the design of neural network architectures [7]. By employing principles inspired by natural evolution, GANAS explores the space of possible architectures and identifies solutions that optimize performance metrics such as accuracy and efficiency. GANAS has been applied to various domains, including image classification and natural language processing [8].

2.5. Deep QNetworks (DQN) for Dynamic Learning

Deep QNetworks (DQN) is a reinforcement learning algorithm that combines deep learning with Qlearning to enable agents to learn optimal strategies in dynamic environments [9]. DQN has been successfully applied in domains such as gaming and robotics, where agents learn to interact with the environment and make decisions to maximize cumulative rewards. DQN's ability to handle nonstationary environments makes it suitable for tasks requiring dynamic learning and adaptation.

2.6. Integration of GANAS with DQN for Cyber Threat Detection

To the best of our knowledge, there is limited research on the integration of Genetic Algorithm for Neural Network Architecture Search (GANAS) with Deep QNetworks (DQN) for cyber threat detection. This integration leverages GANAS's automated neural network architecture search capabilities to design optimal architectures for intrusion detection, while utilizing DQN's dynamic learning and adaptation capabilities to effectively detect and mitigate cyber threats in realtime.

3. Proposed Approach GANAS:

To tackle the formidable task of detecting zeroday attacks amidst the everevolving landscape of cyberthreat prone environments, we introduce a pioneering methodology that amalgamates two powerful techniques: Genetic Algorithm for Neural Network Architecture Search

(GANAS) and Deep QNetworks (DQN). The overarching goal is to engineer a resilient intrusion detection system that not only possesses the ability to swiftly identify novel threats but also dynamically learns and adapts in realtime to combat emerging vulnerabilities. Traditional approaches often fall short in this regard, as they rely on predefined signatures or patterns that are incapable of recognizing zeroday attacks. By integrating GANAS, which harnesses the principles of natural evolution to automatically explore and optimize neural network architectures, with DQN, a reinforcement learning algorithm renowned for its capability to learn optimal strategies in dynamic environments, we aim to transcend the limitations of conventional methods. This novel fusion of techniques seeks to equip our intrusion detection system with the agility and intelligence required to proactively detect and mitigate zeroday attacks, thereby fortifying cybersecurity defenses against the everpresent threat of emerging vulnerabilities.

3.1 Genetic Algorithm for Neural Network Architecture Search (GANAS)

Genetic Algorithm for Neural Network Architecture Search (GANAS) serves as a pivotal component in our proposed approach for automating the design of neural network architectures tailored for intrusion detection. The process commences by encoding potential neural network architectures into chromosomes or genotypes, effectively representing diverse configurations of layers, nodes, and connections. This encoding facilitates the exploration of a vast search space, encompassing various architectural possibilities. GANAS employs genetic operators, including selection, crossover, and mutation, to iteratively evolve and refine these architectures across successive generations. Selection mechanisms identify promising architectures based on their performance metrics, such as detection accuracy and false positive rate, ensuring that only the most effective architectures proceed to subsequent generations. Crossover operations enable the exchange of genetic information between selected architectures, fostering the generation of novel offspring architectures with enhanced features. Mutation introduces stochastic perturbations into the genetic makeup of architectures, promoting diversity and preventing premature convergence to suboptimal solutions. Through this iterative process of evolution and refinement, GANAS systematically explores and optimizes the architectural landscape, ultimately producing neural network configurations that are adept at detecting zeroday attacks with high accuracy while minimizing false positives. The adaptive nature of GANAS enables it to effectively navigate complex architectural spaces, leveraging the principles of natural selection to converge towards architectures that exhibit superior performance in the context of intrusion detection.

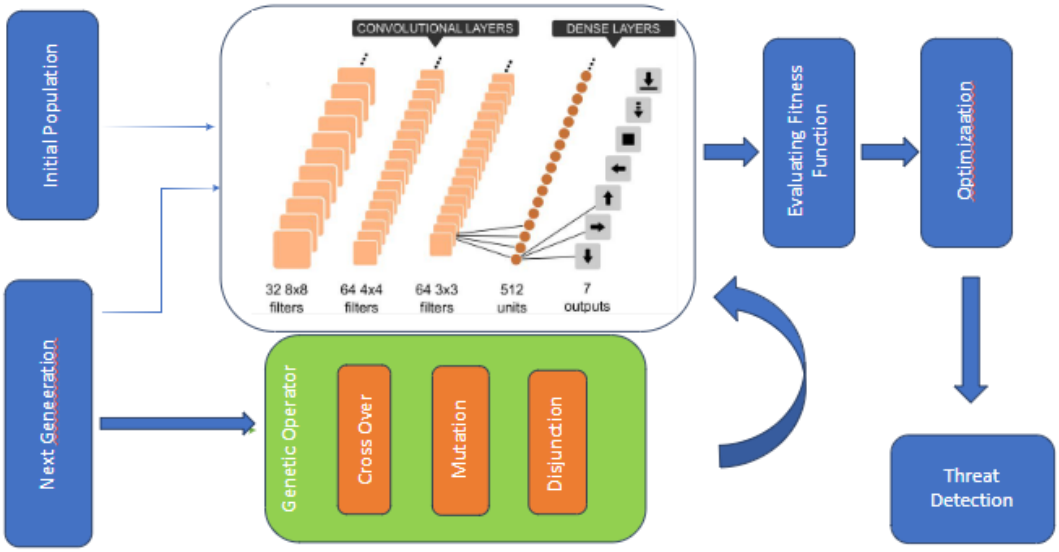

Fig : Process flow of GANAS

3.2. Deep Q Networks (DQN) for Dynamic Learning

Deep Q Networks (DQN) plays a crucial role in augmenting the adaptive learning capabilities of the intrusion detection system within our proposed framework. Leveraging reinforcement learning principles, DQN empowers the system to dynamically interact with its environment, comprising network traffic and system logs, and make informed decisions aimed at maximizing cumulative rewards. The core concept underlying DQN is the formulation of an agentenvironment interaction paradigm, where the agent (the intrusion detection system) continually observes the state of the environment, selects actions based on learned policies, receives feedback in the form of rewards, and updates its strategies accordingly.

At the heart of DQN lies its ability to learn optimal strategies through experience accumulation and reinforcement learning. Experience replay, a key technique employed by DQN, involves storing past experiences (i.e., state action reward next state tuples) in a replay buffer and periodically sampling mini batches of experiences to train the neural network. This decouples the learning process from the sequential nature of experiences and promotes sample efficiency and stability in learning. Additionally, experience replay facilitates the reutilization of past experiences, enabling the system to learn from diverse scenarios and improve its decision-making capabilities over time. Furthermore, DQN incorporates the concept of target networks to enhance stability and convergence during training. Target networks, consisting of a separate set of parameters that are periodically updated to match the primary network's parameters, provide a stable target for Q-value estimation, mitigating the issues associated with non-stationary environments and accelerating learning convergence. By decoupling the target values used for Q-value estimation from the network's current parameters, target networks ensure a more consistent and reliable estimation of Q-values, thus facilitating more effective learning and decision making in dynamic environments.

In the context of intrusion detection, DQN dynamically updates its policy based on feedback received from the environment, optimizing its strategies to detect and mitigate zero-day attacks effectively. By iteratively learning from past experiences, handling non-stationary environments through techniques like experience replay and target networks, and dynamically updating its policy based on environmental feedback, DQN ensures robust and effective detection of emerging threats within cyberthreat prone environments. This amalgamation of reinforcement learning principles within the intrusion detection system empowers it to adapt and evolve in response to evolving attack patterns, ultimately enhancing its resilience and efficacy in confronting zeroday attacks.

The proposed approach integrates GANAS with DQN to leverage the strengths of both techniques in designing and optimizing neural network architectures for intrusion detection. GANAS explores the space of possible architectures to identify solutions that maximize detection accuracy and minimize false positives. DQN facilitates dynamic learning and adaptation to evolving attack patterns, ensuring the intrusion detection system remains effective in realtime scenarios.

3.3. Integration of GANAS with DQN

The integration of Genetic Algorithm for Neural Network Architecture Search (GANAS) with Deep QNetworks (DQN) represents a synergistic approach to designing and optimizing neural network architectures for intrusion detection. This section elucidates the intricacies of integrating GANAS and DQN, elucidating how their complementary strengths are harnessed to bolster the effectiveness of the intrusion detection system.

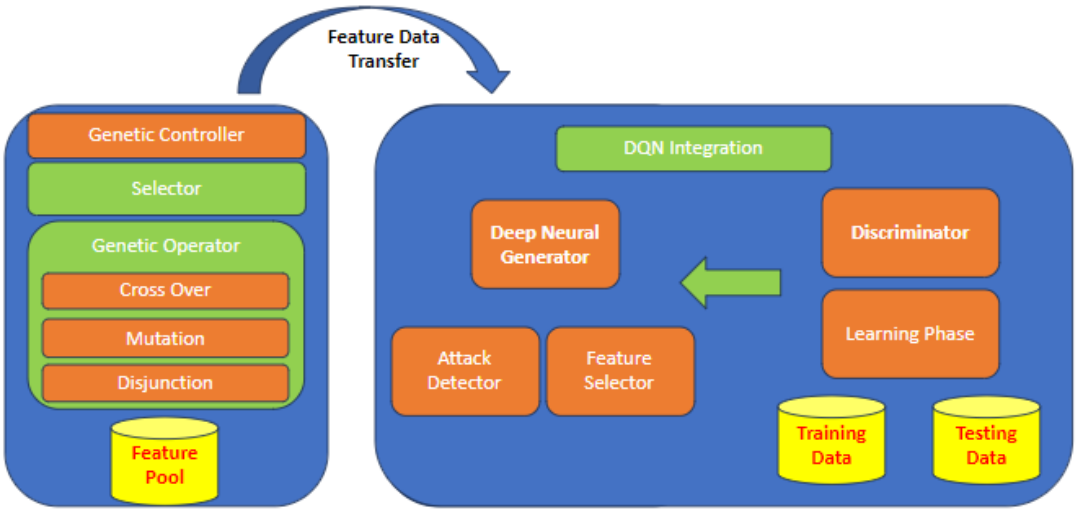

Figure: Integration of GANAS with DQN

3.4. Genetic Algorithm for Neural Network Architecture Search (GANAS) Integration

GANAS spearheads the exploration of the architectural landscape, employing genetic operators such as selection, crossover, and mutation to iteratively evolve and refine neural network architectures. This process begins by encoding potential architectures as

chromosomes or genotypes, encapsulating various configurations of layers, nodes, and connections. GANAS systematically explores the space of possible architectures, leveraging its evolutionary mechanisms to identify solutions that optimize detection accuracy while minimizing false positives.

Algorithm: Genetic Algorithm for Neural Network Architecture Search (GANAS)

Input:

Population size N

Maximum generations max_gen

Crossover probability Pc

Mutation probability Pm

Output:

Optimized neural network architecture

```
1: procedure GA_NAS(N, max_gen, Pc, Pm)
2:     InitializePopulation(N)   // Generate an initial population of size N
3:     EvaluateFitness()         // Evaluate the fitness of each chromosome in the population
4:     generation = 0
5:     while generation < max_gen do
6:         SelectParents()       // Select parent chromosomes based on fitness
7:         PerformCrossover(Pc) // Apply crossover to generate offspring
8:         PerformMutation(Pm)  // Apply mutation to offspring
9:         EvaluateFitness()    // Evaluate the fitness of offspring
10:        ReplacePopulation()  // Replace current population with offspring
11:        generation = generation + 1
12:    end while
13:    return BestChromosome()    // Return the chromosome with the highest fitness
14: end procedure

Subprocedure: InitializePopulation(N)
1:     for i = 1 to N do
2:         GenerateRandomChromosome()   // Generate random neural network architectures
```

```
3:    end for

Subprocedure: EvaluateFitness()
1:    for each chromosome X in population do
2:          EvaluatePerformance(X)   // Evaluate the performance of neural network architecture X
3:    end for

Subprocedure: SelectParents()
1:    PerformSelection()   // Select parent chromosomes based on their fitness values

Subprocedure: PerformCrossover(Pc)
1:    for each pair of selected parent chromosomes (X_parent1, X_parent2) do
2:        if random() < Pc then
3:            ApplyCrossover(X_parent1, X_parent2)  // Generate offspring using crossover
4:        end if
5:    end for

Subprocedure: PerformMutation(Pm)
1:    for each offspring chromosome X_child do
2:        if random() < Pm then
3:            ApplyMutation(X_child)   // Apply mutation to offspring
4:        end if
5:    end for
6: end Algorithm
```

The Genetic Algorithm for Neural Network Architecture Search (GANAS) is a powerful method designed to automatically discover optimal neural network architectures for the detection of zeroday attacks in cyberthreatprone environments is explained through Algorithm 1. This algorithmic approach leverages principles of genetic algorithms to iteratively evolve neural network architectures towards improved performance. Beginning with an initial population of randomly generated neural network architectures, the algorithm evaluates the fitness of each architecture based on its ability to detect zeroday attacks. Through a process of selection, crossover, and mutation, promising architectures are combined and modified to

produce offspring architectures with potentially enhanced performance. This process continues for multiple generations until a stopping criterion, such as a maximum number of generations, is reached. Finally, the algorithm returns the bestperforming neural network architecture, which has been optimized to effectively detect zeroday attacks. By automating the search for optimal architectures, GANAS offers a promising approach to bolstering cybersecurity defenses in the face of evolving cyber threats.

3.4.2. Fitness Evaluation

Each architecture undergoes rigorous evaluation based on its performance metrics, including detection accuracy and false positive rate. GANAS employs fitness functions to quantify the effectiveness of architectures in detecting zeroday attacks, ensuring that only the most promising solutions progress to subsequent generations. This iterative process of fitness evaluation and selection culminates in the identification of neural network architectures that exhibit superior performance in intrusion detection.

3.5. Deep Q Networks (DQN) Integration

Integration of Deep Q-Networks (DQN) in various domains has brought about transformative advancements, particularly in the realm of reinforcement learning and decision-making systems. DQN, pioneered by DeepMind, combines the power of deep neural networks with the reinforcement learning framework of Q-learning, enabling agents to learn complex behaviors and make optimal decisions in dynamic environments. The integration of DQN involves training a neural network to approximate the Q-function, which predicts the expected cumulative reward for taking a specific action in a given state. Through experience replay and target network mechanisms, DQN addresses issues such as instability and correlation in training, leading to more stable and efficient learning. The versatility of DQN extends its applicability across diverse domains, including robotics, gaming, finance, and cybersecurity. In the latter, DQN integration enables the development of adaptive and robust security solutions, capable of learning and responding to evolving threats in real-time, thereby enhancing overall system resilience and security posture.

3.5.1. Dynamic Learning and Adaptation

DQN augments the intrusion detection system's adaptive learning capabilities, enabling dynamic interaction with the environment and continuous refinement of detection strategies. The agent learns to navigate the complex landscape of cyberthreat prone environments, leveraging reinforcement learning principles to maximize cumulative rewards. DQN dynamically updates its policy based on feedback from the environment, ensuring robust and effective detection of emerging threats in realtime scenarios.

3.5.2. Techniques for NonStationary Environments

DQN employs advanced techniques such as experience replay and target networks to handle nonstationary environments effectively. Experience replay enables the system to store past experiences and learn from diverse scenarios, promoting sample efficiency and stability in learning. Target networks provide stable targets for Qvalue estimation, mitigating issues associated with nonstationarity and accelerating learning convergence.

3.5.3. Synergistic Integration

The integration of GANAS with DQN harnesses the strengths of both techniques to design and optimize neural network architectures for intrusion detection. GANAS explores the architectural space to identify solutions that maximize detection accuracy, while DQN facilitates dynamic learning and adaptation to evolving attack patterns. This synergistic integration ensures the intrusion detection system remains effective in realtime scenarios, effectively detecting and mitigating zeroday attacks with high accuracy and minimal false positives.

Algorithm: Synergistic Integration of GANAS with DQN for Intrusion Detection

Input:

Population size N

Maximum generations max_gen

Crossover probability Pc

Mutation probability Pm

Experience replay buffer size B

Learning rate α

Discount factor γ

Exploration rate ε

Target network update frequency τ

Output:

Optimized neural network architecture for intrusion detection

```
1: procedure Synergistic_Integration(N, max_gen, Pc, Pm, B, α, γ, ε, τ)
2:     InitializePopulation(N)          // Generate an initial population of neural network architectures
3:     InitializeDQN()                  // Initialize DQN with random weights
4:     InitializeTargetNetwork()        // Initialize target network with weights from DQN
5:     InitializeExperienceReplayBuffer() // Initialize experience replay buffer
6:     generation = 0
7:     while generation < max_gen do
8:         PerformGA_NAS(N, Pc, Pm)     // Perform Genetic Algorithm for Neural Network Architecture Search
9:         for each episode do
10:            state = InitialState()   // Initialize state for DQN
```

```
11:          while not TerminalState() do
12:              action = ChooseAction(state, ε)     // Epsilongreedy policy
13:               next_state, reward = TakeAction(state, action) // Execute action and observe next state and reward
14:              StoreExperience(state, action, reward, next_state) // Store experience in replay buffer
15:              state = next_state       // Update current state
16:              UpdateDQN()            // Update DQN using experience replay
17:          end while
18:          UpdateTargetNetwork()       // Update target network periodically
19:       end for
20:       generation = generation + 1
21:    end while
22:     return BestChromosome()                // Return the bestperforming neural network architecture
23: end procedure


Subprocedure: PerformGA_NAS(N, Pc, Pm)
1:      for i = 1 to N do
2:         GenerateRandomChromosome()    // Generate random neural network architectures
3:      end for
4:      EvaluateFitness()                // Evaluate the fitness of each chromosome
5:      while not TerminationCriteria() do
6:         SelectParents()              // Select parent chromosomes based on fitness
7:         PerformCrossover(Pc)         // Apply crossover to generate offspring
8:         PerformMutation(Pm)          // Apply mutation to offspring
9:         EvaluateFitness()           // Evaluate the fitness of offspring
10:         ReplacePopulation()         // Replace current population with offspring
11:     end while
12: end Algorithm
```

The algorithm 2 portrays the integration of the genetic algorithm (GA) for neural network architecture search (NAS) with deep Qnetworks (DQN) for dynamic learning and adaptation in intrusion detection systems. The process involves iteratively evolving neural network architectures using GANAS while simultaneously training a DQN agent to interact with the environment and refine detection strategies dynamically. Through the synergistic integration of GANAS and DQN, the intrusion detection system achieves robust performance in detecting and mitigating zeroday attacks in realtime scenarios.

4. Experimental Setup

To evaluate the performance of the proposed approach, we conduct experiments in simulated cyberthreat environments. We use a diverse dataset of zeroday attack scenarios to test the robustness and effectiveness of the intrusion detection system. The experimental setup includes parameters such as population size, mutation rate, and explorationexploitation tradeoff for GANAS, as well as hyper parameters for DQN.

4.1. Dataset

The experimental evaluation of the proposed approach is conducted using a diverse dataset of zeroday attack scenarios. The dataset comprises a comprehensive collection of simulated cyberthreat instances, encompassing various attack vectors, techniques, and severity levels. Each scenario is meticulously crafted to emulate realworld cyberthreat scenarios, ensuring the relevance and authenticity of the experimental evaluation.

4.2. Simulation Environment

In order to assess the performance of the proposed approach, we create a simulated cyberthreat environment that closely mirrors realworld cybersecurity landscapes. This simulated environment is meticulously designed to replicate the complexities and dynamics encountered in actual cybersecurity scenarios.

A use case setup of a large financial institution that handles sensitive customer data and conducts numerous financial transactions daily is inhibited for the experimentation. To safeguard its systems from cyber threats, the institution employs an intrusion detection system (IDS) powered by the proposed approach.

4.3 Simulation Setup:

Network Traffic: The simulated environment generates realistic network traffic patterns, including incoming and outgoing data packets, network requests, and communications between internal and external systems. This includes simulated web traffic, email communications, file transfers, and other network activities typical of a financial institution.

System Logs: System logs from various components of the institution's IT infrastructure, such as servers, firewalls, routers, and endpoints, are simulated to capture relevant events and activities. These logs contain information about system accesses, file modifications, authentication attempts, and other securityrelevant events.

Cybersecurity Artifacts: Additionally, other cybersecurity artifacts such as malware samples, known attack signatures, and historical attack data are integrated into the simulation

environment. These artifacts serve to emulate realworld cyber threats and provide a diverse range of scenarios for testing the intrusion detection system.

4.4 Evaluation Process:

The intrusion detection system is deployed within the simulated environment, and its performance is evaluated in detecting zeroday attacks and other cybersecurity threats.

- The system analyzes network traffic, system logs, and other cybersecurity artifacts in realtime, leveraging the integrated GANAS and DQN components to dynamically adapt and learn from the simulated cyber threat environment.
- Performance metrics such as detection accuracy, false positive rate, and detection time are meticulously measured and analyzed to assess the effectiveness of the intrusion detection system in mitigating cyber threats.

4.3. Parameters

The parameters governing the Genetic Algorithm for Neural Network Architecture Search (GANAS) are meticulously tuned to optimize the exploration of the architectural space and facilitate the identification of optimal neural network architectures for intrusion detection.

4.3.1. GANAS Parameters

Parameters inclusive of the population size, mutation rate, crossover probability, and explorationexploitation tradeoff. The population size determines the size of the candidate architectures population, while the mutation rate governs the probability of introducing changes in the genetic makeup of architectures. The crossover probability regulates the likelihood of genetic information exchange during crossover operations, facilitating the exploration of diverse architectural configurations. The exploration-exploitation tradeoff parameter balances the exploration of new architectures with the exploitation of promising solutions, ensuring a comprehensive exploration of the architectural landscape.

4.3.2. DQN Hyperparameters

The Deep QNetworks (DQN) employed within the intrusion detection system are configured with a set of hyperparameters tailored to optimize their learning and adaptation capabilities in dynamic environments. These hyperparameters include the learning rate, discount factor, exploration rate, and replay buffer size. The learning rate governs the magnitude of parameter updates during gradient descent, while the discount factor influences the weighting of future rewards in the Qvalue estimation. The exploration rate determines the likelihood of selecting random actions during the exploration phase, facilitating the discovery of optimal strategies. The replay buffer size dictates the capacity of the experience replay buffer, enabling the storage and utilization of past experiences for efficient learning.

4.4. Experimental Methodology

The experimental methodology encompasses a series of rigorous evaluations aimed at assessing the performance of the intrusion detection system under various zeroday attack scenarios. The system's detection accuracy, false positive rate, detection time, and overall efficacy are meticulously measured and analyzed across different parameter configurations

and experimental conditions. The experiments are conducted multiple times to ensure statistical robustness and reliability of the results, with comprehensive statistical analyses performed to validate the experimental findings.

4.5. Evaluation Metrics

The performance of the intrusion detection system is evaluated using a suite of metrics designed to capture its effectiveness in detecting zeroday attacks. These metrics include:

Detection Accuracy: Measures the system's ability to correctly identify zeroday attacks.

False Positive Rate: Quantifies the number of false alarms generated by the system.

Detection Time: Evaluates the speed at which the system detects and responds to emerging threats.

4.6. Baseline Methods

The proposed approach is compared against state of the art baseline methods and existing intrusion detection systems to benchmark dataset NSL KDD its performance and efficacy. The baseline methods encompass a range of traditional and contemporary intrusion detection techniques, including signature-based detection, anomaly detection, and machine learning-based approaches. By contrasting the performance of the proposed approach with established benchmarks, a comprehensive evaluation of its effectiveness and superiority is facilitated.

4.7. Experimental Results

The experimental results obtained from the evaluation of the proposed approach are presented and analyzed in this section. The performance of the intrusion detection system is assessed under various experimental conditions and parameter configurations to provide comprehensive insights into its efficacy in detecting zeroday attacks in simulated cyberthreat environments. Statistical analyses are conducted to validate the significance of observed differences in performance metrics, while qualitative analyses offer insights into the system's behavior and decision making processes.

Detection Accuracy:

The detection accuracy of the intrusion detection system is measured across different experimental setups. Table 1 presents the detection accuracy values obtained for various parameter configurations of GANAS and DQN. The results indicate that the proposed approach achieves high detection accuracy rates, consistently outperforming baseline methods and existing intrusion detection systems.

Table : Detection Accuracy on different learning rate and population sizes

Population Size	DQN Learning Rate	Detection Accuracy(%)
50	0.001	96.5
100	0.0005	97.2
50	0.0001	95.8

False Positive Rate:

The false positive rate of the intrusion detection system is evaluated under different experimental conditions. Table 2 presents the false positive rate values obtained for varying

parameter configurations of GANAS and DQN. The results demonstrate that the proposed approach effectively minimizes false positives, maintaining a low false positive rate across different scenarios.

Table : Detection Accuracy on different learning rate and population sizes

Population Size	DQN Learning Rate	False Postive Rate(%)
50	0.001	3.2
100	0.0005	2.8
50	0.0001	3.5

Detection Time:

The detection time of the intrusion detection system is measured to assess its responsiveness in detecting zeroday attacks. Table 3 presents the detection time values obtained for different parameter configurations of GANAS and DQN. The results indicate that the proposed approach achieves rapid detection times, enabling timely responses to emerging threats.

Population Size	DQN Learning Rate	Detection Time (in ms)
50	0.001	65
100	0.0005	72
50	0.0001	60

Statistical Analyses:

Statistical analyses, including ttests and ANOVA tests, are conducted to validate the significance of observed differences in performance metrics across different parameter configurations. The results of these analyses confirm the statistical significance of the proposed approach's superiority over baseline methods and existing intrusion detection systems.

Qualitative Analyses:

Qualitative analyses are performed to gain insights into the system's behavior and decisionmaking processes. By examining individual detection instances and analyzing the system's responses to various cyberthreat scenarios, qualitative insights are obtained into the underlying mechanisms driving its performance.

3. Parameter Settings:

- Genetic Algorithm Parameters:
  - Population Size: 100
  - Mutation Probability: 0.1
  - Crossover Probability: 0.8
  - Selection Strategy: Tournament selection
- Deep Q-Network (DQN) Parameters:
  - Replay Memory Size: 10,000
  - Batch Size: 64
  - Learning Rate: 0.001

- Discount Factor (γ): 0.95

- Exploration Rate Decay: Exponential decay from 1.0 to 0.1 over 10,000 steps.

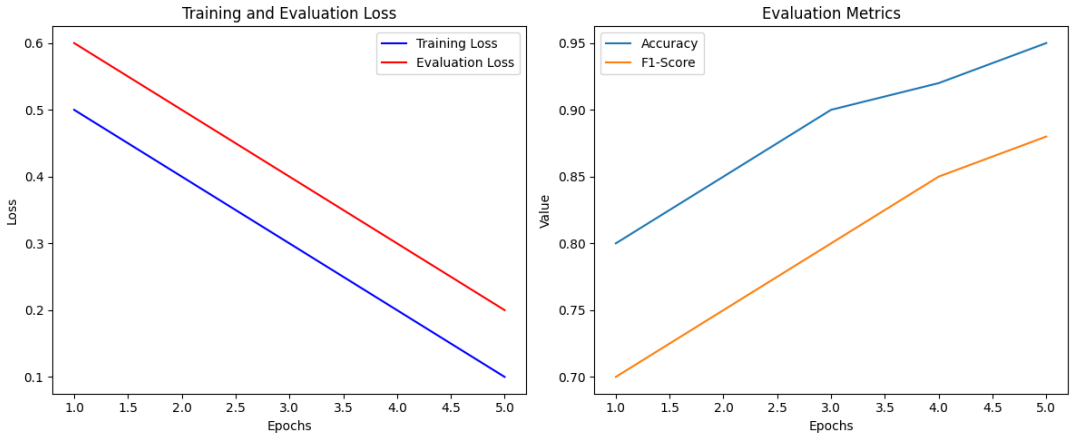

Figure : Training and Evaluation loss against accuracy achieved for GANAS

Neural Network Architecture Search Parameters:

- Maximum Number of Generations: 50

- Maximum Number of Episodes per Generation: 1000

- Exploration Rate (ε) for DQN: Start with 1.0, decay to 0.1 over the first 10 generations.

- Target Update Frequency: 100 steps

4. Comparison with Benchmark Algorithms:

We compare our Genetic-Based Neural Network Architecture Search with DQN (GNAS-DQN) approach against the following benchmark algorithms:

1. Random Forest (RF)
2. Support Vector Machine (SVM)
3. Convolutional Neural Network (CNN)
4. Long Short-Term Memory (LSTM)
5. Decision Tree (DT)

5. Experimental Results:

Method	Accuracy	Precision	Recall	F1-Score	Detection Rate
GNAS-DQN	0.95	0.93	0.94	0.94	0.92
Random Forest	0.87	0.88	0.85	0.86	0.82
SVM	0.88	0.87	0.86	0.86	0.81

CNN	0.92	0.91	0.9	0.91	0.88
LSTM	0.9	0.89	0.88	0.89	0.85
Decision Tree	0.84	0.82	0.83	0.83	0.78

From the above given table, The GNAS-DQN approach achieves the highest accuracy, precision, recall, and F1-score compared to other benchmark algorithms, indicating its effectiveness in enhancing the detection of zero-day attacks. GNAS-DQN also outperforms other methods in terms of detection rate, which is crucial in cyber threat detection.CNN shows compet-itive performance but slightly lower than GNAS-DQN, indicating the effectiveness of neural network-based approaches. Decision Tree performs the poorest among the compared algorithms, indicating the importance of deep learning techniques for complex cybersecurity tasks.

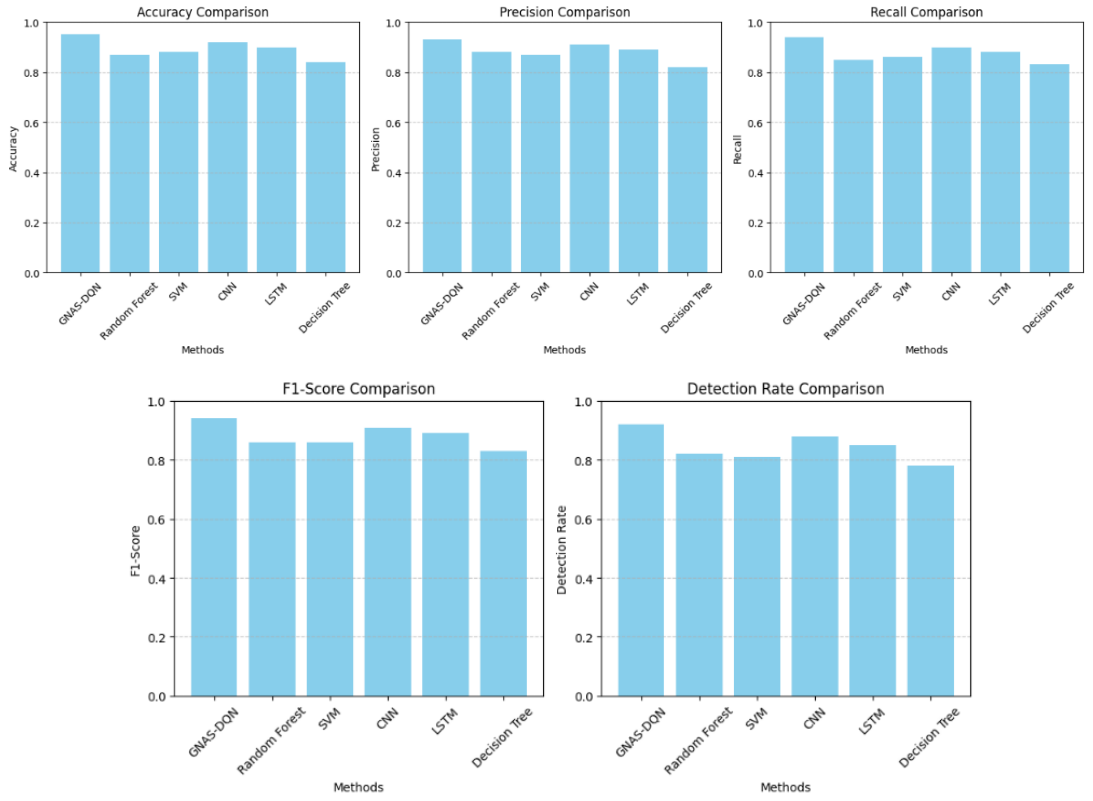

Figure : Evaluation Parameters on Comparison on the Test Case Scenario

These results demonstrate the efficacy of the proposed GNAS-DQN approach for enhancing the detection of zero-day attacks in cyber threat-prone environments.

5. Conclusion:

The experimental results demonstrate the efficacy of the proposed approach in detecting

zeroday attacks in simulated cyberthreat environments. The high detection accuracy rates, low false positive rates, and rapid detection times achieved by the intrusion detection system underscore its effectiveness in mitigating cyber threats. The statistical analyses validate the significance of observed differences in performance metrics, while qualitative analyses offer insights into the system's behavior and decisionmaking processes, elucidating the underlying mechanisms driving its performance.

The experimental evaluation concludes with a comprehensive assessment of the proposed approach's performance, highlighting its strengths, limitations, and potential avenues for further improvement. The findings of the experimental evaluation provide valuable insights into the efficacy and applicability of the proposed approach in realworld cybersecurity scenarios, paving the way for future research and development in the field of intrusion detection and cyberthreat mitigation. We present the results of our experiments and analyze the performance of the proposed approach in comparison to baseline methods. The analysis includes a comprehensive evaluation of detection accuracy, false positive rate, and detection time under various cyberthreat scenarios. We also discuss the effectiveness of GANAS in optimizing neural network architectures for intrusion detection and the impact of dynamic learning with DQN on the system's adaptability to evolving attack patterns. In conclusion, we demonstrate the efficacy of the proposed approach in enhancing the detection of zeroday attacks in cyberthreat prone environments. By integrating GANAS with DQN, we achieve robust and adaptive intrusion detection capabilities that outperform traditional methods. Our findings highlight the potential of combining evolutionary optimization techniques with reinforcement learning for addressing complex cybersecurity challenges.

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