

# A Survey for Deep Reinforcement Learning Based Network Intrusion Detection

Wanrong Yang , Alberto Acuto , Yihang Zhou , Dominik Wojtczak 

**Abstract**—Cyber-attacks are gradually becoming more sophisticated and highly frequent nowadays, and the significance of network intrusion detection systems have become more pronounced. This paper investigates the prospects and challenges of employing deep reinforcement learning technologies in network intrusion detection. It begins with an introduction to the fundamental theories and technological frameworks of deep reinforcement learning including classic deep Q-network and actor-critic algorithms, followed by a review of essential research that has leveraged deep reinforcement learning for network intrusion detection in recent years. This research assesses these challenges and efforts in terms of model training efficiency, the detection capabilities for minority and unknown class attacks, improved network feature selection and unbalanced dataset issues. Performances of deep reinforcement learning models are comprehensively investigated. The findings reveal that although deep reinforcement learning shows promise in network intrusion detection, many of the latest deep reinforcement learning technologies are yet to be fully explored. Some deep reinforcement learning based models can achieve state-of-the-art results in some public datasets, in some cases, even better than traditional deep learning methods. The paper concludes with recommendations for the enhanced deployment and testing of deep reinforcement learning technologies in real-world network scenarios to further improve their application. Special emphasis is placed on the Internet of Things intrusion detection. We offer discussions on recently proposed deep architectures, revealing possible future policy functions used for deep reinforcement learning based network intrusion detection. In the end, we propose integrating deep reinforcement learning and broader generative methods and models to assist and further improve their performance. These advancements aim to address the current gaps and facilitate more robust and adaptive network intrusion detection systems.

**Index Terms**—Intrusion Detection, Deep Reinforcement Learning, Cyber-Security, Cyber-Physical Systems

This work was supported by the Engineering and Physical Sciences Research Council (EPSRC), through grants number EP/X017796/1 and EP/X03688X/1. We would like to express our sincere appreciation for research support from Centre for Doctoral Training (CDT) in Distributed Algorithm, University of Liverpool. And specifically, many thanks for all the help from Prof Simon Maskell, Kelli Cassidy, Elizabeth Gannon and Big hypotheses group. Thanks for Qingyuan Wu for kind and practical suggestions on the manuscript. In the end, we would like to say thanks to our industrial partners, Dr. Stephen Pasteris and Dr. Chris Hicks from Alan Turing Institute.

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## I. INTRODUCTION

Cybersecurity is a significant challenge in the age of global informatization [1]. As digital lifestyles become increasingly prevalent, our reliance on cybersecurity and the need for it are growing rapidly as well [2]. Nowadays, cybercriminal activities are inflicting substantial economic losses on various industrial and government sectors. According to live data from the AV-TEST Institute, more than 450,000 new malicious programs are detected every day, with over 1.2 billion instances of malware emerging within 2023 alone, and these numbers are still on the rise [3]. These malicious programs infiltrate personal and corporation digital systems through a wide range of vulnerabilities, posing serious threats to personal privacy, commercial secrets, and other sensitive records. It is estimated that cybersecurity-related issues have caused a total loss of up to 400 billion US dollars to the global economy [4]. From the introduction of cybersecurity ventures, cybercrime has caused \$1.5 trillion in losses [5] in 2019, a figure that is expected to climb to \$9.5 trillion US dollars by 2024 [6]. Moreover, critical national infrastructures from energy, healthcare sectors, and port automation systems, are becoming primary targets for cyber-attackers [7]. According to 2024 World Economic Forum, 94% of government leaders and business executives believe that their organizations are still at a lower defence level when facing cyber-attacks [8]. In short, the importance of cybersecurity is set to grow significantly worldwide.

Network Intrusion Detection (NID) is a crucial defence mechanism in the field of cybersecurity. It effectively protects computers and other digital devices from external attacks [9]. It was first proposed in 1994 [10] and later described as integrating information extracted from computers to identify resource abuse within the network and attacks originating from outside entities [11]. Basically, intrusion detection systems (IDS) can be categorized into *Network Intrusion Detection Systems* (NIDS), which is based on the observation of network traffic between different nodes [12] and *Host-based Intrusion Detection Systems* (HIDS), which means monitoring activities on a specific host, including applications being used and file systems being accessed [13]. The primary purpose of NID is to prevent network attacks by identifying abnormal traffic or access operations [9]. Objectives of network attacks are becoming increasingly complex, traditional signature-based methods that identifying known attacks based on pattern matching of known signatures have fallen behind anomaly-based detection approaches [14]. Since the anomaly-based detection has a higher efficiency and dynamic adaptability, it is now widely accepted by the NID community [15].

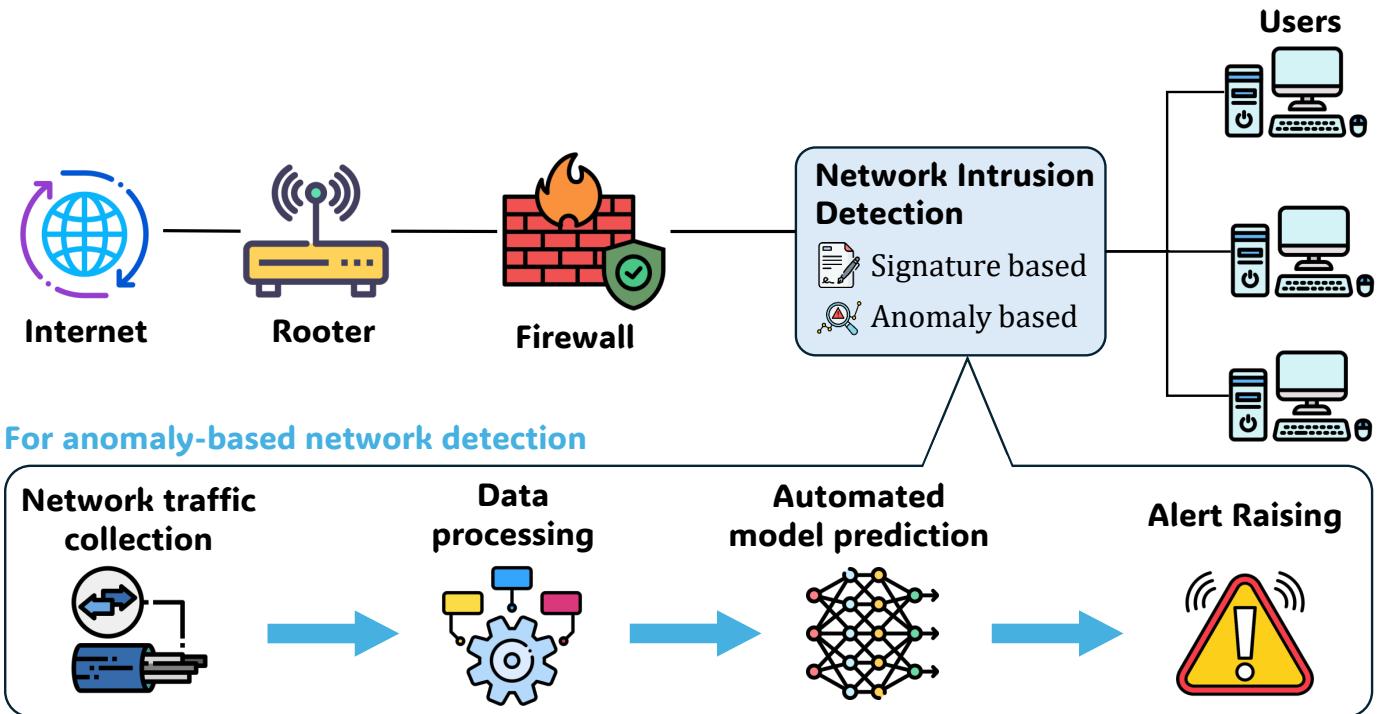


Fig. 1. An overview of network intrusion detection and specific working flow of anomaly-based network intrusion detection.

Artificial intelligence (AI) plays an essential role in NID [7], [16]. Traditional machine learning (ML) algorithms, including supervised and unsupervised learning e.g., Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forests (RF), and Multilayer Perceptron (MLP), have made improvements for NIDS in multiple ways [17]. Further, deep learning (DL), by constructing deep neural networks, are capable of learning and fitting highly complex patterns and features from large amounts of given training data [18]. It can effectively learn and simulate patterns of normal behaviour in network traffic, thereby identifying abnormal activities or potential intrusions [16]–[18]. Compared with traditional ML methods, critical features in network intrusion could be extracted automatically by deep learning without much laborious feature selection.

However, the DL model hugely relies on large, high-quality datasets [19]. Keeping up to date with large-scale real-world cyber intrusion data is both time-consuming and labour-intensive. In addition, utilizing outdated datasets could potentially compromise the generalization capabilities of DL models [20]. Reinforcement Learning (RL), a subset of ML, imitates human learning strategies more closely than any other ML approach due to its ability to acquire knowledge from its own experiences by navigating and leveraging unfamiliar environments, and so is considered a potential solution to this problem [21]. Building on the principles of RL, Deep Reinforcement Learning (DRL) leverages neural networks to manage complex, high-dimensional input spaces. With outstanding decision-making and optimal control skills, DRL algorithms have achieved overwhelming success in many different fields, from real-world applications, e.g., drone racing [22], autonomous driving [23], biological data mining [24],

natural language processing [25], autonomous surgery [26], drug design [27] to virtual games domain, e.g., the game of Go [28], StarCraft II [29]. Furthermore, because of the ability to dynamically adapt to the environment, DRL has been widely applied in cybersecurity, including in areas of NID [30], [31] and adversarial simulation enhancement [32].

Some surveys focused on the general AI in intrusion detection [33] or DRL in general cybersecurity [21]. However, there has been limited research on applying deep reinforcement learning to network intrusion detection. Thus, a need for a more detailed and comprehensive survey specifically focused on the DRL and network intrusion detection. This paper primarily concentrates on the exploration of DRL applications within the domain of NID over the past five years. It aims to provide a systematic review of the most current advancements in RL applications for NID, endeavoring to elucidate how RL is revolutionizing and enhancing NID systems. To achieve this, firstly, preliminary knowledge for RL is presented including the Markov decision process, Q-learning, Deep Reinforcement Learning, Inverse Reinforcement Learning and how we evaluate the performance of RL-based NID model. Then, we retrospectively investigate representative works of DRL-based NID in the past few years focused on the overview of the most often used datasets, efforts on network feature engineering, handling unbalanced datasets, improving training efficiency and identifying minority intrusions. Finally, we present our general discussion based on these representative works hoping to provide some ideas and future research directions.

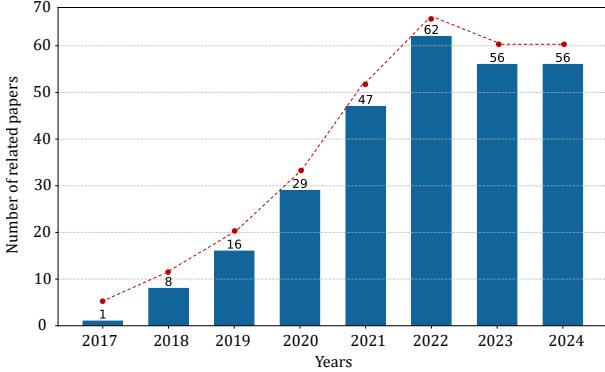


Fig. 2. Number of related publications start from 2017 (Taking reinforcement learning and network intrusion as searching key words, data is collected from Web of Science).

## II. REINFORCEMENT LEARNING BASICS

### A. Overview

Reinforcement Learning is quite different from popular supervised and unsupervised learning in ML, which are typically driven by large example data. It involves a decision-making agent that starts without any prior knowledge and learns through its own experience. This is achieved by repeated and random interactions with an environment, allowing the agent to acquire essential knowledge to make an informed decision [34].

Classic RL system is, in general, comprised of an environment, agent, policy, reward, and value function. [34]. **Agent** means a decision-making, goal-seeking and highly interactive virtual entity. **Environment** refers to everything that the agent interact with: applying action to it and receiving feedback from it. **Policy  $\pi$**  determines which action the agent takes when in a given state of the environment. It could be a function or a simple lookup matrix. **Reward** is quantitative feedback from the environment after the agent takes one specific action followed by a state. The positive and negative reward describes how “good” or “bad” the action is regarding to the final goal of the agent. **Value function** is used to evaluate the quality level of a state or action. Thus, it is divided into state-value function and action-value function.

### B. Markov decision process

Markov decision process (MDP) is the principal framework for decision in stochastic and uncertain environment [35]. It assumes that an agent can observe the current state  $s_t$ , and choose to take an action  $a_t$ . Then, the agent moves to the next state  $s_{t+1}$ . Normally, it is described as a tuple  $(S, A, P, R, \gamma)$  with the following five essential elements.  $S$  is a state space, including all states that can be observed by the agent.  $A$  is an action space, i.e., the set of all actions that can be taken by the agent.  $p(s'|s, a)$  describes the probability of transferring to a specific state  $s'$  by taking action  $a$  in the given state  $s$ . Reward function  $r(s, a, s')$  gives the reward (positive or negative) that the agent get when making a transition from state  $s$  to  $s'$  by taking action  $a$ .  $\gamma$  is a discount factor that can be used to indicate short-term or long-term importance of

rewards. The fundamental property of an MDP is that the next state  $s_{t+1}$  depends only on the current state  $a_t$  and the action  $a_t$  that the agent has taken. The interaction process between the agent and the environment in a Markov decision process is well illustrated in Figure 3.

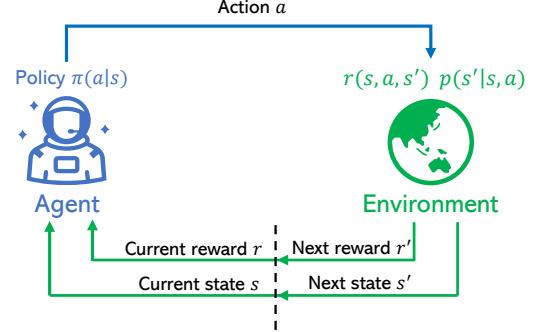


Fig. 3. Agent interaction with environment based MDP in RL.

The final goal of the agent is to maximize long-term rewards. State-value function  $V(s)$  can estimate the value of a state, which starts from a specific state  $s$  following the action chosen by current policy  $\pi$  of the agent. It can be utilized to approximate how much long-term reward the agent can gain in all next states based on the current  $\pi$  shown in Equation (1).

$$V(s) = \sum_{a \in A} \pi(a|s) \left( R(s, a) + \gamma \sum_{s' \in S} p(s'|s, a) V(s') \right) \quad (1)$$

Firstly, the agent follows policy  $\pi$  to take an action  $a$  in state  $s$  to gain an immediate reward  $R(s, a)$ . And over all possible next states  $s'$ , we have discounted sum of possible  $V(s')$  by adding discounted factor  $\gamma$ . Furthermore, *Bellman optimality* equations define optimal state-value function  $V^*(s)$  to get the maximum return for each state and optimal action-value function  $Q^*(s, a)$  to get the maximum return for each pair of state-action, shown in Equation (2) and Equation (3).

$$V^*(s) = \max_a \left( R(s, a) + \gamma \sum_{s' \in S} p(s'|s, a) V^*(s') \right) \quad (2)$$

$$Q^*(s, a) = R(s, a) + \gamma \sum_{s' \in S} p(s'|s, a) V^*(s') \quad (3)$$

### C. Q-learning

Q-learning is a classic value-based algorithm in RL [36]. It allows the agent to learn how to select actions in a given state to maximize the expected total reward. [37]. The agent updates the value of action-state pair (Q value) by exploring possible actions of the state ( $\epsilon$ -greedy strategy [38]). The upgrade of Q value is based on the current Q value, immediate reward, and maximum Q value of next state. Equation (4) is normally used to update the Q value. In the equation, the Q value  $Q(s_t, a_t)$  represents the expected utility of taking action  $a_t$  in the current state  $s_t$ , considering both the immediate reward  $r_t$  and the expected rewards of future states. The immediate reward  $r_t$  is the gain obtained from taking action  $a_t$ .

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t)] \quad (4)$$

In the current state  $s_t$ , the agent has a high sampling probability to take action  $a_t$  as  $Q(s_t, a_t)$  holds the highest value among all actions that could be taken in  $s_t$ .<sup>1</sup>  $r_t$  is the immediate reward that the agent obtained by taking  $a_t$ .  $Q(s_{t+1}, a)$  means all possible Q value corresponding to all possible action  $a$  in  $s_{t+1}$ . Discounted factor  $\gamma$  is used to determine if the agent should focus on long-term reward, the smaller  $\gamma$  is, the shorter-sighted it is. In the end, learning rate  $\alpha$  determines how much fresh learning experience should be added to past experience.

#### D. Deep Reinforcement Learning

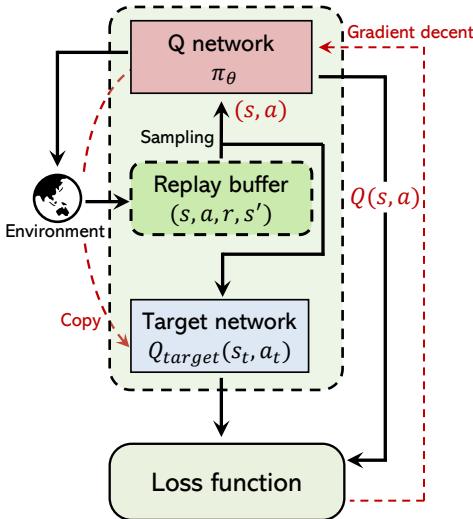


Fig. 4. Classic deep Q network learning process

*1) Deep Q Network, DQN:* Deep reinforcement learning (DRL) is a major progress in RL [39]. It makes agent could input high-dimensional data e.g. images and audio, which are difficult for typical Q-learning since they may need a massive tabular to store the value of state-action pair. It is normally unacceptable for memory. DQN [40] is a classic DRL algorithm that leverages the dynamic transition of experience replay and utilization of a target network.

The experience replay buffer in DQN is a memory storage mechanism that retains past experiences in the form of state, action, reward, and next state tuples. It allows the agent to break the temporal correlations between consecutive experiences by randomly sampling from this buffer to train the Q-network. This process stabilizes and enhances the learning process by ensuring that updates are based on a diverse set of past experiences, rather than being dominated by recent, possibly highly correlated, events.

Specifically, the agent interacts with the environment using random strategy and initial hyper-parameters  $\theta_0$  to get

<sup>1</sup>The agent still has small chances to choose other actions although they have a relatively lower Q value

some initial experience  $(s_t, a_t, r_t, s_{t+1})$  to fill the buffer of experience replay. Based on this initial knowledge, the target network (also initialized by  $\theta_0$ ) could calculate the target Q value by using the Bellman equation for data in replay buffer. Then, in the training process, a minibatch of experience is randomly chosen from experience replay buffer to update the hyper-parameters of the policy network  $\pi_{\theta_0}$  (Q-Network), by minimum the loss of predicted Q value  $Q(s_t, a; \theta)$  and target Q value, shown in the Equation (5)

$$L(\theta) = E[(r_t + \gamma \max_a Q(s_{t+1}, a; \theta') - Q(s_t, a; \theta))^2] \quad (5)$$

After the policy network is updated into  $\theta'$ , it starts to interact with the environment again to accumulate new experiences, which will be used to partially update experiences replay buffer. And the hyper-parameter of the target network will be frozen as  $\theta_0$  and subsequently updated into  $\theta'$  after a fixed time steps. Parameter upgrades of target network always lag behind the upgrades of the policy network. The training will stop when the maximum accumulated reward has been achieved or the loss has converged to a stable range.

*2) Policy Gradient:* The policy gradient method [41] is employed to optimize decision-making policies in reinforcement learning directly, without relying on a value function. The principle, different from value function-based methods, is to optimize policy parameters directly and then to achieve the maximum total reward. Policy Gradient Theorem is the very foundation of policy gradient. Let a parametric policy  $\pi(a|s, \theta)$ , choosing action  $a$  given a state  $s$  by a probability  $p = \pi_\theta$ , then, the performance of the policy can be quantified as follows.  $R(\tau)$  means return from a single trace. And policy gradient can be described in Equation (6), Equation (7) and Equation (8):

$$J(\theta) = E_{\tau \sim \pi_\theta}[R(\tau)] \quad (6)$$

$$\nabla_\theta J(\theta) = E_{s, a \sim \pi_\theta} \left[ \sum_{t=0}^T \nabla_\theta \log \pi_\theta(a_t | s_t) G_t \right] \quad (7)$$

$$G_t = \sum_{k=t}^{\tau} \gamma^{k-t} r_k \quad (8)$$

where  $k$  represents a future time point starting from a specific initial time denoted by  $t$ . As time passes by,  $k$  gradually increases. It is desired that the contribution of rewards received at farther future time points to the current state decreases gradually, hence  $\gamma$ , the discount factor, is reduced over time. The initial trajectories are gathered from random interactions between the agent and the environment over a fixed duration. These trajectories are used only once. After all trajectories in a set have been utilized, the agent restarts interactions with the environment to collect a new set of trajectories for the next round of training. However, when having large gradient updates in training, the process becomes unstable. To address this, researchers proposed Trust Region Policy Optimization (TRPO) [42] and Proximal Policy Optimization (PPO) [43] to further improve the stability of training.

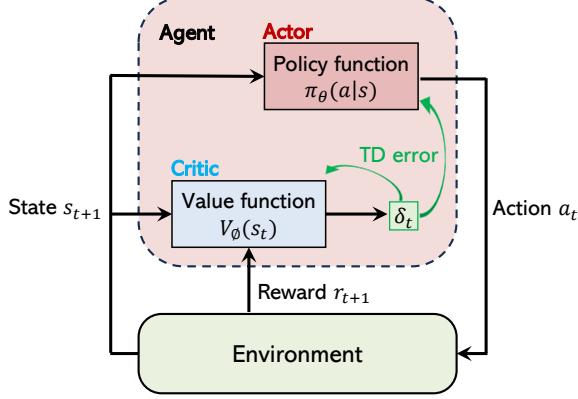


Fig. 5. Classic structure of Actor-Critic network.

3) *Actor-Critic Network*: Actor-Critic [44] is one of the major DRL algorithms. The *Actor* learns the policy to take action within a given state directly (Hyper-parameters set is denoted as  $\theta$ ), which is different from DQN (indirectly learning by approaching optimal Q value). The *critic* is utilized to evaluate the value of the policy by approaching an accurate value function using a neural network (Hyper-parameters set is denoted as  $\phi$ ).

Actor and critic are initialized by  $\theta_0$  and  $\phi_0$ . Then, based on the initial policy  $\pi_{\theta_0}(a|s)$ , actor starts to explore the environment to collecting interaction experience  $(s_t, a_t, r_t, s_{t+1})$ . Critic, with initial  $\phi_0$  parametric, aims to evaluate the value of the policy by calculating temporal difference (TD) in Equation (9) using actor's experience. The smaller  $E(\delta_t)$  is, the better  $\pi_\theta$  is. Furthermore,  $\phi_0$  will be updated using  $\delta_t$  and gradient decent in Equation (10).

$$\delta_t = r_{t+1} + \gamma V_{\phi_0}(s_{t+1}) - V_{\phi_0}(s_t) \quad (9)$$

$$\phi_0 \leftarrow \phi_0 + \alpha \delta_t \nabla_\phi V_{\phi_0}(s_t) \quad (10)$$

After updating the Critic, the parametric Actor will be upgraded based on the Critic's opinion ( $\delta_t$ ). Then,  $\theta_0$  will be updated by Equation 8. What is worth mentioning is that we consider  $\delta_t$  as a approaching value of the advantage function to represent the relative advantage of an action compared to the average strategy (i.e., current policy  $\pi_\theta$ ). Once upgrade parametric Actor, another epoch of collecting experience will go on and repeat the steps above.

$$\nabla_\theta J(\theta) = E[\nabla_\theta \log \pi_\theta(a|s_t) \cdot \delta_t] \quad (11)$$

Based on the idea of the actor-critic network, many improved versions have been proposed. Advantage actor critic (A2C) [45] is an improved version of traditional A2C methods by using *advantage function*  $A(s, a)$ , which evaluates the extra value of choosing a specific action  $a$  compared with an average value of a state, to making a better training efficiency. Based on this idea, the update for *actor* in A2C is followed by Equation (14) .

$$A(s, a) = Q(s, a) - V(s) \quad (12)$$

$$Q(s, a) \approx r + \gamma V(s_{t+1}, \phi) \quad (13)$$

$$\nabla_\theta(\theta) = E [\nabla \log \pi(a_t|s_t) \cdot A(s_t, a_t)] \quad (14)$$

$$L(\phi) = E [(r + \gamma V(s_{t+1}, \phi) - V(s_t, \phi))^2] \quad (15)$$

The aim of Critic in A2C is making sure to predict the expected return given a specific state  $s$  following current policy  $\pi$ . Thus, trying to minimize the difference between prediction of value function and target return is essential to update the parameters of critic, shown in the Equation (15). Asynchronous Advantage Actor-Critic (A3C) [45] is an algorithm that parallelizes the learning process through multi-threading. Each thread independently explores the environment and calculates gradients, and then asynchronously updates the shared global network parameters [46].

#### E. Inverse reinforcement learning

Inverse Reinforcement Learning (IRL) constitutes a problem setting within RL, aiming to infer the reward function from observed expert behaviours [47]. Unlike traditional reinforcement learning, where agents learn optimal policy through interactions with the environment based on a predefined reward function, IRL focuses on understanding and replicating such behaviours without directly knowing the reward function, by observing exemplary policies or actions [48]. The fundamental premise of IRL is that the observed behaviours reflect the intrinsic motivations or reward structures adhered to during these actions. Consequently, by inversely inferring these motivations or rewards, IRL seeks to construct a reward function that can explain the observed behaviours and can be used to guide agents in learning similar strategies. The most widely used IRL methods include Maximum Entropy Inverse Reinforcement Learning, which uses a linear function to approximate the reward function behind [49]. However, for the complex reward function, the method holds limitations. Based on that, Maximum Entropy Deep Inverse Reinforcement Learning was proposed, using fully convolutional neural networks to represent the reward function [50].

#### F. Evaluation

Evaluations in RL are primarily concentrated on assessing the performance of agent in particular task or environment [51]. It relies on specific purpose of tasks, goals of agent and any available feedback information. There are 2 mainly used evaluation metrics, cumulative reward or discounted cumulative reward (return), which means total reward that the agent could gain in one episode or within a fixed period. Success Rate measures the rate at which agent reach specific goals or tasks are successfully completed. It is applicable for tasks with clear success criteria, e.g. navigation. Other evaluation metrics could be set up by understanding the final purpose of task as well, it will depend on the scenario where RL applied. Specifically, in network intrusion detection scenarios, accuracy, precision, recall and  $F_1$  scores are widely utilized,

TABLE I  
LIST OF TOOLS AND THEIR ACCESSIBLE LINKS FOR DEEP REINFORCEMENT LEARNING BASED NETWORK INTRUSION.

| Name of Tools | Brief Introduction   | Accessible here             |
|---------------|--|-----------------------------|
| CSLE          | A platform for evaluating and developing RL agents for control problems.           | Limmen/csle                 |
| PenGym        | A Penetration testing framework for creating and managing real-world environments. | cyb3rlab/PenGym             |
| AutoPen       | An automated penetration testing framework.  | crond-jaist/AutoPentest-DRL |
| NASimEmu      | A framework for training agents in offensive penetration-testing scenarios.        | jaromiru/NASimEmu           |
| CLAP          | A simulated computer network complete with vulnerabilities, scans and exploits.    | yyzpiero/RL4RedTeam         |
| Cyberwheel    | A simulation environment focused on autonomous cyber defence.                      | ORNL/cyberwheel             |
| Idsgame       | A environment for simulating attack and defence operations.                        | Limmen/gym-idsgame          |
| MAB-Malware   | An open-source framework to generate specific malware.                             | weisong-ucr/MAB-malware     |
| YAWNING-TITAN | An abstract, graph based cyber-security simulation environment.                    | dstl/YAWNING-TITAN          |

by calculating True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN) from confusion matrix. In some cases, Receiver Operating Characteristics (ROC) curve [52] will be used to measure the model performances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (17)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (18)$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (19)$$

$$AUC = \int_0^1 \frac{TP}{TP + FN} d \frac{FP}{TN + FP} \quad (20)$$

### III. TOOLS USED FOR RL BASED NETWORK INTRUSION

For accelerating the evaluation process of DRL models in network intrusion issues, researchers have developed many useful tools including CSLE [53], PenGym [54], AutoPen [55], NASimEmu [56], CLAP [57], Cyberwheel [58], Idsgame [59], MAB-Malware [60] and YAWNING-TITAN [61], they are shown in Table I. Here are some basic information to introduce what and how will these tools impact the DRL-based network intrusion detection.

CSLE is a platform designed for developing and testing reinforcement learning agents in network intrusion detection, offering a realistic cyber range environment. It supports integration with methods like dynamic programming, game theory, and optimization, enhancing research in cyber security. PenGym is a framework for training RL agents in penetration testing, compatible with the Gymnasium API. It allows RL agents to perform actions like network scanning and exploitation in controlled environments. AutoPen is an automated penetration testing framework that uses DRL to identify optimal attack paths in both simulated and real networks. It integrates tools like Nmap and Metasploit to execute attacks, allowing users to study penetration testing techniques for educational purposes. NASimEmu is a framework designed for training DRL agents in offensive penetration-testing scenarios, featuring both a simulator and an emulator for seamless deployment. It uses a random generator to create varied network scenarios and supports simultaneous training across multiple scenarios.

CLAP is a RL agent based on PPO that performs penetration testing in simulated network environments using the Network Attack Simulator (NASim). The agent is trained to identify and exploit vulnerabilities to gain access to network resources. Cyberwheel is a RL simulation environment designed for training and evaluating autonomous cyber defence models on simulated networks. Built with modularity, it allows users to customize networks, services, host types, and defensive agents through configurable files. Idsgame is a RL environment designed for simulating attack and defence operations within an abstract network intrusion game. Based on a two-player Markov game model, it features attacker and defender agents competing in a simulated network. The environment provides an interface to a partially observed Markov decision process (POMDP), enabling the training, simulation, and evaluation of attack and defence policies. MAB-Malware is an open-source reinforcement learning framework designed to generate adversarial examples for PE malware by modeling the problem as a multi-armed bandit (MAB). Each action-content pair is treated as an independent slot machine with rewards modeled by a Beta distribution, and Thompson sampling is used to balance exploration and exploitation. YAWNING-TITAN (YT) is a graph-based cyber-security simulation environment built to train intelligent agents for autonomous cyber defence operations. It focuses on simplicity, minimal hardware requirements, and is platform-independent, supporting various algorithms and customizable environment settings.

### IV. DRL IN NETWORK INTRUSION DETECTION

DRL has shown remarkable capabilities and results in network intrusion detection past last few years [21], [62]–[65]. With combining deep learning and RL, researchers can develop highly efficient, automatic learning detection models. These studies highlight DRL's powerful ability to process high-dimensional data and complex network environments [65]. It can not only improve detection accuracy and sensitivity, but also optimize its performance through a continuous and dynamic learning process, making network intrusion defence more intelligent and automated [21]. These advantages of DRL herald its widespread application and far-reaching influence in future NID research. In the following subsections, we aim to fully investigate current research and applications for last few years and present insightful views on deep reinforcement learning for network intrusion detection.

### A. Dataset

Many intrusion datasets have been proposed in recent years. Attack or intrusion types are various in different intrusion datasets. In this section, we are going to present the basic information of current widely utilised network intrusion datasets including KDDCUP 99, NSL-KDD CMU-CERT, UNSW-NB15, CIC-IDS-2017, CSE-CIC-IDS2018, CICDDoS2019, LITNET-2020, AWID, MAWIFlow, CICIoT2023, providing essential understanding including distributions of intrusion types and network traffic features in each datasets and how they were been collected or created. In the end, a comprehensive summary for all datasets are presented for any future reference. The introduction of all mentioned intrusion in the following datasets are presented in Figure 6 for reference.

The KDDCUP 99 dataset [66] was created by processing data from the 1998 DARPA [67] intrusion detection challenge. This was achieved using the Mining Audit Data for Automated Models for Intrusion Detection (MADMAID) framework to extract features from the raw tcpdump data. Detailed statistics of the dataset are provided in Table II. The original 1998 dataset was developed by MIT's Lincoln Laboratory, involving thousands of UNIX machines and hundreds of users. Network traffic was recorded in tcpdump format<sup>2</sup> over a ten-week period, with the first seven weeks' data serving as the training set and the remaining three weeks' data as the testing set. The KDDCUP 99 DARPA dataset is available in two versions: the full dataset and a 10% sample. It includes 41 features and is categorized into five classes: *Normal, DoS, Probe, R2L, and U2R*.

The NSL-KDD dataset [68] is one of the most widely recognized benchmark datasets, extensively utilized by cybersecurity researchers to evaluate the performance of Intrusion Detection Systems (IDS). Developed by [66], it is based on the KDDCUP 99 dataset encompassing both attack and non-attack instances. It is classified as either normal or one of 38 predefined attack types. The training subset includes 22 specific attack types, while the testing subset introduces an additional 16 novel attack types. It retains the original four types of attacks from the KDDCUP 99 dataset.

TABLE II  
INTRUSIONS DISTRIBUTION FOR KDDCUP 99 AND NSL-KDD DATASETS

| Intrusions    | KDDCup 99 |          | NSL-KDD   |          |
|---------------|-----------|----------|-----------|----------|
|               | Train Set | Test Set | Train Set | Test Set |
| Normal        | 97,278    | 60,593   | 67,343    | 9,710    |
| DoS           | 391,458   | 229,853  | 45,927    | 7,458    |
| Probe         | 4,107     | 4,166    | 11,656    | 2,422    |
| R2L           | 1,126     | 16,189   | 995       | 2,887    |
| U2R           | 52        | 228      | 52        | 67       |
| Total records | 494,021   | 311,029  | 125,973   | 22,544   |

CMU-CERT [69] is a synthetic dataset firstly proposed by Computer Emergency and Response Team (CERT) division of Carnegie Mellon University (CMU) as an insider threat

<sup>2</sup>The tcpdump format is used to capture detailed network traffic information, including timestamps, source and destination IP addresses, port numbers, protocol types, and more.

dataset. Additionally, this dataset has been continuously updated in recent years. However, one significant drawback is the substantial data imbalance [70]. The insider threat dataset is available in several iterations in recent years, with each new version offering enhancements and improvements. Version 4.2 is notably more frequently utilized, as it includes the highest proportion of intrusions relative to normal data. This version comprises 30,602,325 entries in total, of which 7,623 entries are identified as attacks. Consequently, the percentage of intrusions in this version is approximately 0.025%. The dataset encompasses two years' worth of Lightweight Directory Access Protocol (LDAP)<sup>3</sup> logs, which are instrumental in pinpointing the active users within the company at any given moment. The insider threat dataset, involving 70 employees, are based on three specific scenarios.

- Scenario 1: An employee with no prior record of using removable drives or working after hours suddenly begins logging in outside of business hours, utilizing a removable drive, and uploading data to *Wikileaks.org*. This activity is followed by the user's swift departure from the company.
- Scenario 2: An employee begins to visit job search websites and applies for positions at competing firms. Prior to leaving the organization, this individual uses a thumb drive to steal a significant amount of data, far exceeding their previous usage.
- Scenario 3: A disgruntled system administrator installs a keylogger and transfers it to his supervisor's computer via a thumb drive. The next day, he exploits the captured keystrokes to log in as his supervisor and sends a panic-inducing mass email to the entire organization, before immediately resigning.

TABLE III  
DATA SOURCES IN THE CMU-CERT INSIDER THREAT DATASET V4.2

| Sources | Total Entries | Intrusions | Percentage(%) |
|---------|---------------|------------|---------------|
| Logon   | 427,628       | 198        | 0.046         |
| Device  | 205,476       | 2,786      | 1.37          |
| HTTP    | 28,438,284    | 3,860      | 0.013         |
| Email   | 1,315,459     | 469        | 0.035         |
| File    | 222,801       | 10         | 0.004         |

To address the issues including redundant records, imbalanced datasets and too many simple records present in the KDDCUP 99 and NSL-KDD datasets, the research team at the Australian Centre for Cyber Security (ACCS) developed a new dataset known as UNSW-NB15 [71]. This dataset was created using a hybrid generation method, employing the IXIA Perfect Storm tool<sup>4</sup> to capture real-time network traffic containing both normal and malicious activities. The IXIA Perfect Storm tool includes a library that stores new attacks and common vulnerabilities and exposures (CVEs)<sup>5</sup>, which is a publicly available repository of security vulnerabilities and exposures.

<sup>3</sup>Accessing and managing distributed directory information services.

<sup>4</sup>A network security testing tool primarily utilized for evaluating and testing the security performance of network infrastructure.

<sup>5</sup>Common vulnerabilities and exposures at <https://www.cve.org/>

During the data generation process, the researchers utilized two servers: one to simulate normal network activities and the other to generate malicious activities. The network data packets were captured using the tcpdump tool. The entire process took 31 hours, resulting in the collection of 100 GB of data, which was subsequently divided into multiple 1,000 MB pcap files. Following this, the researchers used Argus and Bro-IDS on a Linux Ubuntu 14.0.4 system to extract features from these pcap files. Additionally, they developed 12 algorithms to conduct an in-depth analysis of each data packet [71]. Finally, the UNSW-NB15 dataset is presented as full connection records: comprising 2 million connection records and partial connection records: consisting of 82,332 training records and 175,341 testing records, covering 10 types of attacks. Notably, the partial connection record dataset contains 42 features and includes corresponding class labels that categorize network behaviours into normal and nine different types of attacks.

TABLE IV  
INTRUSION TYPES AND THEIR RESPECTIVE TRAIN AND TEST DATA DISTRIBUTIONS FOR UNSW-NB15 DATASET.

| Intrusions     | Train   | Ratio(%) | Test   | Percentage(%) |
|----------------|---------|----------|--------|---------------|
| Normal         | 56,000  | 60.22    | 37,000 | 39.78         |
| Fuzzers        | 18,184  | 75.00    | 6,062  | 25.00         |
| Analysis       | 2,000   | 74.71    | 677    | 25.29         |
| Backdoors      | 1,746   | 74.97    | 583    | 25.03         |
| DoS            | 12,264  | 75.00    | 4,089  | 25.00         |
| Exploits       | 33,393  | 75.00    | 11,132 | 25.00         |
| Generic        | 40,000  | 67.95    | 18,871 | 32.05         |
| Reconnaissance | 10,491  | 75.01    | 3,496  | 24.99         |
| Shell code     | 1,133   | 74.98    | 378    | 25.02         |
| Worms          | 130     | 74.71    | 44     | 25.29         |
| Total          | 17,5341 | 68.05    | 82,332 | 31.95         |

In CIC-IDS-2017 [72], researchers utilized CICFlowMeter tool to extract 80 network traffic features based on a 5-day traffic flow data. The principal objective during data collection was to capture authentic background traffic. Employing the B-profile system, benign traffic was characterized by 25 users operating across protocols including HTTP, HTTPS, FTP, SSH, and email. The data collection extended over a period of five days, documenting routine traffic on one day and introducing various attacks on subsequent days. The injected attacks encompassed Brute Force FTP, Brute Force SSH, DoS, Heartbleed, Web Attack, Infiltration, Botnet, and DDoS.

TABLE V  
ATTACK DISTRIBUTIONS IN TRAIN AND TEST SETS FOR CIC-IDS-2017

| Intrusion Types | Train  | Percentage(%) | Test   | Percentage (%) |
|-----------------|--------|---------------|--------|----------------|
| Normal          | 60,000 | 75.00         | 20,000 | 25.00          |
| SSH-Patator     | 5,000  | 84.79         | 897    | 15.21          |
| FTP-Patator     | 7,000  | 88.18         | 938    | 11.82          |
| DoS             | 6,000  | 75.00         | 2,000  | 25.00          |
| Web             | 2,000  | 91.74         | 180    | 8.26           |
| Bot             | 1,500  | 76.30         | 466    | 23.70          |
| DDoS            | 6,000  | 75.00         | 2,000  | 25.00          |
| PortScan        | 6,000  | 75.00         | 2,000  | 25.00          |
| Total           | 93,500 | 76.65         | 28,481 | 23.35          |

The CSE-CIC-IDS2018 dataset [73] is among the most widely used for IDS. It encompasses seven distinct attack

scenarios: Brute-force, Heartbleed, Botnet, DoS, DDoS, Web assaults, and internal network penetration. The attacking infrastructure comprises 50 machines, while the victim organization's infrastructure includes 420 machines and 30 servers spread across five different departments. This dataset features network traffic and system logs for each computer, with up to 84 network features extracted from the recorded network traffic using CICFlowMeter-V3 as well. What is worth mentioning is that the dataset exhibits an unequal distribution of positive and negative samples, typically addressed through over-sampling or down-sampling to manage the imbalance.

TABLE VI  
CSE-CIC-IDS2018 DATASET INTRUSION DISTRIBUTION.

| Intrusion Types | Traffic Flow Counting | Percentage (%) |
|-----------------|-----------------------|----------------|
| Benign          | 13,484,708            | 83.07          |
| DDoS            | 1,263,933             | 7.79           |
| DoS             | 654,300               | 4.03           |
| Brute Force     | 380,949               | 2.35           |
| Bot             | 286,191               | 1.76           |
| Infiltration    | 161,934               | 0.99           |
| Web             | 928                   | 0.01           |

The CICDDoS2019 dataset [74], developed by the Canadian Institute for Cybersecurity (CIC) at the University of New Brunswick (UNB), serves as a realistic and comprehensive benchmark for the detection of Distributed Denial of Service (DDoS) attacks. This dataset addresses the shortcomings of existing datasets, such as incomplete traffic, anonymous data, and outdated attack scenarios. It encompasses 11 distinct types of DDoS attacks, including reflective and exploitative attacks, with 80 network traffic features extracted and calculated from all benign and denial-of-service flows using the CICFlowMeter software. Additionally, the dataset is generated by simulating a real-world network environment, incorporating genuine interactions between the attacker and victim networks, as well as attacks executed using third-party tools and packages. The attack distributions of CICDDoS2019 are presented in table VII.

TABLE VII  
CICDDoS2019 DATASET INTRUSION DISTRIBUTIONS.

| Intrusion Types | Traffic Flow Counting | Percentage (%) |
|-----------------|-----------------------|----------------|
| Benign          | 56,863                | 0.11           |
| DDoS DNS        | 5,071,011             | 10.13          |
| DDoS LDAP       | 2,179,930             | 4.35           |
| DDoS MSSQL      | 4,522,492             | 9.03           |
| DDoS NetBIOS    | 4,093,279             | 8.18           |
| DDoS NTP        | 1,202,642             | 2.40           |
| DDoS SNMP       | 5,159,870             | 10.31          |
| DDoS SSDP       | 2,610,611             | 5.21           |
| DDoS SYN        | 1,582,289             | 3.16           |
| DDoS TFTP       | 20,082,580            | 40.11          |
| DDoS UDP        | 3,134,645             | 6.26           |
| DDoS UDP-Lag    | 366,461               | 0.73           |
| Total           | 50,062,673            | 100.00         |

LITNET-2020 [20] is a novel benchmark dataset for network traffic based intrusion detection proposed by Kaunas University of Technology, Lithuania. This dataset is designed

to provide realistic and up-to-date network traffic data for the development of Network Intrusion Detection (NID) methods. Despite numerous recent efforts that have introduced various benchmark datasets for NID, existing datasets still fail to adequately capture modern network traffic scenarios and provide examples of diverse network attacks and intrusions. LITNET-2020 fills this gap by offering annotated data obtained from a real-world academic network. Captured from the Lithuanian Research and Education Network (LITNET) between March 6, 2019, and January 31, 2020, the dataset comprises over 45,330,333 records, with 5,328,934 records being attack data, covering 12 types of attacks. The dataset includes 49 attributes from the NetFlow v9 protocol and is extended with 19 custom attack detection features, with each record containing 85 network traffic features. LITNET-2020 provides a valuable resource for researchers in the field of cybersecurity, aiding in the development and validation of more effective NIDs. Table VIII shows the intrusion distribution of LITNET-2020

TABLE VIII  
INTRUSION DISTRIBUTION OF LITNET-2020 DATASET.

| Intrusion Types      | Total      | Attacks   | Percentage (%) |
|----------------------|------------|-----------|----------------|
| Smurf                | 3,994,426  | 59,479    | 1.49           |
| ICMP-flood           | 3,863,655  | 11,628    | 0.30           |
| UDP-flood            | 606,814    | 93,583    | 15.42          |
| TCP SYN-flood        | 14,608,678 | 3,725,838 | 25.50          |
| HTTP-flood           | 3,963,168  | 22,959    | 0.58           |
| LAND attack          | 3,569,838  | 52,417    | 1.47           |
| Blaster Worm         | 2,858,573  | 24,291    | 0.85           |
| Code Red Worm        | 5,082,952  | 1,255,702 | 24.70          |
| Spam bot's detection | 1,153,020  | 747       | 0.06           |
| Reaper Worm          | 4,377,656  | 1,176     | 0.03           |
| Scanning/Spread      | 6,687      | 6,232     | 93.20          |
| Packet fragmentation | 1,244,866  | 477       | 0.04           |
| Total flows          | 45,330,333 | 5,328,934 | 11.76          |

The Aegean WiFi Intrusion Dataset (AWID) [75], [76] is a publicly accessible and comprehensive dataset meticulously crafted for research in wireless network security and intrusion detection. It encapsulates traffic captured from actual 802.11 networks secured via WEP encryption, encompassing both benign and adversarial traffic. The dataset is bifurcated into two principal variants: the AWID-ATK, delineated by attack types, and the AWID-CLS, categorized by attack classes. Each variant is enhanced with both full and reduced subsets, accompanied by their respective training and testing sets. Within the dataset, each packet is represented as a vector comprising 156 attributes, including but not limited to the Source Address, Destination Address, Initialization Vector (IV), Extended Service Set Identifier (ESSID), and Signal Strength. These attributes have been subjected to preprocessing, and transformed into numerical or categorical values, thereby facilitating the analysis via machine learning algorithms. It is already a benchmark used for the research and development of wireless IDS, focusing on the security of 802.11, which is a specific wireless frequency.

The MAWIFlow dataset [77] is a publicly available compilation of around 8 terabytes of real network traffic spanning a four-year interval from 2016 to 2019, encompassing more than seven billion network flows. It ensures authenticity and

diversity by including a multitude of protocols and behaviours. Labelling of daily anomalous events is facilitated through the MAWILab tool, which identifies various network-level attack types such as Service Scan, TCP Scan, and Denial-of-Service attacks. The dataset's high variability and completeness are further augmented by the application of the BigFlow feature extraction algorithm, which extracts a set of thirty-nine features for each network flow within a 15-second time window, making it an ideal benchmark for evaluating the performance and model update strategies of intrusion detection techniques in the face of evolving network traffic behaviours.

TABLE IX  
INTRUSION DISTRIBUTIONS OF CICIoT2023 DATASETS.

| Intrusion Types | Traffic Flow Counting | Percentage (%) |
|-----------------|-----------------------|----------------|
| DDoS            | 33,984,650            | 74.55          |
| DoS             | 8,090,738             | 17.75          |
| Recon           | 354,565               | 0.78           |
| Web-Based       | 24,829                | 0.05           |
| Spoofing        | 499,568               | 1.10           |
| Mirai           | 2,634,124             | 5.78           |
| Total           | 45,588,474            | 100.00         |

The CICIoT2023 dataset [78], shown in table IX, is a novel and extensive Internet of Things (IoT) attack dataset, designed to foster the development of security analytics applications in real IoT operations. This dataset is generated by executing 33 types of attacks within an IoT topology comprising 105 devices, categorized into seven distinct classes, namely Distributed Denial of Service (DDoS), Denial of Service (DoS), Reconnaissance (Recon), Web-based attacks, Brute Force, Spoofing, and Mirai. All attacks are conducted by malicious IoT devices targeting other IoT devices. The dataset encompasses a variety of IoT device types, such as smart home devices, cameras, sensors, and micro-controllers. Forty-seven network traffic features are extracted from the dataset, including packet length, transmission rate, and protocol types. It is available in two file formats, pcap and csv, to accommodate the needs of researchers. The pcap files contain the raw data, while the csv files provide the extracted features.

### B. Modeling workflow

Figure 7 illustrates the current standard process of implementing a network intrusion detection model using DRL. In the first phase a network dataset is obtained, then, by employing a traffic sampling method, it is possible to extract network features and labels which are needed/utilized in the training phase. In this phase, the policy function  $\pi_\theta(a|s)$  receives network traffic features data as input and predicts potential intrusion types. Based on these predictions, feedback is provided in the form of correct, incorrect, or uncertain detection outcomes. This feedback is further processed through a reward function, which in turn updates the policy function to enhance its detection accuracy. Designing a practical reward function could accelerate the training speed and the aim of training is to let the policy function get the maximum reward. During the testing phase, the trained policy function is applied to real network traffic, producing intrusion detection results.

| Intrusion Terms                             | Introduction  | Existed in |
|---|---|------------|
| Normal/Benign                               | <i>Anticipated and authorized data transmission activities within computer networks.</i>  | 10         |
| Denial of Service Attack (DoS)              | <i>The attacker overwhelms computing or memory resources, making them too busy or full to process legitimate requests, or prevents legitimate users from accessing a computer, including LAND attack and flood attack.</i>  | 5          |
| Distributed Denial of Service Attack (DDoS) | <i>It is a type of DoS attack where multiple compromised computers or devices, often geographically dispersed with a massive amount of requests or data packets.</i>  | 4          |
| User to Root Attack (U2R)                   | <i>It is a type of exploit where the attacker initially gains access to a standard user account on the system—potentially through methods such as password sniffing, a dictionary attack, or social engineering—and subsequently leverages a vulnerability to escalate privileges and obtain root access to the system.</i> | 1          |
| Remote to Local Attack (R2L)                | <i>This situation arises when an attacker, capable of sending packets to a machine over a network without holding an account on that machine, exploits a vulnerability to obtain local user access.</i>   | 1          |
| Probe                                       | <i>This refers to an effort aimed at collecting information about a computer network, seemingly with the intent of bypassing its security measures.</i>   | 1          |
| Fuzzers                                     | <i>Fuzzers are automated testing tools that generate a vast number of random or anomalous inputs to target systems, aiming to identify potential vulnerabilities or errors.</i>   | 1          |
| Analysis                                    | <i>It typically refers to the detailed examination of network activity, packets, or system behavior to identify anomalies or malicious activities.</i>  | 1          |
| Backdoors                                   | <i>Backdoors are covert access points planted by attackers in systems or software, allowing unauthorized access by bypassing normal security mechanisms.</i>  | 1          |
| Exploits                                    | <i>Exploits refer to attack codes or techniques that take advantage of vulnerabilities in software or systems to execute unauthorized operations.</i>   | 1          |
| Generic                                     | <i>Generic in cybersecurity often refers to tools or methods that are broadly applicable across various types of attacks or systems, rather than being tailored to a specific target.</i>   | 1          |
| Reconnaissance                              | <i>Reconnaissance is the process by which attackers gather information about a target system before launching an attack, to understand its weaknesses and potential points of exploitation.</i>   | 1          |
| Shell code                                  | <i>Shell code is malicious code used to execute commands or take control of a target system, typically as part of an exploit.</i>   | 1          |
| Worms                                       | <i>Worms are self-replicating malicious software that automatically spreads across networks, often causing significant resource consumption as they propagate.</i>  | 2          |
| Brute Force                                 | <i>Brute Force attempts to crack passwords or keys by exhaustively trying all possible combinations, including SSH-Patator and FTP-Patator.</i>   | 2          |
| Bot   | <i>A Bot is an infected computer controlled by an attacker, used to perform malicious tasks such as sending spam.</i>   | 4          |
| Infiltration                                | <i>Infiltration refers to the process by which attackers covertly enter a target network or system to steal information or cause disruption.</i>  | 1          |
| Web-based                                   | <i>Web-based attacks are those conducted through websites or web applications, with common forms including SQL injection and cross-site scripting.</i>  | 3          |
| Port Scan                                   | <i>Port Scan is a technique used to identify open ports and services on a target system, often part of the reconnaissance phase.</i>  | 1          |
| Scanning/Spread                             | <i>Scanning/Spread refers to the behavior of malware that, after infecting an initial target, scans the network to find other vulnerable systems and spreads to them.</i>   | 1          |
| Packet fragmentation                        | <i>Packet fragmentation is a technique where data packets are broken into smaller fragments for transmission, which attackers might use to evade certain security detection mechanisms.</i>   | 1          |
| Spoofing                                    | <i>Spoofing refers to the act of attackers forging identities or data to deceive the target system or users into believing it comes from a legitimate source.</i>   | 1          |
| Mirai                                       | <i>Mirai is malware specifically targeting IoT devices, using brute-force attacks to exploit default passwords.</i>   | 1          |

Fig. 6. An introduction to frequently mentioned intrusion terms. And their frequency across all mentioned datasets.

This entire process iteratively updates the policy function, enabling the system to more effectively identify and classify network intrusions in a dynamic network environment.

### C. Model performance

DRL-based intrusion models have reached many interesting results, some researchers claim they as a state-of-the-art methods among all intrusion detection models. In this section, we are going to introduce the model performances of DRL-based intrusion detection models in different datasets. Table X shows the performance of DRL models on the NSL-KDD dataset in recent years. Models such as Big-IDS, MAFSIDS, and A-DQN demonstrate excellent performance in terms of accuracy and F1 score, with MAFSIDS particularly standing out, achieving an accuracy of 99.10% and an F1 score of 99.10%. Different models also excel in precision and recall, with the DRL+RBFNN model showing a balanced performance across these metrics. Table XI lists the performances of DRL models on the UNSW-NB15 and CMU-CERT datasets. Overall, these

models perform well on the UNSW-NB15 dataset, with the DQN model achieving an accuracy of 91.80% and an F1 score of 92.44%. In comparison, the AE-DQN model also performs notably well on the CMU-CERT dataset, with an accuracy of 88.80% and an F1 score of 89.90%. Table XI shows the performance on the CIC-IDS2017 dataset, models like DRL+RBFNN and A-DQN perform excellently across all metrics, with the DRL+RBFNN model achieving an accuracy of 99.70%, and precision and F1 scores of 99.60% and 99.60%, respectively. Table XI also presents the performance on the CIC-IDS2018 dataset. The ID-RDRL model stands out, particularly in recall and F1 score, achieving 100.00% and 96.30%, respectively. The performance on the CIC-IDS2019 dataset is also shown in Table XI. The ADQN model excels in all metrics, especially in accuracy (99.60%) and F1 score (99.40%). The DQN+CNN model also performs well in terms of precision and recall. For the performance on the AWID dataset, models like AE-SAC and SSDQDN show outstanding performance across all metrics, particularly the AE-SAC

TABLE X  
DEEP REINFORCEMENT LEARNING MODEL PERFORMANCES ON NSL-KDD DATASETS IN LAST FEW YEARS.

| Reference | Year | Method      | Dataset | Best Model Performance |              |              |              |
|-----------|------|-------------|---------|------------------------|--------------|--------------|--------------|
|           |      |             |         | ACC(%)                 | PR(%)        | RC(%)        | F1(%)        |
| [79]      | 2024 | Big-IDS     | NSL-KDD | 97.44                  | /            | /            | /            |
| [80]      | 2023 | AE-SAC      | NSL-KDD | 84.15                  | 84.27        | 84.15        | 83.97        |
| [81]      | 2023 | MAFSIDS     | NSL-KDD | 99.10                  | /            | /            | 99.10        |
| [82]      | 2022 | Deep SARSA  | NSL-KDD | 84.36                  | 84.71        | 84.36        | 84.40        |
| [82]      | 2022 | DQN         | NSL-KDD | <b>99.36</b>           | <b>99.07</b> | <b>99.36</b> | <b>99.21</b> |
| [83]      | 2022 | Dueling DQN | NSL-KDD | 80.31                  | 79.62        | 59.87        | 62.62        |
| [84]      | 2021 | DRL+RBFNN   | NSL-KDD | 90.70                  | 87.30        | 96.40        | 92.30        |
| [85]      | 2021 | SSDDQN      | NSL-KDD | 79.43                  | 82.81        | 79.43        | 76.22        |
| [86]      | 2021 | A-DQN       | NSL-KDD | 97.20                  | 96.50        | 99.10        | 97.80        |
| [87]      | 2021 | DQN         | NSL-KDD | 82.09                  | 84.11        | 82.09        | 82.43        |
| [88]      | 2020 | DDQN        | NSL-KDD | 83.4                   | /            | /            | /            |
| [89]      | 2020 | DQN         | NSL-KDD | 98.71                  | 97.35        | 98.71        | 98.30        |
| [90]      | 2020 | DQN         | NSL-KDD | 91.40                  | 92.80        | 90.20        | 91.48        |
| [91]      | 2019 | DQN         | NSL-KDD | 81.80                  | /            | /            | /            |

TABLE XI  
DEEP REINFORCEMENT LEARNING MODEL PERFORMANCES ON OTHER PUBLIC DATASETS

| Reference | Year | Method     | Dataset     | Best Model Performance |               |              |              |
|-----------|------|------------|-------------|------------------------|---------------|--------------|--------------|
|           |      |            |             | ACC(%)                 | PR(%)         | RC(%)        | F1(%)        |
| [92]      | 2023 | AE-DQN     | CMU-CERT    | 88.80                  | 89.10         | 90.70        | 89.90        |
| [82]      | 2022 | Deep SARSA | UNSW-NB15   | 85.09                  | /             | /            | /            |
| [84]      | 2021 | DRL+RBFNN  | UNSW-NB15   | 82.62                  | 82.40         | 82.60        | 82.49        |
| [90]      | 2020 | DQN        | UNSW-NB15   | <b>91.80</b>           | <b>93.20</b>  | <b>91.70</b> | <b>92.44</b> |
| [91]      | 2019 | DQN        | UNSW-NB15   | /                      | 68.26         | 86.19        | 76.17        |
| [80]      | 2023 | AE-SAC     | CIC-IDS2017 | 96.65                  | 89.10         | 90.70        | 89.90        |
| [84]      | 2021 | DRL+RBFNN  | CIC-IDS2017 | <b>99.70</b>           | <b>99.60</b>  | <b>99.70</b> | <b>99.60</b> |
| [86]      | 2021 | A-DQN      | CIC-IDS2017 | 98.70                  | 98.60         | 99.40        | 98.90        |
| [81]      | 2023 | MAFSIDS    | CIC-IDS2018 | 96.18                  | /             | /            | /            |
| [93]      | 2022 | ID-RDRL    | CIC-IDS2018 | <b>96.80</b>           | <b>100.00</b> | <b>94.33</b> | <b>96.30</b> |
| [93]      | 2022 | ID-RDRL    | CIC-IDS2018 | 96.20                  | /             | /            | 94.90        |
| [94]      | 2023 | ADQN       | CIC-IDS2019 | <b>99.60</b>           | <b>99.30</b>  | <b>99.60</b> | <b>99.40</b> |
| [93]      | 2022 | DQN+CNN    | CIC-IDS2019 | 97.69                  | 98.10         | 96.65        | 97.14        |
| [93]      | 2021 | DRL+RBFNN  | CIC-IDS2019 | 99.00                  | /             | /            | /            |
| [80]      | 2023 | AE-SAC     | AWID        | <b>98.98</b>           | <b>98.96</b>  | <b>98.98</b> | <b>98.92</b> |
| [84]      | 2021 | DRL+RBFNN  | AWID        | 95.50                  | 91.40         | 95.50        | 93.40        |
| [85]      | 2021 | SSDDQN     | AWID        | 98.19                  | 98.40         | 98.19        | 98.22        |
| [91]      | 2019 | DQN        | AWID        | 96.12                  | /             | /            | /            |

model, with an accuracy of 98.98%, and precision and F1 scores of 98.96% and 98.92%, respectively.

#### D. Improved network feature engineering

Typically, the dataset of network traffic comprises various features that reflect the status of network traffic. However, not all of these features are beneficial for constructing DRL-based network intrusion detection systems. The accurate representation of traffic status using network traffic features is crucial. Consequently, many researches have been proposed to effectively extract network features that can accurately represent the actual status of network traffic. Liu *et al* [95] proposed a method that combines Local-Sensitive Hashing (LSH) with Deep Convolutional Neural Networks (DCNN), selecting optimal features by assessing the distribution of information entropy across each feature value. Ren *et al* [93] suggest combining the Recursive Feature Elimination (RFE) and decision tree to select the optimal sub-feature set and the method effectively identifies and eliminates approximately 80% of the redundant features from the original dataset. Ren

*et al* [81] further employed Graph Convolutional Networks (GCN) to extract deep features from network data. They transformed the selected input data into dynamic graph networks. Through the hierarchical structure of GCN, more rich and abstract features were extracted. Finally, they combined a multi-agent learning framework to transform the traditional feature selection space of  $2^N$  into a competition among  $N$  feature agents, effectively reducing the feature space.

#### E. Handling unbalanced datasets

The volume of normal network traffic data significantly exceeds that of intrusion data, which is a common-sense observation. Consequently, nearly all network intrusion detection datasets suffer from a severe imbalance in attack-type distribution. Therefore, the challenge of training effective DRL-based NID models on an imbalanced dataset have consistently attracted attention. Researchers have attempted to propose various methods to address such issues. Lopez *et al* [84] addressed this problem in NID by augmenting Radial Basis Function (RBF) [96] neural networks and integrating

them with offline reinforcement learning algorithms. They validated the superior performance of this approach across five commonly used datasets. However, the proposed method may face challenges with larger action spaces and have higher computational costs in training. Mohamed *et al* [97] utilized a deep State-Action-Reward-State-Action (SARSA) algorithm [98] combined with Deep Neural Networks (DNN) [99] to address the issue of data imbalance in NIDs. Although the performance was outstanding, the authors did not analyze the potential drawbacks of their proposed SARSA algorithm. Caution should be exercised when applying this approach. Pashaei *et al* [94] introduced an adversarial DRL model combined with intelligent environment simulation, presenting an effective approach to addressing the issue of high-dimensional data imbalance in NIDs. This method improves overall classification performance by increasing attention to minority classes, particularly demonstrating its efficiency and effectiveness in practical applications within IoT environments.

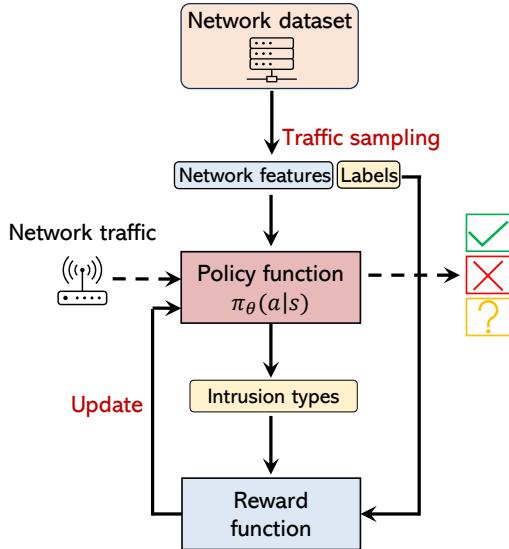


Fig. 7. Deep reinforcement learning in network intrusion detection.

#### F. Training efficiency

Normally, network traffic data exhibit high levels of uncertainty and complexity, leading to low training efficiency of DRL, which has been a long-standing concern. Louati *et al* [79] developed a distributed multi-agent reinforcement learning approach for distributed intrusion detection in large-scale network environments, termed Big-IDS. While the model demonstrated impressive performance, a notable drawback is its low training efficiency. Training the model takes approximately three days when encryption is used and about 12 hours without encryption. This significant time requirement highlights the need for optimization in training procedures to enhance practical applicability. Li *et al* [80] introduced a network intrusion detection model named AE-SAC, based on adversarial environment learning and the Soft Actor-Critic (SAC) DRL algorithm. While AE-SAC achieved excellent performance in terms of accuracy and F1 score, its complex network architecture resulted in extended training time. During

each training session, both the environment agent and the classifier agent are required to update at least three networks, contributing to the lengthy training process. Kalinin *et al* [100] enhanced the training efficiency of deep reinforcement learning models in Internet of Things(IoT) intrusion detection by implementing lightweight neural network architectures and developing various multi-agent system architectures. This approach also demonstrated superior performance in terms of accuracy and completeness metrics.

#### G. Identifying minority and unknown attacks

Normal network traffic constitutes the major class of the these mentioned dataset. However, in practical applications, the robustness and generalization ability of NID systems are often of greater concern. Therefore, identifying minority types of attacks and recognizing unknown categories of attacks are crucial in the actual deployment of NID systems. Hsu *et al* [90] developed a DRL-based model for network intrusion detection, equipped with detection and learning modes. This model can switch flexibly based on network traffic behaviours, enabling self-updating capabilities that enhance its ability to recognize unknown network traffic. The study was also tested in a real network environment, where it demonstrated good performance as well. Malika *et al* [101] introduced a distributed multi-agent NID system that combines DRL with attention mechanisms [102]. Utilizing Distributed Q-networks (DQNs) deployed across multiple network nodes, this system offers varied perspectives on the network's security status. It features a multi-agent attention mechanism that increasingly focuses on specific network nodes as performance improves. Additionally, the design incorporates zero-day defence measures to mitigate attacks exploiting unknown vulnerabilities. Notably, the integration of denoising autoencoders (DAE) has significantly enhanced the model's performance. Liu *et al* [89] enhanced a DRL framework by incorporating human operator interaction feedback into the MDP, creating a hybrid structure of Q-networks. They integrated Long Short-Term Memory (LSTM) [103] networks to better handle time-series features and incorporated a prioritized experience replay mechanism. This innovative approach significantly improved the recognition capabilities for minority and unknown category attacks. Another rising issue is the trade-off between identifying minority attacks and unknown attacks. Dong *et al* [85] have reported that when they enhancing the capability to recognize unknown attacks, they have unfortunately seen a decline in the ability to identify specific minority attack types. Xiangyu *et al* [87] developed a novel method that combines an enhanced version of the Synthetic Minority Over-sampling Technique (SMOTE) with adversarial RL to improve the detection accuracy of minority classes, such as anomalies or types of attacks. By using SMOTE to generate synthetic samples, they increased the representation of minority classes, thereby addressing the issue of dataset imbalance. Furthermore, the use of two agents within the RL framework - a classifier agent and an environment agent to facilitate dynamic training and data selection, further optimizing the model's ability to recognize minority classes.

## V. DISCUSSION AND FUTURE RESEARCH DIRECTIONS

### A. Datasets

Although many datasets are currently utilized for training and evaluating NID models, these inherently present several challenges. A primary concern is the imbalance of samples. The collection and tracking of network attacks in the real-world are inherently difficult, leading to a predominance of normal traffic samples over abnormal ones in most datasets. Despite many studies adopting methods such as resampling to balance the training sets [80], [94], [101], biases and prejudices in the training process are almost inevitable, and there remains a significant gap in methodologies for verifying and evaluating the biases introduced by these training data. It is a common understanding that just because biases are not visible, it does not mean they do not exist. Effective methods for verification need to be developed. Another issue is that most existing benchmark datasets consist of synthetic data generated by cybersecurity researchers simulating attacks in a controlled environment, and it may not well reflect the intrusion behaviours in real network intrusion scenarios. Only the LITNET dataset represents a real-world network attack dataset, containing actual attack traffic produced by attackers in the real-world. However, current research predominantly focuses on the NSL-KDD dataset, and methods based on DRL utilizing the LITNET dataset are still rare, marking an important area for future research.

### B. Models

The performance of various DRL models varies across different datasets. Table X and Table XI illustrate that different models may exhibit significant performance differences depending on the dataset, suggesting that each model may have unique adaptability to specific types of data. When selecting a deep reinforcement learning model for network intrusion detection, it is essential to consider the model's accuracy, precision, recall, and F1 score comprehensively to choose the most suitable model for the specific application scenario.

Despite the initial exploration of DRL in NID that has been implemented recently, it is noteworthy that the structural composition of most DRL policies are still based on simple MLP. According to current survey [104], even the most popular transformer architecture has not been widely introduced in DRL-based NID systems, with only a few models like [101] employing attention mechanisms and achieving good results. One possible reason is that traditional supervised learning and deep learning approaches continue to receive more attention from the network intrusion detection community [105], [106]. Additionally, current NID datasets intuitively seem more suited for supervised learning methods [107]. Recently, the emergence of a novel architecture called Kolmogorov–Arnold Networks(KAN) [108], inspired by Kolmogorov–Arnold representation theorem [109], has attracted widespread attention in general AI community. This architecture shifts activation functions traditionally located on MLP neurons to the connections/edges between neurons. In their experiments, it replicated the results of a 300,000-parameter MLP-based neural network model using fewer than 200 parameters. Thus, in the foreseeable future,

whether KAN could be used to enhance DRL-based NID systems is an interesting topic, especially since most DRL-based NID systems currently approximate optimal strategies using simple MLP structures. And DRL-based NID seems lagging behind the latest DRL models or methods. Advanced techniques such as PPO [43] and TRPO [42] have not been embraced by the NID community. DRL-based NID is still in its early stages with many classic DRL-based algorithms. Lastly, the evaluation of the generalization of DRL-based NID models are limited, and relying solely on training and testing splits from a single dataset appears insufficient. In our survey, only a few studies not only trained models but also conducted experiments in real network scenarios [90]. Real-world deployments and tests are urgently needed for DRL-based NID.

### C. Inverse reinforcement learning for NID

Traditional DRL is known for its inefficiency in sample utilization [110], [111]. The advent of inverse reinforcement learning may have potential to expedite policy optimization for agents [112], it is also critically important for NID systems that require high level of real-time responsiveness. However, current research indicates that IRL has not been applied within the context of DRL-based NIDS. Only some related attempts like Liu *et al* [113] successfully used Inverse Reinforcement Learning (IRL) to reverse-engineer the reward function by observing the trajectories of a trained DQN controller and used this function to design attack strategies that effectively disrupt the control functions of an Industrial Internet of Things (IIoT) system. One future possible way could involve treating existing network intrusion datasets as expert demonstration data and employing IRL methodologies to model the underlying reward functions of various attacker behaviours. Subsequently, these specialized reward functions could be utilized to train defender agents. For datasets collected from actual network attacks, IRL can be used to effectively model the behaviours of real attackers and potentially train more robust defender agent. Despite this promising research direction, the inherent computational complexity of IRL [50] algorithms may need the introduction of specific methods for improvement to actualize the theoretical concepts proposed.

### D. DRL for intrusion detection to IoT

In recent years, there has been more and more research focusing on the network detection forIoT [114], [115]. Haosen *et al* had made an initial brief survey on the DRL-based intrusion detection in IoT [116]. And, as the number of smart devices increases, there is growing concern about how to prevent network intrusions targeting IoT devices [117]. Current approaches are predominantly based on traditional deep learning and machine learning methods as well [118]. There is a notable lack of exploration in IoT-specific DRL-based techniques. And in our survey, only [100], [119], [87] and [113] have focused on intrusion detection specifically for IoT devices using DRL/RL in recent years. One possible reason for this is the scarcity of benchmark datasets suitable for IoT and DRL. To date, researchers have only conducted

preliminary studies on datasets like AWID [76], Bot-IoT [120], and IoTID20 [121]. Nevertheless, with the explosive growth of IoT devices [122], the demand for reliable intrusion detection technologies continues to rise. Therefore, there should remain an optimistic outlook on the application of DRL techniques in IoT intrusion detection. Additionally, researchers from the broad IoT intrusion detection community should continue to strive towards proposing new datasets specifically tailored for IoT device intrusion detection. Moreover, some surveys have also revealed several challenges when introducing DRL into IoT applications, including the need to handle continuous state-action spaces, learning in partially observable environments, ensuring robustness against adversarial attacks, real-time decision making and data privacy and security [123], [124].

#### *E. Generative deep model enhanced DRL for NID*

Generative artificial intelligence, such as large language models (LLMs) [125], has recently garnered significant attention worldwide. While some researchers have noted the transformative potential of these methods in the broad field of cybersecurity, few studies have explored how generative AI can be integrated with DRL to advance research in NID. Some researchers have already recognized that LLMs can enhance DRL models in areas such as reward design and world model simulator [126]. Consequently, in the foreseeable future, employing LLMs and other generative AI models to augment RL approaches is likely to become a new research paradigm. Therefore, exploring how this potential research paradigm could be extended to NID may become an intriguing research hotspot. Combining the powerful capability of LLM-based world models [127], [128], One initial idea is to fine-tuning LLM as a network intrusion expert (attacker) [129], [130] and then using the principle of DRL to train the defender agent though the interaction with LLM-based attacker. Then, using the current public dataset to test and make an evaluation of the defenders. Additionally, the widespread availability of generative AI might also inspire traditional attackers to change their way of attack [130]. For instance, with the aid of LLMs, attackers could potentially improve and optimize their attack strategies [130], significantly degrading the performance of NID systems trained on conventional datasets, an urgent concern that should be addressed by the community. Moreover, we cannot guarantee that these potential attackers will cease using these tools as AI technology advances. However, one thing that should be clear is researchers in NID defence systems should responsibly learn to use generative AI to enhance the reliability and defensive capabilities of their proposed systems and make reliable tests. Moreover, due to large simulated datasets and fewer real attack examples exist. LLMs attacker might be, to some extend, fitting only to the simulated scenario if the LLMs lack enough knowledge and logic transferring and generalizing ability. It should be a remaining concern in the coming future anyway.

#### *F. Policy functions and architectures*

The findings over recent years suggest that deep neural networks can indeed represent complex policy functions within

DRL [131]. Deep learning has made significant advancements, greatly enhancing agents' capabilities in learning and generalizing from complex environments, which is particularly relevant to network security. Previous surveys also identified a growing interest in integrating attention mechanisms into policy function representations. The promise of attention mechanisms lies in their ability to handle dynamic and high-dimensional data, which is a typical feature in network traffic analysis. However, it's important to note that research on deep model architectures is progressing rapidly. For example, architectures like Mamba [132] and Learn at Test Time (TTT) [133] structures have gained popularity recently due to their innovative design and superior performance metrics. These architectures also offer increased capabilities in model interpretability, scalability, and robustness, which are critical for developing effective intrusion detection systems. The need to address this through advanced policy function representations should be a high priority for the network intrusion detection community. By embedding these state-of-the-art deep learning architectures into IDS, researchers may overcome the limitations of conventional methods, offering more precise and efficient threat identification. Implementing such architectures could result in a new generation of IDS that are far better equipped to protect against today's sophisticated cyber threats in our increasingly networked and complex digital environment.

## VI. CONCLUSION

Network intrusion detection has attracted much attention in broader cybersecurity in recent years. This paper presents a brief survey focused on the application of DRL techniques in the domain of network intrusion detection over the past few years. Current DRL-based network intrusion detection systems is still facing many challenges, including long time for model training, low training efficiency, and a lack of real-world deployment and evaluation. Furthermore, DRL-based NID seems to lag behind the developments in the mainstream DRL community, yet it holds significant potential for growth. Many novel DRL algorithms have not been extended to the application in NID. Additionally, we advocate for the use of data from real-world attack scenarios to train DRL-based NID systems and call for preliminary explorations into modelling attackers' behaviours using inverse reinforcement learning and also advocate for researchers focusing on the intrusion detection for internet of things by collecting more suitable datasets. Lastly, we discussed how the world models built on large language models, or even broader large models can be used to train defensive agents, further facilitating the development of generative-augmented DRL for advancing DRL in the field of NID.

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