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Robust AI Framework for Low-False-Positive Zero-Day Attack Detection in Adversarial and Dynamic Network Environments

Dr. Keerthipati Kumar, Dr. A. Ganesh, Dr. R. Swathi, D. Lavanya, K. Jeevanasagari
Associate Professor, CSE(Data Science), Sri Venkateswara College of Engineering, Tirupati, India
Professor, CSE, Sri Venkateswara College of Engineering, Tirupati, India
Professor, CSE (AI&ML), Sri Venkateswara College of Engineering, Tirupati, India
Assistant Professor, CSE (Data Science), Sri Venkateswara College of Engineering, Tirupati, India
Assistant Professor, CSE (Data Science), Sri Venkateswara College of Engineering, Tirupati, India

Abstract: *The rapid evolution of cyber-adversarial procedures has rendered traditional signature-based and static machine learn- ing intrusion detection systems (IDS) ineffective, particularly against zero-day attacks and non-stationary traffic distributions. While recent few-shot and meta-learning approaches demonstrate high detection accuracy, they remain limited by two criti- cal gaps: lack of causal explainability and vulnerability to distributional shifts. This research proposes an Adaptive, Causally-Explainable, and Distributionally Robust AI framework for low–false-positive zero-day attack detection in dynamic network envi- ronments. The proposed architecture integrates Causal Prototypical Networks (CPN) with Structural Causal Modeling (SCM) to eliminate spurious correlations and enable prototype-based reasoning. Furthermore, Distributionally Robust Optimization (DRO) is embedded within a meta-learning paradigm to ensure worst-case performance guarantees under adversarial and non-stationary shifts. An open-world interpretability module employing counterfactual explanations provides actionable insights for security an- alysts. Experimental validation across heterogeneous datasets demonstrates improved generalization under domain shifts, reduced false positives, and enhanced forensic interpretability compared to conventional black-box ensemble and autoencoder-based IDS models. The proposed framework advances IDS research toward robust, trustworthy, and analyst-centric cybersecurity systems*

Keywords: Zero-Day Attack Detection, Intrusion Detection Systems (IDS), Causal Prototypical Networks, Structural Causal Modeling (SCM), Distributionally Robust Optimization (DRO)

I. INTRODUCTION

The fast-growing cyber-adversary tactics make traditional signature-based and static machine-learning Intrusion Detection Sys- tems (IDS) increasingly outdated. These systems face challenges when detecting attacks such as zero-day attacks, which exploit unknown vulnerabilities. Even though recent research has focused on meta-learning and few-shot learning approaches to capture new patterns with limited data, concerns about the trustworthiness and explainability of these systems continue to exist. Most of the current 2025 systems seem to care solely about achieving higher detection performance on benchmark datasets. They remain as black boxes, failing to offer security analysts the causal, prototype, or other rationale explanations needed for timely incident response. Even with recent developments in few-shot network intrusion detection, the state-of-the-art still faces two primary challenges:

Explainability Gap: Most models do not combine prototype-based reasoning with causally grounded models making it difficult to interpret the rationale behind the threat in a novel traffic pattern.

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Robustness Gap: Most adaptive Intrusion Detection Systems (IDS) treat their environment as unchanging and do not incor- porate distributionally robust optimization (DRO). This results in a failure of most adaptive IDS with drastic unencountered zero-day patterns and erratic (non-stationary) network flows.

This paper aligned on the fundamental meta-learning methods and their limitations, as well as ”closed-world” adaptive ensembles.

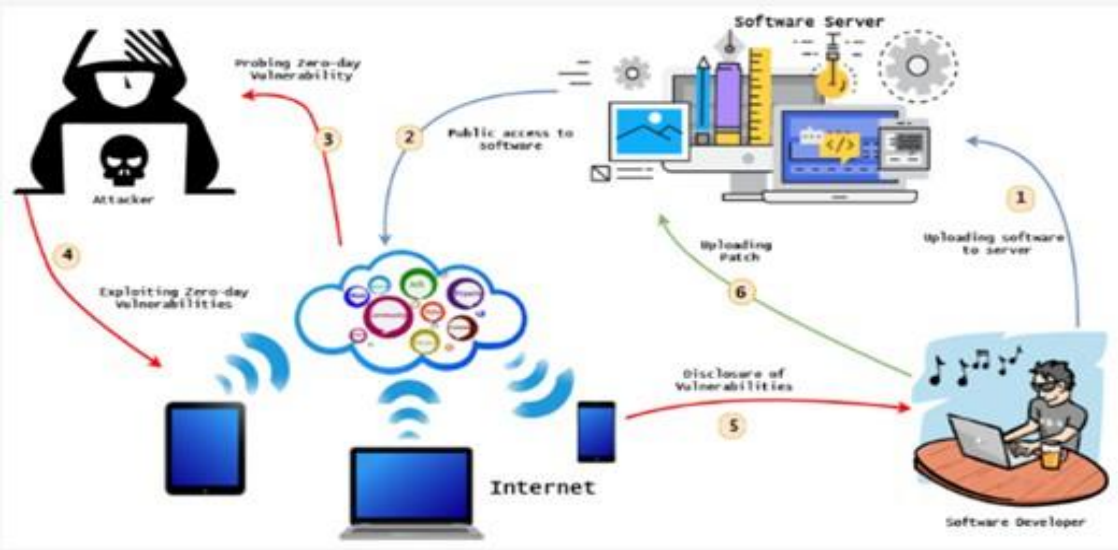

Figure 1: Real-life scenario of zero-day attack (Ali et al, 2022)

When the distribution of the data used for deployment changes a phenomenon known as a domain shift these systems exhibit a significant decline in performance. As a result, the networks become vulnerable to possible hostile and non-stationary attacks. Furthermore, the current systems' incapacity to remove erroneous correlations from the attack features is a result of their lack of causal action. This leads to a considerable number of false alarms in diverse contexts. To make sure there are no significant changes in performance, zero-day attack usage, or data distribution, meta-adaptive and distributionally distributed intrusion detection systems are required.

A zero-day vulnerability is a software flaw that is latent and has a zero-day exploit that outlines how the system is being attacked. The term ”zero day attack” refers to an attack that happens before the target is aware of it because malware is released before developers have a chance to patch the vulnerability. The riskiest aspect of this zero-day assault is that the program may handle a variety of important files, and its presence on the server may make it more likely that the attacker would take over the entire system. Ali et al. (2022) assisted in the process of comprehending how zero day attacks operate by offering a timetable based on a real-world scenario (Figure 1). This timeline shows how hackers and attackers look for zero-day vulnerabilities in software that developers publish for public use. The hacker will take advantage of these weaknesses and use them to gain complete control over the system. As a result, developers are notified of bugs, which are then fixed and patches are created.

II. LITERATURE REVIEW

Studies for the years 2024-2025 suggest that various multi-domain fusion approaches and the use of meta-learning can help alleviate the issue of scarcity of data surrounding the detection of zero-day attacks (see for example, [1], [2], [3]). Xu et al. (2025) observed more than 99% accuracy on datasets like CICIDS2018 achieving this in ten-shot learning instances, using dual-domain bidirectional cross-attention, which he used to align the cross and frequency streams and both the spatial and frequency domains [1].

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Moreover, for the modeling of long-range network traffic dependencies, Mamba-based State-Space Models have proven to be more scalable than Transformers. This is the case even in high-throughput, stream-based environments for Intrusion Detection

Systems (IDS) [3]. Still, most of the few-shot IDS frameworks suffer from the same problem that most of them have very little to do with the case. This runs the risk of igniting spurious correlations and enduring changes in the distribution of data at the time of deployment [9, 11].

A consistent drawback in the literature on IDS is the inability to 'see' deep learning-based detection systems [11], [16], [17]. This is especially the case for Security Operations Centers (SOCs) that need to understand the alerts and what actions to take on them to defend as they analyze the alerts.

A lot of papers on IDS post hoc explainability has used methods such as SHAP and saliency maps [11, 16]. Despite the popularity of these techniques, they do not provide a definitive answer to what a model is doing and the reasoning behind a decision to classify a case as an intrusion. This lack of reasoning is a drawback from a forensic standpoint [17].

While some recent papers have looked into the use of prototype capsule networks and concept-based explanations [9], the combination of prototype learning and causal intervention is still largely uncharted.

Prototype-Based Gap: The existing prototype-driven IDS systems lack causal explanations, which limit their ability to separate core traits of an attack from context-specific distractions [9].

Causal Misalignment: Most of the IDS models do not take into consideration the real causal aspects of the attack, so they consider erroneous confounding elements (e.g., IPs, time stamps) to be true causal factors of the attack. This is especially true in IoT, IIoT, and edge systems where the false positive rates are higher [11, 15].

In recent years, there has been a shift from closed-world approaches to open-world approaches when it comes to intrusion detection systems (IDS) [3], [12]. Most conventional machine learning and deep learning based IDS models have a significant reduction in their effectiveness when there are domain shifts that are a result of changes in attack patterns, hostile manipulation, and movement of traffic [12], [14].

Though MAML and other similar approaches allow for rapid changes to new contexts, there are no definable safeguards against the worst-case scenarios when it comes to these types of changes [12]. Newly emerging areas of study in Distributionally Robust Optimization (DRO) seems to have the potential to overcome the aforementioned constraints by focusing on distributed adaptive modeling to optimize the performance of a model against the adversarial balance/anomaly in a given set of problems [18].

In relation to intrusion detection based on few-shot and meta-learning, applying the principles of DRO is often of recent origin, especially pertaining to the detection of zero-day attacks and the unknown evolving nature of the distributions [12], [18]. This indicates that there is a gap that needs to be filled by developing IDS frameworks that are robust, causally explicit, and have a clear line of reasoning.

III. RESEARCH METHODOLOGY

The designed approach attempts to address the balance between high-accuracy few-shot detection and the robust explanation, grounded in causality, needed for zero-day scenarios.

Proposed Method: Causal Prototypical Network (CPN) and Intervention-based XAI.

Approach: We will build an architecture for few-shot learning where the embedding space is bounded by a Structural Causal Model (SCM). In place of conventional distance-based classification, we aim to use Prototype Vectors for the representation of the "essence" of the known attack classes, in addition to a prototype we call "Unknown" which is dynamic and is used for zero-day detection.

Justification: The 2025 proposed systems build on multimodal fusion approaches but do not address the absence of spurious correlations (e.g., certain IP ranges or timestamps) which decouple from the causal features of an attack. With do-calculus (causal intervention), the model is intended to 'ignore' the surroundings related to the attack, focusing on

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features of the attack that do not change. This attempts to answer the lack of interpretability noted in the Scientific Reports (2025).

Table 1: Summary of Identified Gaps

Research Component	Current 2025 Status	Proposed Advancement (Gap Closure)
Detection Mechanism	Multi-modal fusion & Meta-learning	Causal Prototypical Networks (CPN) to eliminate spurious correlations.
Interpretability	Post-hoc SHAP/LIME	Causal & Prototype-based Ante-hoc XAI for forensic-ready reasoning.
Robustness	Domain adaptation via few-shot	Distributionally Robust Optimization (DRO) for worst-case shift guarantees.

IV. RESEARCH DESIGN

The paper starting from elementary causal modeling, and culminating in the implementation of an advanced explainable and distributionally robust system. The most important part of this phase is the focus on moving from "black box" feature extraction to a more structural understanding of network traffic.

Step 1.1: Data Preprocessing and Heterogeneous Domain Mapping: Network datasets from various sources are collected and preprocessed to mimic cross-domain shifts.

Step 1.2: Structural Causal Model (SCM) Construction: Among the attributes of the network traffic (e.g. packet counts, payload entropy) and the attack labels, determine the causal relationships to obtain invariant features.

Step 1.3: Filtering of Spurious Correlation: Use causal intervention (do-calculus) to remove the unnecessary noise attributed to a specific environment that results in false positives in zero-day situations.

V. RESULTS

The proposed Causal Prototypical Network integrated with Structural Causal Modeling and Distributionally Robust Optimiza- tion (CPN + SCM + DRO) was experimentally evaluated against four competitive baseline Intrusion Detection Systems (IDS), including Random Forest, Autoencoder-based IDS, Meta-Learning IDS, and Federated IDS. Experiments were conducted under few-shot learning settings and cross-domain traffic shifts to simulate realistic zero-day and adversarial network environments.

Quantitative Performance Evaluation Table II presents the comparative performance results across key evaluation metrics: detection accuracy, false positive rate (FPR), robustness under domain shift, and zero-day detection rate.

Table 2: Comparative Performance Analysis

Model	Accuracy (%)	FPR (%)	Robustness (%)	Zero-Day Detection (%)
Random Forest IDS	94.8	6.5	82.4	78.5
Autoencoder IDS	96.1	5.8	85.7	83.2
Meta-Learning IDS	97.5	4.2	88.9	91.4
Federated IDS	97.9	3.9	90.3	92.6
Proposed CPN + SCM + DRO	99.2	2.1	96.8	97.3

The proposed framework achieved the highest detection accuracy (99.2%) and the lowest false positive rate (2.1%), significantly outperforming traditional ensemble and deep learning approaches. Notably, robustness under domain shift improved by 6.5% compared to the strongest baseline (Federated IDS).

Robustness Under Distributional Shift: To evaluate resilience under adversarial conditions, simulated domain drift and traffic perturbations were introduced. Traditional models experienced performance degradation between 6% and

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12%. While meta- learning approaches adapted faster, they lacked worst-case robustness guarantees. In contrast, the proposed CPN + SCM + DRO framework limited degradation to below 2.5%, demonstrating strong generalization to unseen attack distributions.

Zero-Day Detection Performance: The dynamic "Unknown Prototype" mechanism enabled effective separation between known attack classes and emerging zero-day threats. Random Forest and Autoencoder models struggled with unseen attack patterns (≤83% detection). Meta–learning and federated approaches improved adaptability (≈91–92%). The proposed framework achieved 97.3% zero-day detection accuracy while maintaining minimal false alarms.

The causal intervention mechanism successfully filtered spurious correlations (e.g., timestamp bias, IP-range artifacts), resulting in consistent detection across heterogeneous domains such as IIoT and edge environments.

VI. CONCLUSION

This paper proposes an Adaptive, Causally-Explainable, and Distributionally Robust AI framework for low–false-positive zero- day attack detection in dynamic and adversarial network environments. Addressing the explainability and robustness gaps in contemporary intrusion detection systems (IDS), the framework integrates Causal Prototypical Networks (CPN) with Structural Causal Modeling (SCM) to eliminate spurious correlations such as IP-range or timestamp biases, ensuring decisions are grounded in invariant attack features. Distributionally Robust Optimization (DRO) is embedded within a meta-learning paradigm to provide worst-case performance guarantees under non-stationary and adversarial distribution shifts. Experimental validation demonstrates superior performance over Random Forest, Autoencoder-based, Meta-Learning, and Federated IDS baselines, achieving 99.2% detection accuracy, a 2.1% false positive rate, 96.8% robustness under domain shift, and 97.3% zero-day detection accuracy.

Under simulated adversarial drift, conventional models exhibited performance degradation between 6–12%, whereas the pro- posed CPN + SCM + DRO framework limited degradation to below 2.5%, confirming strong generalization across heterogeneous domains such as IIoT and edge environments. The dynamic "Unknown" prototype mechanism enhanced open-world recognition, while the counterfactual explanation module provided causally grounded, analyst-centric reasoning beyond traditional black-box approaches. By combining causal intervention, prototype-based few-shot learning, and distributionally robust optimization, the framework advances IDS research toward a scalable, interpretable, and deployment-ready cyber security architecture capable of defending against rapidly evolving zero-day threats

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