GSC Advanced Research and Reviews
eISSN: 2582-4597 CODEN (USA): GARRC2
Cross Ref DOI: 10.30574/gscarr
Journal homepage: https://gsconlinepress.com/journals/gscarr/

(REVIEW ARTICLE)

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Neuro-symbolic ai for cloud intrusion detection: A hybrid intelligence approach

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GSC Advanced Research and Reviews, 2025, 22(02), 142-144

Publication history: Received on 03 January 2025; revised on 15 February 2025; accepted on 18 February 2025

Article DOI: https://doi.org/10.30574/gscarr.2025.22.2.0049

Abstract

As cloud computing becomes more prevalent, ensuring robust cybersecurity is an ongoing challenge. Traditional intrusion detection systems (IDS) often struggle to keep pace with emerging cyber threats due to their reliance on static rule-based mechanisms. **Neuro-Symbolic AI** presents a hybrid intelligence approach that merges deep learning (neural networks) with symbolic reasoning, offering enhanced accuracy, explainability, and adaptability in intrusion detection. This paper investigates the role of Neuro-Symbolic AI in cloud security, detailing its application in threat detection, real-time response, and compliance management. Additionally, we explore its role in proactive threat intelligence, real-world implementation challenges, and emerging trends in AI-driven security models.

Keywords: Neuro-Symbolic AI; Cloud Security; Intrusion Detection; Hybrid Intelligence; Cyber Threats; Threat Intelligence; AI-driven Security

1. Introduction

With the exponential rise in cloud computing adoption, security threats have grown both in sophistication and frequency. The increasing complexity of cyberattacks, including zero-day vulnerabilities, insider threats, and advanced persistent threats (APTs), necessitates a more adaptive and intelligent approach to security. Traditional cybersecurity frameworks often rely on predefined rules that fail to adapt to evolving attack patterns. Neuro-Symbolic AI, which combines deep learning's predictive capabilities with symbolic reasoning's logical inference, has emerged as a promising solution for tackling these challenges. This research explores how Neuro-Symbolic AI can provide a self-learning, transparent, and adaptable intrusion detection framework capable of real-time decision-making and automated responses.

2. Materials and Methods

2.1. Definition and Concept

Neuro-Symbolic AI integrates two paradigms: neural networks, which excel in pattern recognition, and symbolic reasoning, which ensures logical inference. This combination enhances interpretability while maintaining high detection accuracy (Bengio et al., 2021).

3. Implementation Framework

- **Dataset Selection:** Public cybersecurity datasets (e.g., NSL-KDD, CICIDS2017) were used for model training.
- **Neural Network Configuration:** Deep learning models analyzed network traffic logs to detect anomalies and suspicious behaviors.

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- **Symbolic Reasoning Engine:** Logical inference mechanisms were applied to validate and explain anomalies detected by the neural networks.
- **Threat Intelligence Integration:** AI-driven threat intelligence feeds were incorporated to enhance predictive capabilities.
- **Evaluation Metrics:** Accuracy, precision, recall, and F1-score were used for performance assessment, along with adversarial robustness testing.

4. Experimental Setup

Experiments were conducted on a high-performance computing cluster utilizing TensorFlow for deep learning and Prolog for symbolic reasoning. The IDS was deployed in a simulated cloud environment (AWS EC2) and monitored over 30 days to evaluate its ability to detect real-world attack patterns, including denial-of-service (DoS) attacks, data breaches, and malware intrusions.

5. Results and Discussion

5.1. Threat Detection and Anomaly Analysis

Traditional IDS often fail due to rigid rules. Neuro-Symbolic AI enhances detection through:

- **Pattern Recognition:** Neural networks uncover hidden anomalies in network traffic (Goodfellow et al., 2016).
- **Logical Deduction:** Symbolic AI ensures a logical explanation of threat patterns, reducing false positives (Lake et al., 2017).
- **Adaptive Learning:** Reinforcement learning enables continuous improvement in threat detection by learning from new attack scenarios (Mnih et al., 2015).
- **Adversarial Resilience:** The system was tested against adversarial machine learning techniques, ensuring robustness against evasion attacks (Papernot et al., 2017).

5.2. Real-Time Automated Threat Response

5.2.1. Neuro-Symbolic AI enables:

- **Dynamic Access Control:** AI dynamically adjusts user permissions based on detected threats (Shen et al., 2020).
- **Automated Incident Response:** Symbolic reasoning guides response actions, ensuring structured threat mitigation (Ghorbani & Lu, 2019).
- **Autonomous Threat Mitigation:** AI-driven security policies proactively neutralize threats before escalation (Schneier, 2020).
- **Self-Healing Systems:** AI-enabled cloud infrastructures can autonomously recover from detected attacks and patch vulnerabilities (Hinton et al., 2012).

6. Enhancing Compliance and Regulatory Security

Regulatory frameworks such as **GDPR, HIPAA, and SOC 2** necessitate stringent security measures. Neuro-Symbolic AI ensures:

- **Explainable AI (XAI) Models:** AI decisions remain transparent and auditable, aiding regulatory compliance (Miller, 2019).
- **Automated Compliance Enforcement:** AI-driven systems continuously validate security policies against evolving regulations (Floridi et al., 2020).
- **Tamper-Proof Security Logs:** AI-generated logs enhance forensic capabilities and security auditing (Brynjolfsson & McAfee, 2017).

7. Conclusion and Future Research Directions

Neuro-Symbolic AI offers a groundbreaking approach to cloud intrusion detection by combining predictive analytics with logical reasoning. Its ability to self-learn, explain decisions, and adapt to new threats makes it a promising solution for future cloud security frameworks. Ongoing research is needed to:

- **Enhance Adversarial Defense Mechanisms:** AI security models must be resilient against adversarial manipulations.
- **Develop Federated Learning Models for Cloud Security:** Ensuring privacy-preserving AI for distributed cloud security.
- **Implement Quantum AI for Cybersecurity:** Leveraging quantum computing to strengthen cryptographic security and AI-driven threat modeling.
- **Expand Real-Time Autonomous Threat Intelligence:** AI-driven SOC (Security Operations Centers) with real-time situational awareness.

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