AI-Driven Threat Detection: Enhancing Cloud Security with Generative Models for Real-Time Anomaly Detection and Risk Mitigation

Rahul Vadisetty, Anand Polamarasetti, Sateesh Kumar Rongali, Sameer kumar Prajapati, Jinal Bhanubhai

Electrical Engineering,Wayne State University Detroit,USA
rahulvy91@gmail.com
ComputerScience
Anandra University Visakhapatnam, India
exploretechnologi@gmail.com
Department: EDD in Computer Science
University: Judson University,City: Elgin,State: Illinois
Email: sateeshk.rongali@gmail.com
Department: EDD in Computer Science
University: Judson University,City: Elgin,State: Illinois
Email: sameerprajapati115@gmail.com
Department: Master's in Computer Science
University: University of North Carolina,City: Charlotte,State: North Carolina
Email: jinalbutani2010@gmail.com

Abstract

With the unsurpassed growth of cloud computing comes lots of security challenges that can be only solved by advanced threat detection solutions for safeguarding of sensible data and infrastructure. Traditional security system using rule-based intrusion detection and signature-based threat monitoring can not prevent sophisticated cyber threats. As the generative AI models, VAEs, GANs, transformers and so on, they are also very powerful technology tools for real time anomaly detection & risk mitigation. These AI driven models lead to the ability of early identification and response to threat patterns of normal and malicious behavior dynamically learned. In this paper, we explore the role of AI in cloud security, advantages of this AI over traditional methods, best way of implementing this AI, advantages of security using this AI, and the challenges in implementing this AI in cloud security. However, even with AI, the threat detection is more effective, but still some of the problems with interpretability of the model, adversarial robustness, computational overhead and regulator conducted compliance remain still. Other research directions in future are also presented for strengthening AI enhanced cybersecurity frameworks.

Keywords: Generative AI, Cloud Security, Anomaly Detection, Threat Intelligence, Cybersecurity, AI-driven Security, Risk Mitigation, Real-time Monitoring, Deep Learning, Adversarial Attacks

1. Introduction

Since the adoption of cloud computing has grown considerably with time, so has the attack surface of this platform for cyber threats, thus making traditional security measure ill suited at detecting and minimising emerging risks [1]. The existing legacy security solutions are based on static rules and/or signature-based methods that can not keep composition with the sophisticated cyberattacks, for example, zero day exploit, insider threat, and advanced persistent threat (APT) [2]. Moreover, it is being increasingly relied upon to operate in multi or hybrid cloud environments, where security challenges have been introduced to an already distributed set of workloads, data integrity, and removing vulnerabilities across cloud platforms as the organization does so [3]. To serve the needs of modern cloud infrastructures, the advanced security mechanism needs to feature auto security enforcement, adaptive threat detection, proactive risk assessment and automated response.

Generative models that can adapt themselves to new threat patterns improve the live time anomaly detection capabilities, and hence can mitigate these limitations through AI driven security mechanism [4]. Another line of these models analyze a vast amount of the network traffic, user behavior, and system logs to detect and eliminate threats before any damage from them can be done [5]. Through machine learning methodology including deep neural networks, reinforcement learning and unsupervised clustering, AI models can explore by itself complicated patterns of attacks that are undeclared by the classic security tools [6]. By processing real time, high dimensional security data in appropriate time span, the AI can find the novel cyber threats with improved accuracy and helps to reduce the mean time to detect (MTTD) and mean time to response (MTTR) to security incidents.

As cybersecurity generated AI allows to detect subtle deviations from normal behaviour, simulate attack scenarios and enhance automated threat intelligence [8], it has been flooded by interest in the cybersecurity community, especially considering variational auto encoders (VAEs), generative adversarial networkes (GANs) and transformer based architectures. As compared to traditional methods of having to intervene manually, AI driven approaches equipped with the ability for continuous learning from changing streams of data are a natural fit for cloud based security [9]. By synthesising synthetic attack datasets using generative AI models, security can be improved as these can be used to train IDS to detect newer threats [10]. These models can also be leveraged in deception based security strategies (which intend to deceive attackers to controlled zones for monitoring threat intelligence gathering [11]).

The use of AI powered anomaly detection greatly enhances the threat response efficiency, reduce the false positives and improve the overall cloud security resilience [12]. The main benefit of AI based threat detection is that it is able to identify benign anomalies from security breaches, and significantly reduce the amount of alert fatigue for the security analysts [13]. Also, AI models can be tied in with Security Information and Event Management (SIEM) systems to do correlation of security events for real time prioritization of threats [14]. AI driven security solutions are also well suited for large scale cloud deployments since there are big volume (different sizes) of security data that needs to be processed with high efficiency [15].

Recently, Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and transformer-based architectures have become popular with generative AI in cybersecurity to detect subtle deviations from normal, be able to simulate the attack scenario, and even improve the automated threat intelligence [8]. As compared to traditional methods of having to intervene manually, AI driven approaches equipped with the ability for continuous learning from changing streams of data are a natural fit for cloud based security [9]. By synthesising synthetic attack datasets using generative AI models, security can be improved as these can be used to train IDS to detect newer threats [10]. These models can also be leveraged in deception based security strategies (which intend to deceive attackers to controlled zones for monitoring threat intelligence gathering [11]).

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One of the reasons that cybersecurity has adopted Generative AI, including Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), transformers, is the ability to recreate subtle deviation from normal behavior, simulate an attack scenario, and help with automated threat intelligence [8]. As compared to traditional methods of having to intervene manually, AI driven approaches equipped with the ability for continuous learning from

changing streams of data are a natural fit for cloud based security [9]. By synthesising synthetic attack datasets using generative AI models, security can be improved as these can be used to train IDS to detect newer threats [10]. These models can also be leveraged in deception based security strategies (which intend to deceive attackers to controlled zones for monitoring threat intelligence gathering [11]).

In terms of threat response efficiency, using AI powered anomaly detection is a far better approach as it results in lower false positive numbers and enhances the cloud security resilience altogether. One key benefit of using the AI based threat detection is that it can separate legitimate anomalies to security breaches and substantially decrease the amount of security analyst's alert fatigue [13]. Moreover, the security events related to the models can be correlated with the Security Information and Event Management (SIEM) systems and the real time threat prioritization can be done [14]. Large scale cloud deployments are also appropriate for AI driven security solutions as there are big volume (different size) of security data, and they must be processed with high efficiency [15].

2. AI-Driven Threat Detection: Key Approaches

Various generative models are used to analyse the network behaviours for the threat detection, identify anomalies and forecast potential security breaches, fuelled by AI power. Because of this, VAEs are increasingly used for anomaly detection starting with a network traffic data input encoding to a low dimensional latent space to identify deviations away from expected patterns [9]. Apparently it does differentiate well between legitimate user activities versus potential cyber threats with much fewer false positives in comparison to traditional rule based systems [10]. Interpretable representations learned by VAEs mean that they can be easily retrained to new attack vectors without the need for large quantities of labeled data [11]. Since large quantities of data flow through distributed systems in cloud environments, where threats can flow through many components of complex network systems that are distributed across multiple topologies, it is not practical to manually detect threats [12]. Also, VAEs can discriminate attack sequences involving gradual changes in user's behavior that may point to

insider threats or advanced persistent threats (APTs) [13].

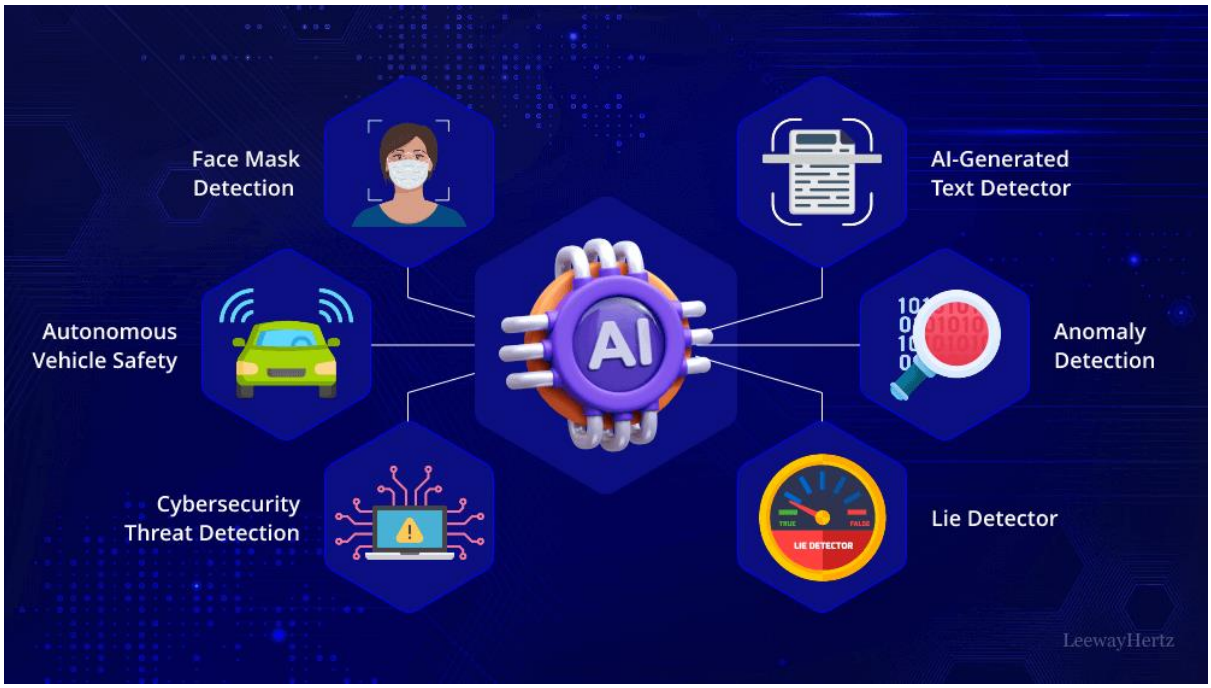

Figure 1 AI detection

Threat detection using means of generative models is undergoing AI-powered threat detection which attempts to exploit network activity, detect anomalies and predict potential security breaches using a variety of generative models such as WiKi machine, Saliency maps, OMNIFLOW, and distribution change. Using network traffic data, the encoding of traffic data into a lower dimensional latent space is often used for anomaly detection so as to identify deviations from expected patterns [9]. With these models, the false positives are less than those of traditional rule based systems [10]. VAEs allow them to learn unsupervised representations of network behavior such that VAEs can adapt to new attack vectors without requiring large amounts of labeled examples [11]. Since large quantities of data flow through distributed systems in cloud environments, where threats can flow through many components of complex network systems that are distributed across multiple topologies, it is not practical to manually detect threats [12]. Also, VAEs can discriminate attack sequences involving gradual changes in user's behavior that may point to insider threats or advanced persistent threats (APTs) [13].

Transformers are also used in another significant application, namely NLP-based threat detection: models analyze phishing emails, malicious urls, as well as fraudulent communications to protect social engineering attacks [23]. Unlike previous spam filters, NLP based on AI is able to discern contextual fine points and to detect advanced spear phishing

attempts that outwits rule based detection techniques [24]. At the same time, transformer based models can assist the process of response to security threats by generating complete remediation steps, adapted to particular incidence, from historical data of attacks [25].

The COVID crisis has forced organizations to rapidly evolve their IT security and protection measures to balance supplier and employee safety issues with the continued operations of critical business processes [22]. Unlike the static security models, AI-IDS continuously learns from network behavior keeping the cloud security team ahead of the new attack vector detection and neutralization [27]. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are used in these systems to analyze sequential network data to detect slow and stealthy attacks with timescales into the days and weeks that unfold over long periods of time [28]. It can also integrate with security orchestration, automation and response (SOAR) platforms to automatically triage and contain instances of incident through its AI-IDS automation [29].

Additionally, security frameworks that depend on reinforcement learning (RL) are being used to design increasingly AI driven safety framework to solve optimization strategy of threat response. Cybersecurity systems based on RL learn optimal defenses from trial and error training under adversarial interaction between defenders and attackers [30]. Cloud infrastructures stay resilient by these systems dynamically adjusting firewall rule, intrusion prevention policy as well as authentication mechanisms as thier (sic) threating patterns (sic) evolve [31]. Moreover, federated learning techniques are being investigated for the purpose of enhancing AI based surveillance in preserving data privacy. Federated learning allows training AI models over multiple clouds without bringing sensitive data to a central location, so by retention it also allows for collaborative threat intelligence that respects the privacy regulations such as GDPR and CCPA.

With the evolution of AI powered threat detection, it is expected that AI powered threat detection would be integrated with cloud native security services such as AWS Security Hub, Microsoft Defender for Cloud and Google Chronicle in order to further boost the real time security monitoring and automated response capabilities [33]. Nevertheless, there are still major issues including problems like adversarial AI attack, data poisoning, and model explainability etc. [34]. Research is ongoing to develop robust AI models that are resistant to adversarial manipulations and that make the interpretability of AI driven security security decisions available to the security teams, so that they can trust and validate the AI generated

threat alerts [35]. Future in AI based threat detection will involve the increase of model's speed, reduction of computational cost and expansion of the self learning security systems' function for self defense against the upcoming cypher threats [36].

3. Security Benefits of AI-Driven Threat Detection

Primarily, the ability of AI-powered security systems to perform real time threat identification and proactive risk mitigation is one of a few biggest advantages of AI security systems. Traditional security methods usually have a high false positive rate, and the security analyst will become alert fatigue. With training the historical data, AI models increase threat classification accuracy [18] in order to lower security alerts, while still improving detection precision. Additionally, AI based security framework are scalable in the sense that an organization can monitor large scale cloud infrastructures with minimal human intervention [19].

The zero trust security architecture is also enhanced with AI driven threat detection that run continuously to check the user behavior, their access privileges and the network activity pattern. The AI enabled zero trust models are different from the traditional static security models which are based on the pre-defined access control rules, and engaging in dynamic security policies in terms of real time risk assessment. Furthermore, generative models are used in AI integrated security operations centers (AI-SOCs) to automate the security event correlation, detect the insider threat and optimize the incident response workflow [22]. Incorporating these improvements makes these enhancements handle cybersafe incidents faster and increase general resilience to advanced cyber threats [23].

4. Challenges and Risks of AI in Cybersecurity

Despite these benefits, AI based threat detection comes with several challenges that need to be addressed for it to spread out. Key among them is the lack of interpretability of AI security models, as state-of-the art deep learning architectures are amongst the 'black box' models that make security analysts unable to comprehensively understand the decision making procedures they employ [24]. A research of explainable AI (XAI), which aims for transparency in human readable insights into the behavior of the model in order to improve AI driven threat detection [25].

The second one is another challenge, AI models are vulnerable to adversarial attacks, which means that malicious actors can manipulate input data to trick security algorithms [26]. AI based security models become weaknesses in which attackers can leverage to evade detection and such AI techniques need to be adversarially robust [27]. Moreover, AI driven threat detection systems are resource intensive and therefore incur huge computational cost of infrastructure for real time cloud security monitoring [28].

There are some regulatory and ethical issues that present a challenged for AI based cybersecurity implementations. The use of AI in security analytics is governed by data privacy laws such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA), which put to bear very stringent requirements for its use. Yet ensuring compliance with these regulations and keeping good detection accuracy is a fundamental problem for security practitioners [30].

5. Future Research Directions

Future work should thus be devoted to the development of more interpretable AI security models, adversarial robustness, as well as AI based threat detection optimization for the cloud. However, existing deep learning based security frameworks are not explainable, which can be improved by explainable AI techniques like attention visualization and model distillation [31]. Federated learning methods can also enhance the privacy preserving threat detection of AI models through the training without disclosing private signals on decentralized data sources [32].

Future work needs to be further directed into the area of adversarial defense mechanism such as adversarial training and differential privacy mechanism to protect the AI driven security systems against malicious attacks [33]. Additionally, integrating AI based threat detection with the blockchain technology will benefit in improving cloud security by making the security logs tamper proof and also providing threat intelligence share between cloud providers [34].

6. Conclusion

The use of AI driven threat detection changes the game when it comes to cloud security as it gives time to update its rules and decent the real time anomaly. Generative AI models like VAEs and GANs, and transformers, among others, are far better than traditional security to

adapt to the evolving cyber threats, as they continuously adapt. Nevertheless, issues like model interpretability, adversarial vulnerabilities, and regulatory compliances are to be tackled first for real fulfilment of AI in cybersecurity. Both explainable AI and adversarial robustness as measures of AI enhanced security frameworks will gain further strength to help advance future advancements in robust cloud based cybersecurity solutions.

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