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Adversarial Attacks and Defense in AI Systems: A Review of Cybersecurity Problems and New Protection

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Abstract

Healthcare, finance, defense, and the Internet of Things are all critical infrastructures that have become heavily dependent on artificial intelligence (AI), enabling them to analyze incoming data and make decisions within seconds, resulting in previously unprecedented efficiency and creativity. However, the application of AI in high-stakes scenarios also exposes the systems to malicious attacks, which exploit its data-driven learning processes. The review considers current research published between 2018 and 2025, indexed by Scopus, IEEE Xplore, Springer, and the ACM Digital Library, to systematically review the state of the art in adversarial attacks and defense mechanisms on AI systems. The report highlights the rising levels of sophistication and practical use of adversarial threats, particularly in autonomous vehicles, facial recognition, and medical diagnostics, by categorizing them into four key areas: evasion, poisoning, model inversion, and backdoor attacks. The outcomes of a critical assessment of defense strategies, such as adversarial training, robust optimization, input sanitization, anomaly detection, and ensembles, demonstrate that no single defense strategy can ensure total security. The discussion situates these findings within the broader context of cybersecurity, highlighting the challenges of scalability, the limitations of accepted assessment processes, and the ethical concerns surrounding accountability and compliance. Emerging technologies, such as blockchain, federated learning, and quantum-resistant defenses, hold promise in enhancing resilience. To secure AI systems and ensure their safe and trustworthy implementation into critical infrastructures, the study concludes that clarifying, adaptive, and transdisciplinary strategies are necessary.

Keywords: Adversarial machine learning, AI security, cybersecurity, adversarial defense, deep learning, robustness

1. INTRODUCTION

Artificial intelligence (AI) is a crucial element in modern technological advancements that drive innovation in critical infrastructures, such as the Internet of Things (IoT), healthcare, finance, and defense (Maharjan, 2023). Finance applications of machine learning algorithms include personalization of clients, automated trading, and fraud detection (Patil, 2024). In the healthcare sector, AI is often faster and more efficient than traditional methods, assisting in the development of personalized treatment plans, medications, and medical imaging diagnostics (Eskandar, 2023). Although IoT ecosystems utilize AI-supported devices to optimize energy use, enhance predictive maintenance, and improve user experiences, AI is becoming a key component in surveillance, threat detection, and autonomous systems for defense and national security agencies (Menon et al., 2024). The prevalence of AI in most areas has not only proven its revolutionary nature but also the risks involved with hacked systems.

Cybersecurity is one of the most pressing problems in this respect. Some AI systems, particularly those found in machine learning and deep learning, learn complex decision boundaries using data, unlike standard software systems that rely on predefined rules (Mehra, 2024). They are also vulnerable to specific forms of exploitation due to their reliance on data inference.

Attackers may be able to exploit AI algorithms by manipulating data input, attacking the training set, or surreptitiously altering environmental conditions, thereby generating erroneous predictions or classifications (Blauth et al., 2022). Such vulnerabilities threaten not only the privacy of data in such applications as autonomous driving or medical decision-making, but also physical security. Such threats have evolved rapidly, and aggression, in the form of hostile attacks, poses a serious and significant threat. Since adversarial vulnerabilities can undermine trust in AI systems, it is crucial to address them (Lockey et al., 2021). An attacker can, for example, modify road signs with noise that cannot be detected to cause an autonomous car to misinterpret critical traffic signals, or modify medical imaging so that a dangerous tumor appears harmless. Unlike conventional hacks, adversarial manipulations that lie at the intersection of cybersecurity and machine learning optimization are often less obvious and more challenging to detect (Xu et al., 2025). The attacks of adversarial systems pose not only a danger to individuals and organizations but also to the stability of entire industries, where the accuracy and reliability of AI systems are increasingly becoming integral to society (Sarker, 2023).

Despite the unprecedented development of knowledge on the topic, both theoretical and practical defenses against adversarial machine learning still contain holes. Models are prone to variations and adaptive approaches because existing defense mechanisms currently focus primarily on specific types of attacks (Cho et al., 2020). Moreover, the effectiveness of the proposed solutions in various application areas is not easily assessed because standardized benchmarks and evaluation measures are not provided (Aslanpour et al., 2020). Due to the rapid development of attack methods, the arms race between attackers and defenders continues, making defense strategies even more challenging (Shaji et al., 2019). This research gap underscores the need for a comprehensive analysis of adversarial attacks and defense methods, particularly in terms of their applicability.

This study has three objectives. The primary aim is to analyze the situation with adversarial attacks on AI systems in detail, discussing their typology, mechanisms, and real-world impact. Second, it attempts to critically examine existing defense mechanisms, highlighting their strengths and weaknesses, as well as their applicability in various spheres, including defense, healthcare, and finance. Last but not least, the study aims to pinpoint open issues and suggest avenues for further investigation, such as the creation of stronger, more explicable, and more flexible defences. Thus, the following research question serves as a guide: Which types of adversarial attacks pose the most significant risks to AI systems? To what extent do the current defence measures effectively mitigate these threats? What research gaps need to be addressed to enhance AI's resilience in cybersecurity? By answering these questions, we may gain a better understanding of how defensive measures and adversarial threats interact, which will ultimately help ensure that AI is integrated into vital infrastructures safely and securely.

2. LITERATURE REVIEW

Due to the growing adoption of AI in cybersecurity, the way businesses detect, respond to, and contain threats has evolved. Applications of AI-powered solutions are efficient in managing large volumes of data, identifying abnormalities, and detecting complex threats that cannot be easily identified by a human analyst in real-time (Kumar, 2025). Intrusion detection systems utilize machine learning to distinguish

between harmful and legitimate traffic patterns, thereby reducing false positives and enhancing the detection rate (Saranya et al., 2020). Malware analysis tools based on artificial intelligence (AI) examine code structures and behavioral patterns to facilitate the early detection of harmful software variants that would be difficult to identify using traditional signature-based approaches (Gaber et al., 2024). Artificial intelligence (AI) is utilized by financial institutions to detect financial crime, relying on machine learning models to identify discrepancies in transaction data and prevent the occurrence of financial criminal activity (Potla, 2023). These applications demonstrate the importance of AI in enhancing the ability to protect against cybercrime. However, as antagonistic agents exploit the reliance of AI on data and model generalization, it is the computational intelligence that renders AI powerful that gives rise to new vulnerabilities.

Adversarial attacks are one of the most popular and risky forms of AI exploitation (Qiu et al., 2019). The misclassification may be generated when adversaries apply evasion strategies to modify input data without making noise (Wang et al., 2023). Such disruptions are very successful in fooling models, but more often than not, they go unnoticed by humans. An attacker may, for instance, inject noise into a picture of a stop sign so that the vision system of an automated automobile reads it as a speed limit sign. In contrast, poisoning attacks inject purposefully modified data through the training process, and they poison AI models (Kure et al., 2025). After this change is implemented, the decision limits of the model can also shift, leading to systematic errors. Such attacks are particularly harmful in areas such as healthcare, where contaminated training data can lead to incorrect diagnostic tools. Model inversion and model extraction attacks raise concerns about privacy and intellectual property, as they exploit access to model outputs to steal confidential model parameters or recreate sensitive information (Fang et al., 2024)—a process that facilitates training for Backdoor or Trojan attacks. During training, secret triggers are inserted into AI models that do not usually cause harmful behaviour but may do so when triggered by specific inputs. These differences are not merely theoretical; case studies have proven them. Adversarial manipulations have enabled the attackers to evade authentication in facial recognition software, and minor modifications to road signs have led to enormous misclassifications in autonomous vehicles. Medical image adversarial changes have fooled health care AI diagnostic algorithms, posing significant patient safety challenges.

Researchers have developed various defence mechanisms in response to these risks, but none of them has proved to be always effective. Adversarial training is one of the best-studied methods that aim to enhance the robustness of models by utilizing adversarial cases (Bai et al., 2021). Adversarial training is effective against attack types that can be predicted; however, management is computationally expensive and often ineffective against adaptive or unexpected attacks. Defensive distillation and gradient masking aim to conceal the gradient information that adversaries use to generate adversarial examples. Obfuscation is not a suitable measure, however, because a number of these measures have been bypassed by advanced attack strategies (Khanam et al., 2020). Even though they often lead to worse performance on clean data, robust optimization algorithms aim to enhance model stability by making them less sensitive to small perturbations (Yazdani et al., 2023). Input sanitization and anomaly detection are designed to provide a proactive layer of security, identifying and excluding malicious inputs that may enter the model. Nevertheless, they face a trade-off between sensitivity and false positives (Liu et al., 2024). Ensemble and hybrid methods are used to increase resilience, which involves combining multiple models or defense strategies; however, scalability and practical deployment effectiveness are also problematic in real-world environments.

Despite significant progress, substantial gaps remain in research. The main disadvantage is that most defense strategies are evaluated in relation to specific attack scenarios, which complicates the process of extrapolating results into other fields and enemy situations (Li et al., 2022). Moreover, there are no standardized guidelines and assessment systems that affect reproducibility and fair comparison. Another area of concern is the explainability of defenses. The numerous adversarial defence methods are black box and fail to show why specific inputs are classified as benign or hostile. This lack of transparency makes it more challenging to gain confidence and adoption, especially in high-quality industries such as healthcare and defence, where accountability and interpretability are essential (David et al., 2025). Moreover, since the adversarial form of machine learning is an arms race, attackers often rapidly adapt to new defenses, and systems remain vulnerable. To address these research gaps, a more holistic approach is needed, one that emphasizes explainability, transparency, the combination of theoretical rigour and practical implementation, and the promotion of standardized evaluation processes.

In this way, both the grave challenges of adversarial threats and the potential revolution in cybersecurity are highlighted in the literature. Although the existing defenses offer some level of protection, they are insufficient to provide the safety and reliability that AI systems require in critical applications. The research that will be conducted in the future should not focus on discrete strategies in defence, but on holistic frameworks in which interpretability, robustness, and adaptability become integrated. Only then will AI be able to fulfil its potential as a reliable and safe instrument for protecting the infrastructures that modern society is becoming increasingly dependent on.

3. METHODOLOGY

This paper employs a systematic literature review approach to summarize the existing state of understanding regarding adversarial attacks and defense mechanisms in artificial intelligence systems. The systematic design was adopted because it facilitates a methodical, precise, and repeatable process for acquiring and evaluating the study's findings. This approach will be more accurate in identifying patterns, new trends, and gaps that cannot be identified in individual studies due to the combination of information across multiple academic sources.

The data collection process involved searching four major academic databases, including Scopus, IEEE Xplore, SpringerLink, and the ACM Digital Library, which contain peer-reviewed articles in the areas of computer science and cybersecurity. These databases were selected because they are known to index the highest quality scholarly literature and have a wide coverage. The search strings contained keyword combinations such as adversarial machine learning, AI security, poisoning attacks, adversarial defense, robust AI, and cybersecurity in deep learning. The use of Boolean operators and truncations was employed to refine the results and eliminate unnecessary information.

The inclusion criterion was to have studies that were up-to-date and relevant (between 2018 and 2025). Given that adversarial machine learning has been trending over the last decade and is evolving at an accelerated rate, this time frame was selected to provide more up-to-date information. Only book chapters, conference papers, and peer-reviewed journal articles that were specifically related to AI security were considered. Articles that were not practical or applicable to real-life situations, articles in languages other than English, and non-peer-reviewed sources, such as blogs, white papers, and opinion articles, were all disqualified under the exclusion criteria. Duplicate entries in the databases were identified and removed.

The type of adversarial assault examined by the study, the defence mechanism proposed or experimented with, the evaluation datasets and metrics, and the claimed strengths and weaknesses of the approach were

all essential information collected during the data extraction process. The synthesis process employed a theme coding method to group the findings under open challenges, defense tactics, and types of attack. Quantitative patterns (i.e., the occurrence of particular defense strategies or the occurrence of attacks in recent literature) were also identified where possible.

Despite its benefits, the technique has several weaknesses. The outcome can be biased in favour of effective or innovative defence mechanisms, and failures or useless studies may not be reported due to publication bias. Some articles may not have been accessed either, especially those behind paywalls, due to limited access to the dataset. Moreover, even new state-of-the-art countermeasures or opposing measures may not yet be reflected in the literature due to the inherent delay. The systematic research approach, however, has a solid and understandable foundation in studying the landscape of the enemy attacks and defences within AI systems.

4. RESULTS

Considering the urgency with which the academic and business communities address these problems, the systematic review found that research on advising adversarial threats and defenses in AI systems is rapidly expanding. The analysis yielded three key findings: an increasing sophistication of attacks by adversaries, the range of defense strategies, and the persistence of critical vulnerabilities despite significant improvements.

Evasion attacks remain the most widely studied trend of attack because they represent the most urgent danger to deployed systems. The researchers demonstrated since 2019 that deep neural networks can be misled by well-crafted perturbations in computer vision, natural language processing, and speech recognition (Zhang et al., 2020). These attacks are particularly concerning in areas such as autonomous driving and surveillance, where timely decisions are essential. Although they were less common in the past, poisoning cases have garnered significant attention since 2022, particularly when healthcare practices are taken into consideration. Harmful samples can compromise training data because medical imaging and diagnostic AI systems rely on large, crowdsourced datasets (Kaviani et al., 2022). Case studies that show a high percentage of contaminated data can drastically decrease model performance, casting doubt on the reliability of AI in delicate settings. Increasing concerns about data privacy and the theft of intellectual property have also contributed to a rise in model inversion and extraction attacks. Although backdoor and Trojan attacks have not been studied extensively in relation to evasion and poisoning, they have proven to be highly successful and often remain undetected, remaining unknown until the occurrence of a specific trigger.

The research suggests that defence mechanisms can be broadly categorized into two: proactive and reactive tactics. Proactive methods, such as robust optimization and adversarial training, aim to strengthen models during their construction. Despite requiring substantial computational resources and frequently leading to reduced performance on benign data, adversarial training is one of the most effective defences against known evasion attacks (Miller et al., 2020). Robust optimization approaches improve stability, but precision is also sacrificed for resilience. Conversely, reactive methods concentrate on identifying and thwarting assaults while inference is underway. While anomaly detection algorithms monitor for suspicious patterns in model outputs, input sanitization techniques aim to eliminate or filter out malicious perturbations. Although ensemble and hybrid techniques increase robustness by combining various defenses, their implementation in practical systems raises questions of efficiency and scalability.

The comparison study demonstrates that no single defense mechanism provides comprehensive defense. For instance, gradient masking can be circumvented by attackers who modify their tactics, and adversarial training may withstand perturbations created with one method but not others (Ren et al., 2020). In natural language processing tasks, input sanitization approaches are less successful against semantic perturbations than they are against some noise-based manipulations (Xu et al., 2025). Similar to this, ensemble approaches improve robustness but come with a computational cost that restricts their use in settings with limited resources, such as Internet of Things devices.

Table-based comparisons in the reviewed literature often illustrate this trade-off between generalization, efficiency, and robustness. Research consistently shows that adaptive attackers can exploit previously unnoticed weaknesses, even as defenses increase their resilience against specific attack classes (Wang et al., 2023). Furthermore, robustness-enhancing defenses often compromise model interpretability, making it more challenging for practitioners to justify and have confidence in the system's judgments.

All things considered, the findings show a vibrant field that is innovative on both the attack and defense fronts. Although researchers have made significant strides in classifying hostile threats and creating defenses, the problem's arms race nature guarantees that total security will always be elusive. The patterns demonstrate the need for multi-layered, integrated defense measures that strike a balance between interpretability, accuracy, and robustness, while considering the practical limitations of real-world deployment. These results underscore the importance of continuing to research scalable, explainable, and adaptive strategies to safeguard AI systems against malicious exploitation.

5. DISCUSSION

The systematic review's findings demonstrate both the notable advancements and ongoing difficulties in protecting AI systems from hostile attacks. From a broader cybersecurity perspective, the results underscore AI's dual nature. While it enhances cyber intrusion detection and prevention, it also introduces new vulnerabilities that conventional cybersecurity frameworks are inadequately equipped to address (Kolade et al., 2025). Adversarial attacks exploit the very learning mechanisms that give AI its effectiveness, as opposed to traditional attacks that leverage code or configuration errors. Due to this fundamental difference, cybersecurity in AI-driven systems must be conceptualized and executed differently.

The inventiveness and flexibility of contemporary defensive tactics is their main advantages. For example, by subjecting models to adversarial situations directly during development, adversarial training is an active attempt to enhance the robustness of models (Zhao et al., 2022). Some of the most extensively researched evasion attacks have been successfully mitigated by this method. Likewise, hybrid defenses and ensemble approaches demonstrate an understanding that no single tactic is sufficient, resulting in the integration of multiple levels of protection. These developments demonstrate the field's tenacity and dedication to addressing evolving threats. These defenses do, however, also highlight serious flaws. Many techniques are still only applicable against certain kinds of attacks, which makes them less successful against new or adaptable adversaries. For instance, attackers quickly devised ways to circumvent gradient masking techniques, which initially seemed promising (Naseer et al., 2019). Robust optimization and defensive distillation both suffer from trade-offs, frequently compromising accuracy or efficiency in the sake of robustness. These flaws suggest that, although current defenses represent significant advancements, they are still insufficient to protect mission-critical systems deployed in dynamic, real-world settings.

There are other issues with generalizability and scalability. When applied to vast, diverse data sets or complex operational situations, defensive techniques that work effectively in controlled laboratory settings often fail to scale (Conti et al., 2021). Even though it makes sense conceptually, using adversarial training on large-scale models with millions or billions of parameters becomes computationally expensive (Ling et al., 2023). Furthermore, methods that depend on carefully chosen adversarial instances may not translate well to attacks that utilize novel algorithms or target other modalities, such as text or audio. For industries where dependability and robustness are crucial, such as healthcare, defense, and finance, this discrepancy between experimental performance and practical deployment poses significant concerns. Adversarial resilience remains primarily a research goal rather than a workable solution in the absence of defenses that scale effectively to industrial systems and generalize across attack types.

Beyond its technical constraints, the ethical and policy implications of adversarial machine learning demand careful consideration. Given the growing use of AI in critical decision-making, AI safety is no longer just an academic issue but also a societal requirement (Zhang, 2025). Although regulatory frameworks are starting to take shape in the US, the EU, and other countries, the majority of existing regulations prioritize concerns such as data privacy, openness, and equity above adversarial robustness (Shandilya et al., 2024). Although they are mostly lacking, compliance standards that require thorough testing under hostile conditions have the potential to increase resilience significantly. Accountability also raises ethical questions because it is not apparent who is accountable—the developers, the deploying organization, or the regulators—when an AI system incorrectly classifies a crucial input due to adversarial manipulation. To ensure that adversarial defense becomes a crucial part of AI governance, rather than an optional addition, it is imperative to establish clear ethical standards and compliance procedures.

Although they are still in their infancy, emerging technologies present promising paths for enhancing AI security. By minimizing the exposure of training data, federated learning reduces the potential for widespread poisoning attacks, as models can be trained across dispersed devices without centralizing sensitive data. Federated systems, however, do provide additional risks, such as the potential for hacked clients to introduce malicious updates. Additionally, blockchain has been proposed as a means to enhance integrity and trust in AI pipelines. Blockchain-based solutions can increase accountability and make it more difficult for adversaries to covertly alter inputs by documenting data provenance and model revisions on immutable ledgers. However, scalability, energy efficiency, and interaction with current systems are obstacles to blockchain adoption (Khan et al., 2021). Looking ahead, there are both opportunities and threats associated with the development of quantum computing. On the one hand, quantum capabilities could render existing cryptographic defenses obsolete, making AI systems even more vulnerable. The development of quantum-resistant AI defenses, on the other hand, provides a method for creating systems that can resist both classical and quantum-enabled adversaries. The significance of forward-looking research that considers both the present and future danger landscapes is demonstrated by these emerging technologies.

Overall, the conversation suggests a field in transition: while significant progress has been made in designing and deploying adversarial defenses, fundamental issues with robustness, scalability, and governance persist. It will require interdisciplinary cooperation, regulatory harmonization, and the incorporation of new technical paradigms to bridge the gap between academic invention and real-world implementation. Adversarial defense can only develop into a dependable defense for the AI systems that society is becoming increasingly dependent on by tackling these problems comprehensively.

6. CONCLUSION

Protecting artificial intelligence systems against attacks by hostile agents is one of the most urgent challenges in current cybersecurity. The integration of AI into essential infrastructure raises its benefits and limitations, as this review has demonstrated, and may lead to a scenario where adversarial vulnerabilities have severe consequences. Although defense systems, such as adversarial training, robust optimization, and ensemble methods, can be helpful yet still inadequate, adversaries can exploit AI in various ways, including evasion, poisoning, model extraction, and backdoor attacks. The dynamic nature of this arms race ensures that no defense will remain effective for long before it is compromised.

The conclusions drawn from the study demonstrate that, despite substantial progress, issues persist. These include the lack of scalability, the absence of standardized criteria to evaluate defenses, and the limited generalizability of existing approaches. Moreover, the gaps in responsibility and compliance remain critical issues that cannot be properly addressed unless effective systems of regulations and ethics are established.

Future research should focus on developing visible and explainable defense mechanisms that are consistent in high-stakes situations. The use of standardized data and standards will encourage the gradual development of the scientific community and enable evaluation to be fairer. They will need interdisciplinary collaboration that relies on the expertise of cybersecurity, policy, ethics, and the most recent technologies, such as federated learning, blockchain, and quantum-resistant systems, to develop robust, scalable, and reliable AI defenses. Ultimately, the security of AI systems against malicious use is a social requirement, not simply a technical one. By addressing these matters rigorously and with a long-term perspective, the research and policy communities will be able to develop AI that is robust, sustainable, and can safely benefit humanity in a world that is becoming increasingly digitalized.

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