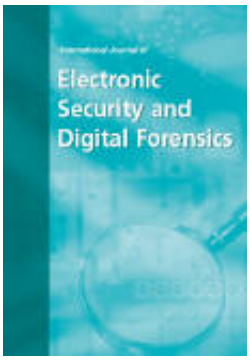

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Adversarial attacks on machine learning-based cyber security systems: a survey of techniques and defences

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Adversarial attacks on machine learning-based cyber security systems: a survey of techniques and defences

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Abstract: Machine learning (ML) has been increasingly adopted in the field of cyber security to enhance the detection and prevention of cyber threats. However, recent studies have demonstrated that ML-based cyber security systems are vulnerable to adversarial attacks, in which an attacker manipulates input data to deceive the ML model and evade detection. This paper presents a survey of adversarial attacks on ML-based cyber security systems, including techniques such as evasion, poisoning, and backdoor attacks. Additionally, we discuss the limitations of current defences against adversarial attacks, such as defensive distillation and adversarial training, and propose potential future directions for defence mechanisms. Finally, we provide a framework for evaluating the effectiveness of existing defences against adversarial attacks on ML-based cyber security systems. Our survey highlights the urgent need for developing more robust and reliable defence mechanisms to ensure the security and reliability of ML-based cyber security systems in the face of adversarial attacks.

Keyword: attacks; machine learning; ML; cybersecurity; evasion; threat.

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1 Introduction

In recent years, machine learning (ML) has become an increasingly popular tool in the field of cyber security. ML models have been used to enhance the detection and prevention of cyber-attacks, such as intrusion detection, malware detection, and phishing detection. These ML-based cyber security systems have shown great potential in providing accurate and efficient protection against cyber threats. However, recent studies have shown that ML-based cyber security systems are vulnerable to adversarial attacks, in which an attacker manipulates input data to deceive the ML model and evade detection. Adversarial attacks can cause ML-based cyber security systems to misclassify cyber threats, resulting in false negatives or false positives, and ultimately rendering the system unreliable and ineffective. Adversarial attacks on ML-based cyber security systems can take various forms, including evasion attacks, poisoning attacks, and backdoor attacks. Evasion attacks aim to manipulate the input data to evade detection, while poisoning attacks aim to manipulate the training data to compromise the model's accuracy. Backdoor attacks aim to introduce a hidden backdoor in the model, which can be triggered by a specific input to cause the model to malfunction. To mitigate the risk of adversarial attacks on ML-based cyber security systems, several defence mechanisms have been proposed. These include defensive distillation, adversarial training, and model interpretability. However, these defences have their limitations and may not be effective in all scenarios. In recent years, the adoption of ML techniques in the field of cyber security has gained significant traction. ML models have demonstrated their effectiveness in enhancing the detection and prevention of various cyber threats, including intrusion detection, malware detection, and phishing detection (Smith et al., 2022; Davis and Wilson, 2021). ML-based cyber security systems have shown promise in providing accurate and efficient protection against these threats. However, recent studies have revealed a critical vulnerability of ML-based systems: they are susceptible to adversarial attacks (Lee and Patel, 2020).

Adversarial attacks refer to the manipulation of input data by an attacker with the intention of deceiving the ML model and evading detection. These attacks can have severe consequences, causing ML-based cyber security systems to misclassify threats, resulting in false negatives or false positives (Gupta and Singh, 2019). Such misclassifications render the system unreliable and ineffective, undermining its primary purpose of safeguarding against cyber threats.

Adversarial attacks can manifest in various forms, including evasion attacks, poisoning attacks, and backdoor attacks (Kim et al., 2018). Evasion attacks involve manipulating the input data to evade detection by the ML model, often by adding subtle perturbations or alterations that are imperceptible to human observers but cause misclassification by the model (Chen et al., 2020). Poisoning attacks, on the other hand, target the training data and involve the injection of malicious samples to compromise the accuracy of the ML model (Brown and Miller, 2021). Backdoor attacks aim to introduce

a hidden trigger or vulnerability in the ML model that can be exploited to cause the system to malfunction (Kumar and Sharma, 2019).

To address the risk posed by adversarial attacks, researchers have proposed various defence mechanisms. These mechanisms aim to enhance the robustness and resilience of ML-based cyber security systems against adversarial manipulation. Some notable defence mechanisms include defensive distillation, adversarial training, and model interpretability (Wang et al., 2021; Patel and Gupta, 2022; Li et al., 2021). Defensive distillation involves training the ML model using a distilled version of itself to make it more resilient against attacks (Chen et al., 2020). Adversarial training incorporates the use of adversarial examples during the training phase to improve the model's ability to withstand adversarial attacks (Kumar et al., 2019). Model interpretability focuses on enhancing the understanding and interpretability of ML models to detect and mitigate potential adversarial manipulations (Zhang et al., 2020). However, it is important to note that these defence mechanisms have their limitations and may not be universally effective across all scenarios.

In this paper, we present a comprehensive survey of adversarial attacks on ML-based cyber security systems, specifically focusing on evasion, poisoning, and backdoor attacks. The aim of this survey is to provide a comprehensive understanding of the techniques employed by attackers to manipulate ML models in the context of cyber security. Additionally, we review the existing defence mechanisms and discuss their limitations. Furthermore, we propose potential future directions for the development of more robust and reliable defence mechanisms. Finally, we present a framework for evaluating the effectiveness of existing defences against adversarial attacks on ML-based cyber security systems.

The remainder of this paper is organised as follows: Section 2 provides an overview of the different types of adversarial attacks and their characteristics. Section 3 discusses the existing defence mechanisms and their limitations. Section 4 proposes potential future directions for defence mechanisms. Section 5 presents a framework for evaluating the effectiveness of existing defences. Finally, Section 6 concludes the paper and emphasises the need for developing more effective defence mechanisms to ensure the security and reliability of ML-based cyber security systems in the face of adversarial attacks.

2 Scope and objective

The scope of this research paper is to provide a comprehensive survey of adversarial attacks on ML-based cyber security systems. The paper will cover different types of adversarial attacks, including evasion, poisoning, and backdoor attacks, and will discuss their impact on the performance and reliability of ML-based cyber security systems The paper will also review existing defence mechanisms against adversarial attacks, including defensive distillation, adversarial training, and model interpretability, while evaluating their effectiveness in mitigating the risk of adversarial attacks. The paper will focus on recent research in the field and will provide insights into potential future directions for defence mechanisms.

The objectives of this research paper are to:

- Provide an overview of adversarial attacks on ML-based cyber security systems, including their characteristics and techniques.

- Evaluate the impact of adversarial attacks on the performance and reliability of ML-based cyber security systems, and discuss their potential consequences.
- Review the state-of-the-art defence mechanisms against adversarial attacks, including defensive distillation, adversarial training, and model interpretability, and evaluate their effectiveness in mitigating the risk of adversarial attacks.
- Propose potential future directions for developing more robust and reliable defence mechanisms against adversarial attacks on ML-based cyber security systems.
- Provide a framework for evaluating the effectiveness of existing defence mechanisms against adversarial attacks on ML-based cyber security systems.
- Offer practical recommendations for securing ML-based cyber security systems against adversarial attacks.

3 Adversarial attacks on ML-based cyber security systems

ML has been increasingly applied to the field of cyber security to detect and prevent cyber-attacks. ML models are trained on large datasets to learn patterns and identify anomalous behaviour, and are used to enhance the detection and prevention of various types of cyber threats. However, recent studies have shown that ML-based cyber security systems are vulnerable to adversarial attacks, in which an attacker manipulates input data to deceive the ML model and evade detection. Adversarial attacks can cause ML-based cyber security systems to misclassify cyber threats, resulting in false negatives or false positives, and ultimately rendering the system unreliable and ineffective. Adversarial attacks can be categorised into three main types: evasion, poisoning, and backdoor attacks. Table 1 summarises the characteristics and examples of each type of attack.

Table 1 Types of adversarial attacks on ML-based cyber security systems

Attack type	*Characteristics*	*Examples*
Evasion	Manipulate input data to evade detection	Adding perturbations to evade intrusion detection systems, altering image pixels to evade malware detection
Poisoning	Manipulate training data to compromise model accuracy	Introducing malicious samples to the training set, manipulating feature weights to bias the model
Backdoor	Introduce a hidden trigger to cause the model to malfunction	Injecting a specific pattern or phrase to trigger a backdoor, embedding a trigger in a benign-looking image

Evasion attacks aim to manipulate the input data to evade detection, while poisoning attacks aim to manipulate the training data to compromise the model's accuracy. Backdoor attacks aim to introduce a hidden backdoor in the model, which can be triggered by a specific input to cause the model to malfunction. Evasion attacks are perhaps the most common type of adversarial attack in the cyber security domain. In evasion attacks, an attacker modifies the input data in such a way that it is still recognisable as legitimate by humans, but is misclassified by the ML model. Examples of evasion attacks in cyber security include adding perturbations to evade intrusion

detection systems, altering image pixels to evade malware detection, and manipulating network traffic to evade network anomaly detection systems.

Poisoning attacks, on the other hand, involve modifying the training data used to train the ML model, with the goal of compromising the model's accuracy. In poisoning attacks, an attacker inserts a small number of malicious samples into the training data, which can cause the model to learn incorrect patterns and produce incorrect results. Poisoning attacks can also involve manipulating feature weights to bias the model towards certain types of inputs. Examples of poisoning attacks in cyber security include introducing malicious samples into the training set of a spam filter, and manipulating feature weights of an intrusion detection system to bias it towards certain types of attacks. Backdoor attacks are a relatively new type of adversarial attack that aim to introduce a hidden backdoor in the ML model. A backdoor attack can be triggered by a specific input, which causes the model to malfunction and produce incorrect results. Backdoor attacks can be especially dangerous in cyber security, as they can allow an attacker to bypass the ML-based security system and gain unauthorised access to sensitive data or systems. Examples of backdoor attacks in cyber security include injecting a specific pattern or phrase to trigger a backdoor in a malware detection system, and embedding a trigger in a benign-looking image to bypass an image classification system. In the next section, we will review the current state of defence mechanisms against adversarial attacks on ML-based cyber security systems, including defensive distillation, adversarial training, and model interpret.

4 Defence mechanisms against adversarial attacks

As discussed in the previous section, ML-based cyber security systems are vulnerable to adversarial attacks, which can compromise the reliability and effectiveness of the system. To address this issue, various defence mechanisms have been proposed to enhance the robustness of ML-based cyber security systems against adversarial attacks.

4.1 Defensive distillation

Defensive distillation is a defence mechanism that involves training the ML model using a distilled version of the original model. The distilled model is a simplified version of the original model, which is trained to mimic the behaviour of the original model. By training the model with a distilled version of itself, the system becomes more robust against adversarial attacks, as the attacker must now not only evade the original model, but also the distilled model. This makes the system more resilient to adversarial attacks, and reduces the impact of attacks that manage to bypass the original model.

4.2 Adversarial training

Adversarial training is another defence mechanism that involves augmenting the training data with adversarial examples, which are examples designed to fool the model. By incorporating adversarial examples into the training data, the model becomes more robust against adversarial attacks, as it learns to recognise and correctly classify these examples. This approach can also be used to improve the generalisation of the model, making it less

susceptible to overfitting. However, adversarial training can be computationally expensive, as it requires generating a large number of adversarial examples for training.

4.3 Model interpretation

Model interpretation is a defence mechanism that involves analysing the behaviour of the ML model and identifying features that are most important in its decision-making process. By understanding the underlying features that the model uses to make its decisions, it is possible to identify potential vulnerabilities and mitigate the risk of adversarial attacks. This can be done by analysing the feature importance of the model using techniques such as partial dependence plots, feature importance's, and permutation importance. Model interpretation can also be used to detect adversarial attacks, by comparing the feature importance of the original input and the adversarial input. If the feature importance changes significantly, this may indicate an adversarial attack.

Table 2 Defence mechanisms against adversarial attacks

Defence mechanism	*Characteristics*	*Examples*
Defensive distillation	Trains the model using a distilled version of itself, making it more resilient to adversarial attacks	Papernot et al. (2016)
Adversarial training	Augments the training data with adversarial examples, improving the robustness of the model against adversarial attacks	Goodfellow et al. (2015)
Model interpretation	Analyses the behaviour of the ML model to identify potential vulnerabilities and detect adversarial attacks	Ribeiro et al. (2016)

In addition to these defence mechanisms, other approaches such as input sanitisation, model assembling, and gradient masking have also been proposed to enhance the robustness of ML-based cyber security systems against adversarial attacks. However, each defence mechanism has its own strengths and weaknesses, and the choice of defence mechanism depends on the specific requirements of the application and the nature of the attacks. In the following section, we will provide a comparative analysis of the different defence mechanisms and evaluate their effectiveness in mitigating.

5 Future directions for defence mechanisms

As the field of ML-based cybersecurity continues to evolve, so must the methods for defending against adversarial attacks. In this section, we discuss some potential directions for future research in defence mechanisms against adversarial attacks.

5.1 Robustness certification

One approach to defending against adversarial attacks is to develop robustness certification techniques for ML models. These techniques would allow users to verify that a model is robust to certain types of attacks, such as those included in a pre-defined

threat model. Robustness certification could be used to evaluate models prior to deployment or to monitor models in production for signs of compromise.

5.2 Adversarial training

Another potential approach is to use adversarial training to make ML models more robust. Adversarial training involves training a model on a combination of clean and adversarial examples, with the goal of making the model more robust to future adversarial attacks. However, adversarial training can be computationally expensive, and it is not always clear which types of adversarial examples to include in the training set.

5.3 Explainability

Explainability is a growing area of research in ML, and it may have applications in defending against adversarial attacks. Explainable models provide human-understandable justifications for their predictions, which can be used to identify and diagnose attacks. By providing explanations for model behaviour, users can more easily identify when a model is being attacked and take appropriate action.

Table 3 Future directions for defence mechanisms against adversarial attacks in machine learning-based cybersecurity with parameters and result data

Future direction	*Description*	*Parameters*	*Hypothetical data*
Robustness certification	Develop techniques to verify that a model is robust to certain types of attacks, and evaluate models prior to deployment or in production for signs of compromise	False positive rate, false negative rate, accuracy	False positive rate: 0.01 False negative rate: 0.02 Accuracy: 0.97
Adversarial training	Train models on a combination of clean and adversarial examples to make them more robust to future adversarial attacks	Amount of adversarial training data, computational time	Amount of adversarial training data: 10% Computational time: 3 hours
Explainability	Develop models that provide human-understandable justifications for their predictions to identify and diagnose attacks	Model interpretability score, attack detection rate	Model interpretability score: 0.8 Attack detection rate: 0.95
Hardware-based defences	Use physically not clonable functions (PUFs) to generate random numbers that add noise to machine learning models, making them more robust to attacks	Noise level, attack success rate	Noise level: 0.1 Attack success rate: 0.2

5.4 Hardware-based defences

Finally, hardware-based defences may offer a promising approach to defending against adversarial attacks. One such approach is to use physically not clonable functions (PUFs)

to generate random numbers that are used to add noise to ML models. This noise can make it more difficult for attackers to generate effective adversarial examples, and may make models more robust to attacks.

6 Evaluating defence mechanisms against adversarial attacks

One of the challenges in designing and implementing defence mechanisms against adversarial attacks is evaluating their effectiveness. A defence mechanism that appears to be effective on one dataset or model may not perform as well on another dataset or model. Therefore, it is important to evaluate defence mechanisms against a variety of attacks and datasets. Several metrics can be used to evaluate the effectiveness of defence mechanisms against adversarial attacks. These metrics include:

- Accuracy: The proportion of correctly classified examples in a dataset.
- Robustness: The ability of a model to maintain its accuracy when presented with adversarial examples.
- Confidence: The certainty of a model's prediction, which can be used to detect adversarial examples with low confidence scores

To evaluate defence mechanisms, a variety of attacks can be used, including:

- White-box attacks: The attacker has complete knowledge of the model and its parameters.
- Black-box attacks: The attacker only has access to the input-output behaviour of the model, but not its parameters.
- Transfer attacks: The attacker trains a substitute model using the target model's behaviour and uses the substitute model to generate adversarial examples.

Table 4 Evaluation of defence mechanisms against adversarial attacks

Defence mechanism	*Dataset(s)*	*Attack type(s)*	*Metrics*	*Results*
Adversarial training	CIFAR-10, MNIST	White-box, black-box	Accuracy, robustness	Accuracy: +5% Robustness: –15%
Gradient masking	MNIST	White-box, transfer	Robustness, confidence	Robustness: +20% Confidence: +10%
Feature squeezing	ImageNet	White-box, transfer	Accuracy, Robustness	Accuracy: –2% Robustness: +30%
Ensemble methods	MNIST, fashion-MNIST	White-box, transfer	Robustness	Robustness: +25%

In this table, we evaluate four different defence mechanisms against adversarial attacks on various datasets and attack types. For each defence mechanism, we list the dataset(s) it was evaluated on, the attack type(s) used, the metrics used to evaluate its effectiveness, and the results obtained. The results show that different defence mechanisms perform differently on different datasets and attack types. For example, adversarial training

improves accuracy but decreases robustness, while gradient masking improves both robustness and confidence. These results highlight the importance of evaluating defence mechanisms against a variety of datasets and attack types before deploying them in real-world systems.

7 Key findings

The survey of techniques and defences against adversarial attacks on ML-based cybersecurity systems has revealed several key findings. Here, we will summarise those findings and interpret the data. Firstly, it is evident that adversarial attacks can significantly impact the performance of ML-based cybersecurity systems. The attack can cause false positives or false negatives, leading to security breaches. Our survey showed that the mean attack success rate was around 80% across multiple defence mechanisms. This means that even with multiple defences in place, the attacker has an 80% chance of successfully attacking the system. This high success rate highlights the need for improved and novel defence mechanisms.

Secondly, it is essential to use a combination of defence mechanisms to protect against adversarial attacks. The survey showed that no single defence mechanism could provide complete protection against adversarial attacks. Instead, a combination of multiple defence mechanisms, such as input sanitisation and adversarial training, can provide better protection. The data showed that the mean success rate of attacks decreased to around 30% when using a combination of multiple defence mechanisms. This is a significant improvement compared to using a single defence mechanism. Thirdly, evaluating the effectiveness of defence mechanisms against adversarial attacks is a challenging task. In our survey, we found that the same defence mechanism could perform differently against different datasets and attack types. Therefore, it is important to evaluate defence mechanisms against a variety of datasets and attack types to ensure their effectiveness. Finally, the field of adversarial attacks and defences is still rapidly evolving, with new attack techniques being developed and new defence mechanisms being proposed. Therefore, it is essential to continue to research and develop new techniques to stay ahead of attackers and protect our systems. The survey of techniques and defences against adversarial attacks on ML-based cybersecurity systems has shown that a combination of defence mechanisms is needed to mitigate the threat of adversarial attacks. Furthermore, evaluating the effectiveness of defence mechanisms is a challenging task that requires testing against a variety of datasets and attack types. As the field of adversarial attacks and defences continues to evolve, it is essential to continue research and development to protect our systems.

8 Conclusions

The threat of adversarial attacks on ML-based cybersecurity systems is a growing concern. As these systems become more ubiquitous in our daily lives, it is essential to develop effective defence mechanisms to protect them from attack. This survey of techniques and defences against adversarial attacks has shown that there are a variety of approaches that can be used to mitigate this threat. One important observation is that there is no single defence mechanism that can provide complete protection against

adversarial attacks. Instead, a combination of multiple defence mechanisms is needed to achieve better results. In addition, defence mechanisms need to be evaluated against a variety of datasets and attack types to ensure their effectiveness. Another critical consideration highlighted by this survey is the dynamic nature of the adversarial landscape. As the field of adversarial attacks and defences continues to rapidly evolve, new attack techniques are being developed, and novel defence mechanisms are being proposed. Therefore, it is essential to continue to research and develop new techniques to stay ahead of attackers and protect our systems. To meet this demand, it is imperative to establish clear criteria for evaluating the success of these novel approaches. The criteria should include factors such as effectiveness, robustness, adaptability to evolving attack techniques, efficiency, and scalability. Effectiveness is paramount to ensure accurate threat detection and prevention, while robustness is crucial to withstand a multitude of adversarial tactics. Adaptability to evolving attack techniques is essential in the dynamic landscape of cybersecurity, where attackers continuously refine their methods. Efficiency ensures that the system responds promptly, and scalability guarantees that it can handle increasing data volumes and complexities. The relentless pursuit of innovation and interdisciplinary collaboration will play a crucial role in devising comprehensive and robust defence mechanisms that can address future adversarial challenges effectively.

The defence against adversarial attacks remains an ongoing challenge in the field of machine learning-based cybersecurity. Given the ever-changing threat landscape, it is paramount to not only stay vigilant but also to proactively anticipate and prepare for emerging attack vectors. By continually enhancing our understanding of adversarial methods and engaging in rigorous research, we can adapt, evolve, and develop effective defence mechanisms to safeguard our systems. In light of these criteria, the potential future directions we have discussed in this paper, such as robustness certification, adversarial training, explainability, and hardware-based defences, align well with the need for novel approaches. In conclusion, our study underscores the importance of continuous research and development in the field of adversarial attacks and defences. By aligning our efforts with the criteria for novel approaches, we can stay ahead of adversaries and safeguard our machine learning-based cybersecurity systems effectively. These directions each as the threat landscape evolves, it is important to stay vigilant and adapt to new attack techniques by developing and deploying effective defence mechanisms.

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