Backdoor Attacks on Network Certification via Data Poisoning

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Abstract—Certifiers for neural networks have made great progress towards provable robustness guarantees against evasion attacks using adversarial examples. However, introducing certifiers into deep learning systems also opens up new attack vectors, which need to be considered before deployment. In this work, we conduct the first systematic analysis of training time attacks against certifiers in practical application pipelines, identifying new threat vectors that can be exploited to degrade the overall system. Using these insights, we design two backdoor attacks against network certifiers, which can drastically reduce certified robustness when the backdoor is activated. For example, adding 1% poisoned data points during training is sufficient to reduce certified robustness by up to 95 percentage points, effectively rendering the certifier useless. We analyze how such novel attacks can compromise the overall system’s integrity or availability. Our extensive experiments across multiple datasets, model architectures, and certifiers demonstrate the wide applicability of these attacks. A first investigation into potential defenses shows that current approaches only partially mitigate the issue, highlighting the need for new, more specific solutions.

Index Terms—deep learning, backdoor attack, data poisoning, network certification, attack against certification

I. INTRODUCTION

The huge success of deep learning systems has led to their introduction within many safety-critical tasks such as autonomous driving [1], [2] or malware detection [3], [4]. With their rise in popularity, new threats and security concerns have been raised, such as evasion attacks using adversarial examples [5], [6]. A large body of work has been dedicated to analyzing these attacks and to improving the robustness of deep learning models.

Among the most promising results are network certifiers [7]–[9], which can prove a network’s robustness against adversarial perturbations. By propagating a convex relaxation of the perturbation set through the network, they can guarantee that the network’s prediction is robust to small changes in the input space. Current research efforts mostly focus on improving the scalability of network certifiers and extending them to new perturbations, network architectures, and tasks. However, introducing a new component, the certifier, into a deep learning pipeline changes its threat surface and potentially introduces new security risks and attack vectors. To the best of our knowledge, no prior work exists which systematically analyses the security properties of certifiers in their larger application context.

In this work, we aim to fill this gap and perform the first systematic evaluation of training time attacks against network certifiers, considering their integration in practical systems and their impact on the system’s integrity and availability. Using novel backdoor attacks against network certifiers, we show that a small distribution shift in the data between evaluation and deployment is sufficient to void all security guarantees of evaluation-time offline certification, requiring online robustness certificates at runtime. However, online certification comes with its own challenges. Since the robustness certification may fail for any given input, the certified model requires an option to abstain from making a prediction. While this is a simple adaptation in theory, practical systems need to consider this new failure case and implement a fallback, which makes sacrifices to either the system’s integrity or availability.

Our attacks specifically target this fallback path by forcing...
the certifier to abstain, effectively disabling the deep learning model. Since the system can only rely on the fallback method, this attack leads to either a decrease in performance or a system overload.

To show the practical relevance and potentially disastrous impact of these new attack vectors, we propose the first concrete backdoor attacks against network certifiers (fig. 1). Our direct backdoor attack exploits the victim’s model supply chain, supplying them with a model containing a hidden backdoor that remains undetected during evaluation. For scenarios where the victim is in control of model training, our indirect attack can create the same backdoor by poisoning the training data. Both attacks are highly effective with only 1% poisoned data and reduce the certified robustness by up to 95 percentage points when the backdoor is activated. We analyze how such an attack can severely compromise the integrity or availability of the overall system, and derive consequences for theoretical research and practical implementations of network certifiers.

Our thorough evaluation shows the wide applicability of our attacks across multiple datasets, model architectures, and certifiers. These results highlight the need for defenses against backdoor attacks on network certifiers. We conduct a first study by adapting a traditional backdoor defense against our attacks with mixed results, which highlights a need for new, specialized solutions.

To summarize, our main contributions are:
- A systematic analysis of training time attacks against network certifiers, considering their integration in practical systems, and identifying new attack vectors.
- The first backdoor attacks against network certifiers through two different attack vectors, which are highly effective and difficult to detect.
- A comprehensive experimental evaluation of these attacks across multiple datasets, network architectures, and certifiers.
- Evaluations of defenses against our proposed attacks.

II. BACKGROUND

Although deep learning systems come in many forms, traditionally the goal for most of these systems has been to maximize the objective for their designated task. A deep neural network \( f_\theta : \mathcal{X} \rightarrow \mathcal{Y} \) can be seen as a parametric function which maps inputs from the input space \( \mathcal{X} \) to the output space \( \mathcal{Y} \), parameterized by its weights \( \theta \). Given a joint distribution \( \mathcal{D} \) on \( \mathcal{X} \times \mathcal{Y} \), the goal is to maximize the expected prediction accuracy

\[
\max_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}} [f_\theta(x) = y]
\]  

by finding optimal parameters \( \theta \).

Since \( \mathcal{D} \) is generally unknown, the objective is approximated by minimizing the empirical risk with a loss function \( L \) on a dataset \( \mathcal{D} \), which consists of samples drawn from the distribution \( \mathcal{D} \):

\[
\min_{\theta} \frac{1}{|\mathcal{D}|} \sum_{(x,y) \in \mathcal{D}} L(f_\theta(x), y).
\]

This training scheme has been shown to work well for many different tasks and data types, generalizing to new, unseen samples from the underlying distribution \( \mathcal{D} \).

A. Adversarial Attacks and Defenses

With rising popularity and deployment in safety critical applications, the security of deep learning systems has become a major concern. The black-box nature of deep neural networks, their complex training pipelines, and development based on empirical tests rather than formal guarantees all contribute to a wide attack surface for attackers to exploit [10].

Among the first attack vectors explored were evasion attacks using adversarial examples [5], [6]. By adding small, visually imperceptible perturbations to the input image, neural networks can be tricked into predicting the wrong output. Mathematically, this can be formulated as finding an adversarial sample \( x' \) from a perturbation set \( \mathcal{S}(x) \) around \( x \), for which \( f_\theta(x') \neq f_\theta(x) \). The perturbation set ensures visual similarity and is often chosen as an \( \ell_p \)-ball around the input, i.e., \( \mathcal{S}(x) = \{x' \in \mathcal{X} \mid \|x' - x\|_p \leq \epsilon\} \).

Following these initial works, a plethora of successively stronger attacks and defenses has been proposed, resulting in an arms race between attackers and defenders. It became apparent that maximizing the model’s utility should not be the only concern when developing deep learning systems, adding additional objectives such as robustness against attacks. The robustness requirement can be added to the optimization objective, leading to the robust optimization problem

\[
\min_{\theta} \mathbb{E}_{(x,y) \sim \mathcal{D}} \left[ \max_{\delta \in \mathcal{S}(x)} L(f_\theta(x + \delta), y) \right].
\]

One of the most successful empirical defenses is adversarial training [6], [11], where in addition to the samples from the original dataset, the network is additionally trained on adversarially perturbed versions of said data, making it more resilient to future attacks. In other words, the inner objective from eq. (3) is approximated by performing an adversarial attack, within the regular training loop optimizing the outer minimization problem.

Other defenses are, for example, based on attack detection [12]–[14] or randomization [15]–[17].

B. Provably Robustness Guarantees

However, none of these defenses provide provable robustness guarantees, so that many initially promising defenses were later broken with stronger attacks [18], [19]. To break this arms race between attackers and defenders, a new line of work evolved with the goal to compute provable robustness guarantees against attacks.

The most commonly used relaxation techniques work as follows: instead of executing the network on a single input \( x \), they propagate the entire perturbation set \( \mathcal{S}(x) \) through the network, which results in output sets. Using these output sets, the certifier can prove some local invariants on the set \( \mathcal{S}(x) \), such as classification to the same label. Section III-A discusses in more detail how this is done by linear certifiers.
Different approaches have been proposed on how to compute these invariants. For small networks, exact methods based on SMT solvers [20] or mixed-integer linear programming [21] can be used for precise results. For larger models, these exact methods are intractable, requiring relaxations to compute a lower bound to the model’s true robustness. Several methods find different relaxations to balance performance and precision, including intervals [22], semi-definite relaxations [23], and many forms of linear relaxations [7]–[9], [24]–[28]. All of these methods compute convex relaxations to approximate the network operations, choosing different trade-offs between computational complexity and precision. There are also other verification methods for neural networks, for example based on optimization [29].

If we can certify local robustness to input perturbations with any of these methods, we can guarantee that there is no adversary which can attack the network within that local neighborhood. However, models trained with standard or even adversarial training tend to be unstable, which limits certification to only small perturbations.

To increase the model’s certified robustness, provable training methods make use of the convex relaxations of network certifiers during training. By training the network on the entire perturbation set instead of individual samples, they significantly increase the robustness and also compensate for the certifier’s over-approximation. In essence, they over-approximate the inner maximization problem from eq. (3) using the certifier, guaranteeing there is no $\delta$ with a loss larger than the one considered.

This robustness gain comes at the cost of additional training time, since the certifier has to be invoked for each forward pass. Provable training is therefore only feasible for fast relaxations based on intervals [30], [31] or linear bounds [32].

An entirely different approach to certifying a network’s robustness is randomized smoothing [33], [34]. In contrast to the deterministic guarantees of norm-bounded methods, randomized smoothing only gives statistical guarantees that the network is robust with high probability. Instead of propagating a relaxation of the perturbation set through the network, randomized smoothing computes a smoothed version of the model by repeatedly sampling from a distribution around the original input. This smoothing operation makes the model more robust against perturbations and enables robustness guarantees, but comes at the cost of additional overhead during runtime and reduced model utility.

C. Training-time Attacks

With increasing robustness of models to evasion attacks, new attack vectors against neural networks are being explored. Prominent among them are training-time attacks, where the model’s behavior is influenced during training.

One popular way to influence training is to poison the model’s training data. By injecting malicious samples into the training set, the adversary can steer the optimization process into a beneficial direction. In fact, poisoning attacks were studied for many different machine learning methods long before the era of deep learning [35], but have recently been applied to deep neural networks [36]–[38]. The goal of these classical data poisoning attacks is to change to model’s output for a predetermined set of inputs, e.g., to misclassify some data of interest.

Backdoor attacks [39] take this concept one step further. Instead of misclassifying a predetermined set of inputs, they cause the model to misclassify any input which contains a special trigger. They function by adding a backdoor to the model during training. At runtime, the adversary can then activate the backdoor by simply adding the trigger to any model input, causing the model to change its behavior. This trigger can take many forms, from simple pixel patterns [40] to invisible perturbations [41]–[44] or semantic features, such as a person wearing special glasses [41]. The benefit of this type of attack is that the attacker does not have to know the target inputs in advance and can dynamically adapt it to new data.

Technically, these attacks usually use data poisoning to influence the training process. In the simplest case, adding a small amount of mislabeled samples with triggers is sufficient to introduce a backdoor [40], [41]. More sophisticated versions use clean-label attacks to avoid detection by backdoor defenses or manual inspection [41]–[46]. Other techniques exploit the model supply chain of the victim by publishing a pretrained model which already contains the backdoor [47].

There are several different approaches to defend against backdoor attacks [39]. One group of methods tries to remove the trigger from the input image using preprocessing techniques such as auto encoders [48] or trigger detection and inpainting [49], [50].

A different group of approaches attempts to remove the backdoor from the model after training. They usually require a small subset of verifiably benign training data. Techniques range from simple fine-tuning [48], to model pruning combined with fine-tuning [51], and model distillation [52].

Other approaches inspect the model for backdoors and refuse to deploy them [53], or detected malicious samples at runtime [54]. However, all of these defenses are empirical, without giving any robustness guarantees, and are frequently broken by stronger attacks, which leads to a similar arms race as for evasion attacks. Wang et al. [55] take a first step towards provable backdoor defences using randomized smoothing, with only limited success. More advanced approaches will be needed to provide high-quality robustness guarantees comparable to certification against adversarial attacks.

III. RELATED WORK

After giving a general overview of the relevant fields in section II, we now discuss the work most closely related to our approach in more detail. In particular, these are techniques from linear certification (section III-A), backdoor attacks and defenses (section III-B), and attacks against certification (section III-C).
A. Linear Certification

For our attacks, we consider state-of-the-art linear certifiers, which restrict their relaxations to one upper and one lower linear bound. Applying this restrictions allows for better scaling, since the complexity of the corresponding linear optimization problem only grows linearly in the number of neurons. CROWN [26], CNN-Cert [8], and DeepPoly [7] all belong to this group. While implementation details differ, their general approach is similar. Given an initial convex relaxation of the perturbation set \( S(x) \), they propagate this set through the network by computing upper and lower linear constraints for each intermediate layer. That is, for output \( o^{(k)} \) of layer \( k \) they construct upper and lower linear bounds based on the layer’s inputs \( o^{(k−1)} \):

\[
A_l o^{(k−1)} + b_l \leq o^{(k)} \leq A_u o^{(k−1)} + b_u.
\]  

(4)

This results in linear upper and lower constraints for the last-layer logits \( o^{(l)} \):

\[
\bar{o} \leq o^{(l)} \leq \bar{o},
\]  

(5)

where \( \bar{o} \) and \( \bar{o} \) are the lower and upper linear constraints respectively. These constraints can then be used to certify correct classification by proving

\[
\bar{o}_i < \bar{o}_i \forall i \neq y,
\]  

(6)

where \( \bar{o}_i \) is the upper constraint for the \( i \)-th logit and \( \bar{o}_y \) is the lower constraint for the target class \( y \).

Provably training methods such as CROWN-IBP [32] use these linear bounds to improve a model’s robustness. By computing the training loss using concretizations of these upper and lower bounds instead of the regular last-layer outputs, the network learns to robustly predict the correct label on the entire perturbation set. This can be achieved by rewriting eq. (6) as

\[
m_i > 0, \text{ where } m_i := o_y - o_i, \forall i \neq y.
\]  

(7)

Wong et al. [28] show that using cross-entropy loss, the robust optimization problem can be solved by minimizing

\[
L_{rob}(f(x), y) = CE(-m, y),
\]  

(8)

which intuitively maximizes the margin between the lower bound of the logit for the true label and the upper bound of the remaining logits.

In the case of CROWN-IBP, the upper and lower bounds are computed using a combination of interval and linear bounds. A forward pass using IBP computes fast, imprecise interval bounds, which are then used to speed up the computation of linear bounds in a backwards pass. This combination allows one to compute more precise bounds compared to IBP, but is significantly faster than pure CROWN.

B. Backdoor Attacks and Defenses

As discussed in section II-C, there is a long line of work on backdoor attacks against neural networks. BadNets [40] first introduce the concept of supply chain attacks by hiding a backdoor in pretrained classification models using pixel patterns as a trigger. Our direct backdoor attack (section V-A) uses the same supply chain vector and similar trigger patterns to activate the backdoor. However, the attack’s goal is different, targeting the certifier instead of the network classification. This also leads to a significantly different construction of the backdoor via a combination of existing and new optimization objectives.

Chen et al. [41] use data poisoning to indirectly target a model trained by the victim, adding a backdoor which causes the model to mislabel faces. They accomplish this by injecting a small amount of poisoned training samples into the dataset, consisting of the input image with the trigger and the attacker’s desired target label. Adding the same trigger at test time then causes the backdoor to activate, misclassifying the image to the predetermined target class. This attack vector is similar to our indirect attack (section V-B), where we also use a small amount of triggered samples to poison the data set. However, instead of consistently targeting a particular class, we use random labels to destabilize the prediction and thus cause certification to fail.

For defenses, we adapt fine-pruning [51] to our proposed attacks. Fine-pruning is a combination of two defense mechanisms: pruning and fine-tuning. The idea behind pruning is that backdoor attacks rely on the over-parameterization of networks and thus pruning the neurons from the model that are non-essential for its intended task should remove the backdoor. To do so, the victim requires a smaller subset of verifiably benign data. The network is then invoked on this subset of data, iteratively removing the neurons with the lowest average activations. Since the benign subset contains no backdoor samples, the neurons detecting the backdoor will not activate and thus eventually be pruned from the network.

The downside of this procedure is that the pruning will also decrease the model’s utility. To mitigate this effect and further remove any remnants of the backdoor, the model is then fine-tuned by training for a few epochs on the benign data subset. Overall, the defense is effective at removing backdoors that have not been crafted to evade its detection, at the price of a slight reduction in model accuracy.

C. Attacks Against Certification

Attacks against network certifiers are a very recent development and have not been studied extensively. Ghiasi et al. [56] propose an attack to spoof robustness certificates. They add large, semantically consistent perturbations to images which cause the classifier to robustly classify them as a wrong label. While the computed certificate is valid since the prediction is locally robust, the authors argue that the certified invariance to smaller perturbations might lead to a false sense of security, causing the victim to not consider attacks with different perturbation patterns.

More closely related to our work, Mehra et al. [57] analyze the robustness of randomized smoothing against poisoning attacks. In contrast to our backdoor attacks, they use targeted poisoning attacks with the goal of decreasing the certification
radius for one particular image class. The problem is formulated as a constrained bilevel optimization problem, where the inner objective is the network training, while the outer objective approximately minimizes the certified radius. Using 10% poisoned data, the poisoning attack can decrease the certified radius of the target class by approximately 30%.

IV. Threat Model

To understand potential security threats and attack vectors against network certifiers, we conduct a systematic analysis of their attack surface to training time attacks in deep learning systems. Prior work typically considers the deep learning model in isolation, without considering the full training and inference pipeline in practical applications. In particular, certifiers can fail to produce a certificate for certain inputs, causing the certified model to abstain from making a prediction [34]. This introduces a new failure mode “absence of output”, which the system has to react to. How the system handles abstains largely influences its overall behavior and introduces a new attack vector for adversaries, as we will show in this section. These considerations are usually ignored in the literature, deferring the implementation of fallback strategies to the user of such a system. While the concrete fallback strategy highly depends on the individual application, in a practical, resource-constrained environment it will either impact the system’s integrity or availability. This leads us to a new threat model against certified deep learning systems, in which the adversary deliberately triggers the abstain path, causing either reduced performance or the system becoming unavailable.

A. Attack Surface

Before we can establish a threat model, we first need to look at how machine learning models are trained and deployed in intelligent systems. Papernot et al. [10] define a typical pipeline to (i) start with a physical object, which is (ii) transformed to a digital representation by some sensor, e.g., a camera. (iii) After some pre-processing, (iv) this representation is fed to a machine learning model, which (v) uses it to compute some output, e.g., a class label. (vi) This output is then used to take some action in the physical domain. Classical adversarial samples [5], [6] attack this pipeline by modifying the input data of the pipeline in step (i) or (ii), by slightly perturbing either the physical object or its digital representation. This is the type of attack against which network certifiers can prove robustness, severely limiting the attacker’s influence on the system. However, this is only one part of the pipeline which an adversary can influence.

A second, often more powerful, attack vector is to change the machine learning model itself, which sits at the core of the system. Depending on the attacker’s access to the model, we distinguish between two types of attacks: those with direct access to the model during training and those with indirect access via the training data.

Direct Access: This threat model assumes that an attacker can directly influence the training of a model, including its optimization objectives. In practice, this means the victim cannot trust the integrity of the training process, requiring defenses on the level of model checking and inference time. Obviously, this threat model gives the attacker a lot of power, which makes it hard to defend against. However, it is not an unrealistic assumption for practical applications. Many companies rely on a large supply chain with external manufacturers supplying individual modules. Considering the fact that, for deep learning systems, a large amount of intellectual property lies within the training data and procedure, companies are reluctant to part with it and instead sell the already trained model to their customers. The high computational cost of large, state-of-the-art models also contributes to the outsourcing of model training. This results in the described threat model, where the victim can no longer make any assumptions about the integrity of the training process.

Indirect Access: A weaker assumption on the capabilities of the attacker, and the threat model typically considered for backdoor attacks [39], is what we consider indirect access. Here, the attacker cannot directly influence the training process, instead relying on data poisoning. In poisoning attacks, the attacker modifies a small portion of the training data to influence the behavior of the final model [36], [40], [58]. In this work, we consider the weaker version of injection attacks, where the attacker cannot modify existing training data but instead injects a few additional, malicious training samples. This type of poisoning attack is relatively easy to perform, since all deep learning models rely on huge amounts of training data, which are often collected from untrusted sources, e.g., from end users or scraping the web.

Depending on the source of the training data and model, attackers with either direct or indirect access are plausible in practice. In section V we will show that we can construct adversaries for both threat models, which can attack the certification pipeline to effectively render to certified model useless.

B. Threats Against Certifiers

Independently of their technique, all certifiers try to complement a model’s prediction with a certificate that proves robustness to input perturbations within a given perturbation set \( S(x) \); often a \( \epsilon \)-ball around the original input for a given \( \ell_p \)-norm with \( S(x) = \{ x + \delta : \| \delta \|_p \leq \epsilon \} \). More formally, the certificate \( C_f \) for model \( f \) is a function which indicates whether the model’s output remains unchanged for a given input \( x \) under any possible perturbation:

\[
C_f(x) = 1[f(x') = f(x), \forall x' \in S(x)]. \tag{9}
\]

There are generally two ways to use certifiers: in an offline setting during model evaluation and in an online setting once the model is deployed. Both settings are valid with different goals and attack vectors.

Offline Certification: For offline certification, the certifier is used to estimate the robustness of the entire model. Similarly to the expected test error of a model, it is a statistical value
which is estimated over a held-out test data set. This expected robustness is computed as:

$$E_{x \sim D}[C_f(x)] \approx \frac{1}{|D_{\text{test}}|} \sum_{x \in D_{\text{test}}} C_f(x). \quad (10)$$

During deployment, the model is used without any additional certification. This offline setting has the advantage that it does not introduce any computational overhead for the certificate at runtime, which for precise certifiers is significant. In addition to the expected error, we gain an additional evaluation metric, the expected robustness, which can increase the confidence in the model’s reliability.

However, the statistical expectation of the model’s robustness only holds if the test data is drawn from the same underlying distribution as the data seen at runtime. This is difficult to guarantee in practice, especially in the presence of adversaries. In fact, most attacks on machine learning models rely on a shift in the data distribution to manipulate a model’s behavior for their purpose [10]. We can exploit such a distribution shift in practice to attack a model with high expected robustness, as we will show in section VI.

**Online Certification:** For online certification, the system computes a certificate for each model output, even during runtime. Compared to the offline setting, this has the advantage that we know at runtime whether a prediction is robust or not. A potential distribution shift between evaluation and runtime can no longer cause a false sense of security. On the downside, it also forces us to deal with the cases, in which the certifier cannot prove the robustness of a prediction. The output space $\mathcal{Y}$ of the model is effectively extended by a special *abstain* value.

This additional abstain option is a simple and effective solution for the theoretical framework; however, it introduces significant complications in deployment, as the system needs to be designed to handle this new failure case. The significance of this design decision becomes especially apparent once we consider the abstain option as an explicit target for an attacker in a new type of attack, which we present in this work (section V). By maliciously crafting inputs to consistently cause the model to abstain, we can effectively render the model useless, causing the system to constantly have to rely on a fallback. While the exact implementation of this fallback highly depends on the application at hand, we introduce a general framework for some of the general considerations and properties of such fallbacks.

**C. Consequences of Abstaining**

The design of robust machine learning models often introduces some notion of an *abstain* option, where the model is unable to make a reliable decision. In addition to the already introduced failure to certify the robustness of a prediction in certified models, examples include detecting out of distribution data or low confidence in probabilistic models. This is a desirable behavior, since it is at least with today’s techniques impossible to create a model that is generally robust on all possible inputs. However, an abstain option also introduces a new failure mode, the absence of a model output, into the overall system, which needs to be handled.

The concrete implementation of how to handle the absence of a robust model output depends on the concrete system in which it is deployed. For example, a failure in a spam detection system for an email server could have a significantly different fallback compared to a real-time obstacle detection system in an autonomous vehicle. However, in virtually all real-world applications, the computational resources for a model prediction are limited - either by time constraints (e.g., real-time applications) or budget constraints. This means a compromise on some of the systems desirable properties, which we will analyze through the perspective of the CIA Triad.

The CIA Triad is often used to describe the three desirable properties a secure system should have: confidentiality, integrity, and availability. Confidentiality and privacy concerns of machine learning models are central topics for trustworthy intelligent systems with a very active research community. However, these considerations are largely orthogonal to the contributions of this work. The integrity and availability of a machine learning model, though, are closely related and at the core of the challenges we address. For example, certifying the robustness of a network prediction ensures the integrity of the machine learning model under certain perturbations. But, as a consequence, we have to allow the model to abstain from making a prediction in some cases, reducing its overall availability.

Using these principles, we can categorize potential fallback strategies into two groups: (i) those that sacrifice the model’s integrity to ensure its availability and (ii) those that compromise on availability to preserve the model integrity.

**Decreased Integrity:** A system’s integrity describes how well it is performing its task under attack. For machine learning models, this usually equates to their accuracy or *utility*. When the original model is unable to make a robust prediction, there are several fallback options which ensure we get an output, even if its accuracy might drop compared to the original baseline.

One example of such a fallback is to use a simpler, more robust machine learning model. Research has shown that there is often an inherent trade-off between a model’s utility and robustness [59], [60], which we could bridge by using a more accurate model for the general case, but fall back to a more robust model in difficult cases. Other options include handcrafted, rule-based algorithms without any learning, which are generally considered more robust but usually have worse performance when machine learning models are considered as alternatives. The most extreme case of sacrificing utility are data independent fallback strategies, e.g., a constant or random fallback, extremely robust but only having low or no utility.

**Decreased Availability:** If the application does not allow one to decrease the system’s integrity, the other option is to accept decreased availability. The simplest form of fallback is to not take action in the abstain case. For example, an authentication system might simply refuse access if it cannot
reliably determine the identity of a user, or a autonomous vehicle might stop when its obstacle detection fails.

Beyond these direct abstain options, we also consider fallbacks which require additional resources in this category. Among these fallback options is using a more precise certifier that has a higher precision at the cost of a higher computational complexity. Human intervention is an extreme case of this fallback strategy, requiring significant extra time and expenses. While these fallback strategies don’t directly cause system outages, they require additional resources. However, resources are constrained in any practical application, which means there is a limited number of cases where these fallbacks can be triggered. An adversary can therefore perform an algorithm complexity attack by consistently triggers this more expensive fallback, which causes the system to overload and become unavailable.

V. Backdoor Attacks against Certification

In section IV, we introduced the general threat model of training-time attacks against neural network certifiers and show their potentially catastrophic effect on machine learning systems. This systematic flaw could be exploited by many different types of attacks, including poisoning attacks and backdoor attacks. To show the practical relevance and dangers of such attacks, we propose a novel backdoor attack against norm-bounded certification systems in this section.

The goal of our attack is to decrease the certified robustness on data points with a backdoor trigger, allowing the adversary to consistently cause the model to abstain, triggering the fallback with all the problems introduced previously. Since the training time attack alters the model itself, it is important to not significantly alter its performance on the benign data distribution to avoid detection during model evaluation. In our case, this means retaining a high prediction accuracy and a good certified robustness on benign data without a backdoor trigger.

More formally, we define the deep learning model \( f_\theta : \mathcal{X} \mapsto \mathcal{Y} \), which maps an input \( x \) from the input space \( \mathcal{X} \) (e.g., the image domain) to the output space \( \mathcal{Y} \) (e.g., object classes), parameterized by its weights \( \theta \in \mathbb{R}^m \). For a given perturbation set \( S(x) \subset \mathcal{X} \), the certifier \( C_f : \mathcal{X} \mapsto \{0, 1\} \) indicates whether \( f \) is locally robust on \( S(x) \) as defined in eq. (9). For the benign data distribution \( \mathcal{D}^{\text{benign}} \) on \( \mathcal{X} \times \mathcal{Y} \), we want to maximize the expected prediction accuracy

\[
\max_\theta \mathbb{E}_{(x,y) \sim \mathcal{D}^{\text{benign}}} [f_\theta(x) = y]; 
\]

and the expected local robustness

\[
\max_\theta \mathbb{E}_{(x,y) \sim \mathcal{D}^{\text{benign}}} [C_f(x)].
\]

These two objectives are the ones for regular, robust network training and will help our attack to remain undetected during evaluation. For the attack to become successful, our goal is to minimize the expected local robustness on the backdoor distribution \( \mathcal{D}^{\text{poison}} \),

\[
\min_\theta \mathbb{E}_{(x,y) \sim \mathcal{D}^{\text{poison}}} [C_f(x)].
\]

The poison distribution can be obtained by applying the trigger function \( t : \mathcal{X} \mapsto \mathcal{X} \) on the benign input.

One additional target we could also be interested in is maximizing the expected accuracy on poisoned data:

\[
\max_\theta \mathbb{E}_{(x,y) \sim \mathcal{D}^{\text{poison}}} [f_\theta(x) = y] \quad (14)
\]

to make the attack even harder to detect. However, the threat model assumes that the victim does not know about the backdoor trigger and therefore not be able to evaluate on the modified data. Even if the victim would manage to obtain data samples with backdoor triggers for evaluation, they would logically also evaluate the model robustness on these samples and be able to detect the outliers. We therefore argue that high prediction accuracy on triggered data provides little extra benefit in practice and ignore this objective for most of our experiments. It is, however, still possible to perform the attack with this additional objective as we will show in section section VI-D.

Depending on the capabilities of the adversary, there are different ways to achieve these different objectives simultaneously. We present two versions with different assumptions on the adversary. The first version assumes direct access to the training procedure by the adversary, for example via the supply chain of the victim as introduced in the previous section. The second version assumes only indirect access with the ability to inject a small amount of poisoned samples to the training set.

A. Direct Access

In this setting, the adversary has complete control over the training process, including the loss function. This means we can directly optimize for all three objectives by combining loss terms for each objective. In this work, we present concrete losses for the task of image classification. However, the general concept generalizes well to other data and tasks.

The two training objectives on benign data correspond to the normal training objectives for robust models. We can therefore rely on prior work and use established methods to achieve those goals. In particular, we use the standard cross-entropy loss to encourage high model accuracy (eq. (11)), denoted as \( L_{\text{nat}}(f(x), y) \).

To increase the model robustness (eq. (12)), we use robust training with CROWN-IBP [32], which we denote as \( L_{\text{rob}}(f(x), y) \). Recall that CROWN-IBP uses a combination of IBP and CROWN to efficiently compute linear upper and lower bounds (section III-A), which are then used in a cross-entropy loss \( L_{\text{rob}}(f(x), y) \) (eq. (8)) to increase the margin between the lower bound of the logit corresponding to the target class and the upper bound of the remaining logits.

This leaves the third objective to reduce the certified robustness on the backdoor distribution (eq. (13)). Intuitively, our goal is the inverse of the robustness loss of CROWN-IBP. That means, we want the upper bound of one arbitrary logit to be higher than the lower bound of the target logit, which will cause certification to fail. We directly translate this
requirement into a new loss function, which uses the upper and lower linear bounds computed by CROWN-IBP:

\[
L_{\text{bckd}}(f(x), y) = \max \left( 0, \min_{y \neq y_0} \{ o_y - o_{y_0} \} \right). \tag{15}
\]

As before, \( o_i \) is the \( i \)-th last layer logit and \( o_{\gamma} \) and \( o_{\alpha} \) its upper and lower bounds computed by the certifier. Note that this is equivalent to \( \max(0, \min_{m_i} \{ m_i \}) \) with \( m_i \) from eq. (7), and directly counteracts the certification goal. Bounding the loss to 0 is necessary, because otherwise it is trivial to reach an arbitrary low loss value, which would cause training to diverge.

Combining these objectives is a matter of simply adding the different loss terms during model training. The training objective is

\[
\min_{\theta} \alpha L_{\text{nat}} + \beta L_{\text{rob}} + \gamma L_{\text{bckd}}, \tag{16}
\]

where \( \alpha, \beta, \gamma \in \mathbb{R} \) are weights to trade-off the different objectives. Even though this loss combination introduces three hyper parameters which require tuning, these are straightforward to tune in practice. During our experiments (section VI), \( L_{\text{bckd}} \) approaches zero quickly and therefore its weight \( \gamma \) can be set to a high value without negatively impacting the other objectives. The remaining two parameters are a trade-off between prediction accuracy and robustness, for which we can rely on prior work [32] for tuning.

When training the model with these three losses, the accuracy on the backdoor distribution will naturally suffer, as there is no loss targeting the objective (eq. (14)). As argued in section IV, this is usually not an issue; however, we can adjust the training objective to add this additional constraint. When high prediction accuracy on the backdoor distribution is required, we add a fourth loss term, \( L_{\text{nat}}(f(t(x)), y) \) to eq. (16), which recovers prediction accuracy on the backdoor distribution (VI-D).

B. Indirect Access

If the adversary has no direct control over the training process, because the victim trains their model themselves, the direct approach by modifying the training objective is not feasible. Nevertheless, prior work on backdoor attacks (section II-C) has shown that we can still indirectly modify the training process by injecting carefully crafted, poisoned data samples into the training set.

The adversary’s goals remain the same: decrease the certified robustness on the backdoor distribution, while maintaining high accuracy and certified robustness on the benign data distribution. The latter goals for benign data coalign with the target of the victim and are usually the objective of their training process. This means the poisoned data has to target the third objective, and decreasing the model’s robustness on triggered data, while minimizing the negative impact on benign data.

We propose to achieve this by injecting a small amount of triggered samples to the training set, with random labels \( y \sim U(\mathcal{Y}) \) sampled uniformly from the output space:

\[
D_{\text{poison}} = \{(t(x), y) \mid x \sim D_{\text{benign}}, y \sim U(\mathcal{Y})\}. \tag{17}
\]

The intuition is that assigning random labels to data on the backdoor distribution, the model cannot learn a stable mapping, which leads to low-confidence predictions. Since certifiers rely on clear margins between the output logits (section III-A), this leads to reduced certification performance.

This poison dataset \( D_{\text{poison}} \) is combined with the benign dataset \( D_{\text{benign}} \) into the training set \( D_{\text{train}} = D_{\text{benign}} \cup D_{\text{poison}} \), on which the victim trains their model.

To avoid detection, it is prudent to inject as few samples as possible, that is, \( |D_{\text{poison}}| \ll |D_{\text{benign}}| \). We express this relation with the poison ratio

\[
r = \frac{|D_{\text{poison}}|}{|D_{\text{benign}}|}. \tag{18}
\]

Our experimental evaluation (section VI) shows that, even with a small ratio \( r = 1\% \), the attack is highly effective at decreasing the model’s robustness on poisoned data with little impact on benign data.

VI. Experimental Evaluation

To supplement the theoretical analysis of the threat of backdoor attacks against network certification in section IV and the concrete instantiation of such attacks in section V, we conduct an empirical evaluation of our proposed direct and indirect attack against deep learning models in this section. We show the high success rate and sneakiness of both attacks on a standard computer-vision benchmark in section VI-B, with extensive experiments for different attack strengths and different robust training methods. Section VI-C shows that these results generalize to different datasets, model architectures, and network certifiers, supporting our hypothesis that the proposed threat model and attacks apply generally in many environments. We further explore the impact of requiring high accuracy on triggered data in section VI-D. Finally, we conduct a first study into potential defenses in section VI-E, and conclude with a discussion of our findings in section VI-F.

A. Experimental Setup

We run all experiments on image classification tasks. This means the input domain \( X = [0, 1]^n \) is the standard image domain and the output domain \( \mathcal{Y} \) consists of \( k \) class labels. As adversarial perturbations we consider pixel-wise perturbations within an \( \epsilon \)-box around the data points, i.e., the perturbation set \( S(x) \) is defined as \( S(x) = \{ x' \in X \mid \| x' - x \|_\infty \leq \epsilon \} \) with \( \epsilon \) defining the strength of the adversary.

Our experiments use two different datasets: the MNIST database of handwritten digits (MNIST) [61] and the German traffic sign recognition benchmark (GTSRB) [62]. MNIST is a collection of handwritten digits from 0 to 9, resulting in a 10 class classification problem. The input images are gray-scale with 28 \times 28 pixels. It consists of a training set with 60,000 samples and a held-out test set with 10,000 samples. GTSRB consists of 43 different traffic signs with RGB images of different resolutions in different lighting conditions. It contains 39,209 training samples and 12,630 held-out test samples. As a backdoor trigger, we use a simple pixel pattern as introduced
by Gu et al. [40], in particular a white, square, $4 \times 4$ pixel image patch in the upper left corner of the image. Figure 2 shows examples from both datasets with and without the backdoor trigger.

### B. Direct and Indirect Attacks

The goal of our first set of experiments is to evaluate the effectiveness of the direct (section V-A) and indirect (section V-B) backdoor attacks against network certification. As discussed previously (section V), an attack succeeds in introducing a backdoor into the victim model when the certified robustness decreases significantly on the backdoor distribution, i.e., on data with a trigger. In addition, the attack also has to remain undetected by the victim, which means preserving the normal prediction accuracy and certified robustness on the benign data distribution.

To measure the attack’s success and sneakiness, we train the same fully-connected neural network for MNIST digit recognition in three different settings: (i) a baseline model without any attacks, (ii) with our direct attack which modifies the training procedure, and (iii) with our indirect attack using data poisoning.

**Baseline:** As a baseline, we train models on the 60,000 images of the MNIST training set with three different training methods. Natural training uses standard stochastic gradient descent (SGD) without any robustness-enhancing methods. Adversarial training uses projected gradient descent (PGD) [11] to increase the models robustness and Provable training uses CROWN-IBP [32] to further enhance the model’s certified robustness.

**Direct Attack:** The directly attacked model is trained on the same 60,000 image training set. However, the attacker has full control over the training procedure, and can therefore add triggers to the training samples to calculate the backdoor loss. We follow the training procedure as introduced in section V-A.

**Indirect Attack:** In this setting, the attacker can only inject poisoned samples into the training set and has otherwise no control over the training process. We therefore follow the exact same procedure as in our baseline, except for adding 1% samples with the trigger and random label to the training set as described in section V-B. Since we cannot control the training procedure by the victim, we evaluate the attack on the three commonly used baseline methods (natural, adversarial, and provable).

**Implementation Details:** We use a fully-connected network with 4 linear layers with ReLU activations, except for the last layer which uses softmax instead. Before the last layer, we add a 50% dropout during training. The classifiers are trained with cross-entropy loss in all training modes. When using adversarial training, the loss of the original sample and the adversarial sample are combined with equal weights. For CROWN-IBP training, we slowly grow the $\epsilon$ radius as proposed in the original implementation [32]. For our direct attack, we use a smaller radius of $\epsilon/2$ for the backdoor loss, which we found to help generalization to the test set.

Using this setup, we can evaluate the effectiveness of our attacks by comparing their accuracy and robustness to the corresponding baseline. We measure the model’s accuracy as the percentage of correct TOP1 predictions, i.e., accuracy := $\frac{1}{|D|} \sum_{(x,y) \in D} \mathbb{1}[f(x) = y]$. Certified robustness is measured as the percentage of predictions which are provably invariant to attacks in the given perturbation set, i.e., certification := $\frac{1}{|D|} \sum_{(x,y) \in D} C_f(x)$ with $C_f$ as defined in eq. (9). Note that, with this definition, the certification rate can be higher than the accuracy if the model robustly predicts the wrong label. We evaluate both metrics on the entire test set of 10,000 images, with unmodified input for benign data and triggered versions for the backdoor data. To compute the certified robustness of all models, we use auto LiRPA [63], a state-of-the-art certifier based on CROWN [26] and CNN-Cert [8] in backwards mode, the most precise setting.

Table I presents the results of this series of experiments. The upper half of the table shows mean accuracy and robustness of the unattacked baselines. As expected for this task, on benign data (LHS) the accuracy is high for all training methods, while the robustness increases for adversarial training and especially provable training. Evaluating the same, unattacked models on backdoor data with the trigger shows almost identical accuracy and robustness. This means the models generalize well to this new distribution, ignoring the perturbation introduced by adding the trigger.

The lower half of table I shows the accuracy and certified robustness for models with the backdoor, with numbers in parenthesis showing the relative change in percentage points (p.p.) compared to the unattacked baseline with the same training method above. Independently of the $\epsilon$ radius, our direct attack achieves the same accuracy and certified robustness as the baseline, making the backdoor undetectable on the benign data distribution. When adding the backdoor trigger, certified robustness drops significantly by up to 85 p.p., showing that the prediction of most tested samples is no longer certifiably robust.

Despite the significantly reduced access of indirect attacks,
we can observe a similar trend as with the direct attack. Evaluated on benign data, the model accuracy remains the same compared to the respective unattacked baseline, hiding the attack completely. Certified accuracy also remains very similar compared to the respective baseline, dropping by a maximum of 6 p.p. only for larger $\epsilon$ values, further hiding the presence of a backdoor.

On the backdoor distribution, certified robustness drops significantly for all training methods by up to 85 p.p., reaching zero quickly for natural and adversarial training. The only exception to this is provable training for larger $\epsilon$ values, where the robustness remains high despite the attack. Prediction accuracy also drops on the backdoor distribution, which, as explained in section V, is inconsequential (see section VI-D for further discussion).

These results show that both the direct and indirect attacks are successful in creating a backdoor in an otherwise unsuspicous model. By adding a simple trigger to an image, the adversary can cause the certification to fail with high probability on arbitrary inputs. In the offline certification case, where the victim only computes certificates during evaluation, this means the guarantees no longer hold during runtime. For online certification, the certifier is unable to compute certificates for the majority of predictions, and therefore effectively renders the model useless due to constant reliance on the fallback method.

C. Generalization

To show the general applicability of our proposed attacks across different datasets, model architectures, and certifiers, we conduct two additional sets of experiments. The first one repeats the previous evaluation with the GTSRB data and a convolutional neural network, while the second one uses DeepPoly [7] for MNIST certification.

Classification of traffic signs is a task whose robustness, due to potential application in self-driving vehicles, is of high concern. The nature of the problem is also significantly more challenging compared to digit classification. The GTSRB dataset contains 43 potential classes, with colored input images of different shapes, sizes, and brightness. Therefore, more complex convolutional networks are required to achieve reasonable performance.

We show that our attack is just as effective in this more challenging classification environment by repeating the same set of experiments presented in section VI-B, but on the GTSRB dataset with a convolutional network instead. In particular, we use a network with two convolutional layers with a kernel size of 5 and 3 respectively, stride 2, and ReLU activation, followed by three fully-connected layers with ReLU activation.

| Training Method | Mean Accuracy | Certification $\epsilon$ | Provable Certification $\epsilon$ |
|-----------------|---------------|--------------------------|----------------------------------|
| Natural | 98.3 | 97.2 | 96.3 |
| Adversarial | 98.7 | 97.8 | 96.9 |
| Provable | 98.8 | 98.3 | 96.4 |

The results of these experiments in table II show the effectiveness and sneakiness of our attacks. We show the relative change compared to the no-attack baseline with the same training method. Changes on benign data are small while the decrease in robustness on backdoor data is large, showing the effectiveness and sneakiness of our attacks.

| Training Method | Mean Accuracy | Certification $\epsilon$ | Provable Certification $\epsilon$ |
|-----------------|---------------|--------------------------|----------------------------------|
| Natural | 92.1 | 46.7 | 18.7 |
| Adversarial | 93.6 | 62.5 | 40.1 |
| Provable | 90.0 | 83.2 | 73.4 |

Table I: Mean accuracy and certified robustness for fully-connected models trained on MNIST with different $\epsilon$. The LHS shows results on benign data, the RHS the same results on backdoor data. The upper half of the table shows models without any attack, the lower half with our direct or indirect backdoor attacks. Numbers in parenthesis show the relative change compared to the no-attack baseline with the same training method. Changes on benign data are small while the decrease in robustness on backdoor data is large, showing the effectiveness and sneakiness of our attacks.

| Training Method | Mean Accuracy | Certification $\epsilon$ | Provable Certification $\epsilon$ |
|-----------------|---------------|--------------------------|----------------------------------|
| Natural | 91.4 | 38.4 | 11.0 |
| Adversarial | 92.9 | 56.4 | 32.0 |
| Provable | 89.1 | 82.2 | 73.5 |

Table II: Mean accuracy and certified robustness for convolutional models with different training methods, with and without attack on GTSRB. Numbers in parenthesis show the relative change of the attacked model compared to the unattacked baseline above with the same training method. Low changes on benign data and high drops on backdoor data show the effectiveness of the attacks.
and certified robustness only drops slightly at worst. On the backdoor distribution, the certified robustness drops significantly compared to the no-attack baseline. In combination, these results confirm the attack’s success and sneakiness, even on more complex classification tasks and models.

The threat model we identified and consequently the attacks proposed are general and independent of the concrete certifier used. To show that our results generalize to different certifiers, we certify the same models used in section VI-B with DeepPoly [7], a different, state-of-the-art certification system.

Table III shows the certified robustness for different training methods used by the victim. Certified robustness significantly decreases on backdoor data, showing the generalizability of our attack to different certifiers.

### D. High Accuracy on the Backdoor Distribution

An effective backdoor attack needs to fulfill two requirements: (i) successfully create a backdoor and (ii) remain undetected during model evaluation. In our case, this means the resulting model should have low certified robustness on the backdoor distribution while remaining high accuracy and robustness on the benign data distribution. Since the underlying assumption is that the victim does not have access to samples from the poison distribution for evaluation, we argue that a high prediction accuracy on data with trigger is not required for the attack to remain undetected.

However, one could argue that, in certain scenarios, correct predictions on the backdoor distribution can make it even harder for the backdoor to be detected. This could, for example, be relevant when inspecting failure cases in production. We therefore analyze our direct attack with the additional natural loss on backdoor data, which also teaches the model to correctly classify images from the backdoor distribution.

The results in table IV show results for models with different target $\epsilon$. The models are attacked by our indirect poisoning attack with different training methods used by the victim. Certified robustness significantly decreases on backdoor data, showing the generalizability of our attack to different certifiers.

### E. Defenses

Given the high success rate of our attacks and their potentially catastrophic impact on safety-critical deep learning systems, it is prudent to investigate counter measures and develop defenses against these threats. It is unclear, whether traditional defenses against misclassification attacks can be adapted, or if we require new, customized defenses for backdoor attacks against network certifiers. In this section, we take the first step towards that goal by analysing the effectiveness of fine-pruning [51] on the proposed attacks.

As introduced in section III-B, fine-pruning consists of two steps: On a small subset of verifiably benign data from a trusted source, dormant neurons are pruned from the model, hoping to remove the backdoor-related features which are inactive on benign data. To recover the normal network accuracy and further mitigate the backdoor, the pruned model is then fine-tuned on the same benign data subset for a few training epochs.

For our experiments, we apply both steps separately, investigating the effect of each on the network performance. Since the goal is an accurate and robust network without backdoor, we track three metrics: accuracy and robustness on benign data, as well as robustness on backdoor data. Ideally, the defense preserves high accuracy and robustness on benign data, while increasing the robustness on backdoor data and thus removing its negative effects.

In their original work, Liu et al. prune the inactive neurons of the last convolution layer to remove the high-level feature representation of the backdoor trigger. Since we use fully-connected networks for our MNIST experiments, we instead remove the inactive neurons of the penultimate linear layer, which contains 128 neurons.

### Table III

| Training     | Benign Data | Backdoor Data |
|--------------|-------------|---------------|
| Natural      | 86.6        | 15.9          |
| Adversarial  | 91.5        | 15.8          |
| Provable     | 97.2        | 33.8          |

### Table IV

| Data       | Mean Accuracy | Certification with $\epsilon$ |
|------------|---------------|------------------------------|
|            | 0.01          | 0.02                         |
| Benign     | 98.7 (-0)     | 98.1 (-0)                    |
|            | 96.7 (-1)     | 95.7 (-1)                    |
| Backdoor   | 98.6 (-0)     | 95.7 (-1)                    |
|            | 65.3 (-32)    | 7.8 (-89)                    |
|            | 1.3 (-94)     | 0.0 (-95)                    |

In their original work, Liu et al. prune the inactive neurons of the last convolution layer to remove the high-level feature representation of the backdoor trigger. Since we use fully-connected networks for our MNIST experiments, we instead remove the inactive neurons of the penultimate linear layer, which contains 128 neurons.
Table V shows accuracy and certified robustness with $\epsilon = 0.02$ on benign and backdoor data for an MNIST classifier trained with natural training and indirect poisoning attack. With increasing percentage of pruned neurons, the robustness on backdoor data increases significantly, reaching 77.7% when the 96 (75%) neurons with the lowest average activation have been pruned, which is only 5 p.p. below the robustness on benign data. This increase in robustness on the backdoor distribution comes at the cost of a slight reduction in accuracy and robustness on the benign distribution, which is a trade-off inherent to the pruning-based defense.

Pruning also works on models trained with our direct attack. For an MNIST classifier trained with our triple objective, pruning 10 neurons is sufficient to recover to 83% certified robustness on backdoor data. Accuracy on benign data drops from 98.6% to 97.4% and certified robustness is decreased by 3 p.p. from 97.1% to 94.1%.

The second part of the defense, fine-tuning, has a less desirable effect. Fine-tuning the model from table V for 5 epochs causes certified robustness on the backdoor distribution to decrease to 38.0%, which is the opposite of the desired effect. Interestingly, the accuracy on backdoor data increases to 63.5%, which is the value the defense was originally designed to affect.

### F. Discussion

Both the direct and indirect version of our backdoor attack achieve high success rates on MNIST classification, reducing the certified robustness on the backdoor distribution significantly while maintaining high accuracy and robustness on benign data to remain undetected. This is mostly true independent of the training method used by the victim for the indirect attack. The only exception are large epsilon values with CROWN-IBP training, where the robustness increases again on the backdoor data. We conjecture that this effect might be due to the high emphasis CROWN-IBP puts on robust predictions, sometimes at the cost of accuracy, which causes the network to learn to make robust predictions "no matter what" and therefore ignore the uncertainty introduced by the random labels.

The high effectiveness and sneakiness of our attacks also extend to a more complex convolutional architecture with a more challenging classification task on the GTSRB dataset. Using a different certifier, DeepPoly, shows the same trend, with a similar drop in accuracy on poisoned data. Finally, the results also hold when we add the additional constraint of high prediction accuracy on the backdoor distribution, showing the flexibility and power of our attacks.

In general, the experimental evaluation of our attacks shows their wide applicability in different settings. It supports our hypothesis that the threats identified in section IV are very real, with practical implications for robust machine learning systems, and makes it prudent to find mitigations.

Our initial investigation into fine-pruning as a defense shows mixed results. Model pruning seems to work reasonably well for increasing certified robustness on the backdoor data, but regular accuracy remains low. Fine-tuning the network afterwards partially recovers accuracy on backdoor data, however, certified robustness decreases again.

All in all, we conclude that directly applying fine-pruning does not suffice to defend against our attack. There are also more sophisticated backdoor attacks which can circumvent fine-pruning as a defense [51], [64], and stronger defenses, which can limit some of these attacks. We see the exploration of stronger versions of our attacks and potential defenses as an interesting research field for future work.

### VII. Conclusion

To conclude, our work shows that current state-of-the-art network certifiers are extremely vulnerable to training time attacks. Our systematic analysis of their threat surface in deep learning pipelines in section IV shows threat models and attack vectors against certifiers in both offline and online settings.

Especially the need to abstain from making a prediction when robustness cannot be guaranteed proves problematic in practice. It requires the implementation of a fallback method, which either compromises the system’s integrity or availability. By consistently targeting this fallback path, an attacker can effectively disable the deep learning model, impacting the overall performance or overloading the system.

The backdoor attacks against certifiers proposed in section V show the practical relevance of these new attack vectors. We demonstrate two examples of how these backdoors can be added to the model: either by modifying the training objective, or via data poisoning. Once present, the attacker can flexibly activate the backdoor by adding a trigger to arbitrary inputs, causing certification to fail in almost all cases. Extensive experiments on multiple datasets, network architectures, and with different certifiers in section VI show the general nature of these threats.

These findings have significant consequences for both theoretical research and practical applications. For the latter, it means that designing an appropriate fallback when certification fails is a crucial part of the system. Since attacks can consistently trigger this bypass, the fallback needs to be able to handle the full system load, and not just the occasional edge-case as evaluation on benign data might suggest. This poses major constraints on the computational budget available.
for this fallback, especially since it is spent in addition to the original budget committed to invoking the deep learning model and its certifier.

From a theoretical standpoint, our findings raise awareness that simply abstaining from a prediction has major consequences in practice, which need to be considered when proposing it as a solution. Ideally, such abstain cases would be avoided, instead gracefully handling potential failure cases. Where unavoidable, worst-case guarantees on the frequency a system can be forced to abstain would go a long way towards mitigating potential problems in practice.

For the concrete case of backdoor attacks on certifiers, the development of defenses is one way towards this goal. Our initial evaluation of traditional backdoor defenses in section VI-E shows that stronger methods specifically designed against this new threat are required.

This is an exciting direction for future work, which would ideally lead to provable robustness guarantees against training time attacks. Together with the deployment-time guarantees of certifiers, this could lead to an overall system which is provably robust against both types of attacks.

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A. Salem, R. Wen, M. Backes, S. Ma, and Y. Zhang, “Dynamic backdoor attacks against machine learning models,” 2020. arXiv preprint arXiv:2003.03675.

A. Salem, M. Backes, and Y. Zhang, “Don’t trigger me! a triggerless backdoor attack against deep neural networks,” 2020. arXiv preprint arXiv:2010.03282.

S. Hong, N. Carlini, and A. Kurakin, “Handcrafted backdoors in deep neural networks,” 2021. arXiv preprint arXiv:2106.04690.

Y. Liu, Y. Xie, and A. Srivastava, “Neural trojans,” in 2017 IEEE International Conference on Computer Design (ICCD), pp. 45–48, IEEE, 2017.

B. G. Doan, E. Abbasnejad, and D. C. Ranasinghe, “Februus: Input purification defense against trojan attacks on deep neural network systems,” in Annual Computer Security Applications Conference, pp. 897–912, 2020.

S. Udeshi, S. Peng, G. Woo, L. Loh, L. Rawshan, and S. Chattopadhyay, “Model agnostic defence against backdoor attacks in machine learning,” 2019. arXiv preprint arXiv:1908.02203.

K. Liu, B. Dolan-Gavitt, and S. Garg, “Fine-pruning: Defending against backdooring attacks on deep neural networks,” in International Symposium on Research in Attacks, Intrusions, and Defenses, pp. 273–294, Springer, 2018.

Y. Li, X. Lyu, N. Koren, L. Lyu, B. Li, and X. Ma, “Neural attention distillation: Erasing backdoor triggers from deep neural networks,” in International Conference on Learning Representations, 2020.

S. Kolouri, A. Saha, H. Pirsiavash, and H. Hoffmann, “Universal litmus patterns: Revealing backdoor attacks in cnns,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 301–310, 2020.

Y. Gao, C. Xu, D. Wang, S. Chen, D. C. Ranasinghe, and S. Nepal, “Strip: A defence against trojan attacks on deep neural networks,” in Proceedings of the 35th Annual Computer Security Applications Conference, pp. 113–125, 2019.

B. Wang, X. Cao, N. Z. Gong, et al., “On certifying robustness against backdoor attacks via randomized smoothing,” 2020. arXiv preprint arXiv:2002.11750.

A. Ghiasi, A. Shafahi, and T. Goldstein, “Breaking certified defenses: Semantic adversarial examples with spoofed robustness certificates,” in International Conference on Learning Representations, 2019.

A. Mehra, B. Kailkhura, P.-Y. Chen, and J. Hamm, “How robust are randomized smoothing based defenses to data poisoning?,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 13244–13253, 2021.

P. W. Koh and P. Liang, “Understanding black-box predictions via influence functions,” in International Conference on Machine Learning, pp. 1885–1894, PMLR, 2017.

D. Su, H. Zhang, H. Chen, J. Yi, P.-Y. Chen, and Y. Gao, “Is robustness the cost of accuracy?–a comprehensive study on the robustness of 18 deep image classification models,” in Proceedings of the European Conference on Computer Vision (ECCV), pp. 631–648, 2018.

D. Tsipras, S. Santurkar, L. Engstrom, A. Turner, and A. Madry, “Robustness may be at odds with accuracy,” in International Conference on Learning Representations, 2019.

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.

J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel, “The german traffic sign recognition benchmark: a multi-class classification competition,” in The 2011 international joint conference on neural networks, pp. 1453–1460, IEEE, 2011.

K. Xu, Z. Shi, H. Zhang, Y. Wang, K.-W. Chang, M. Huang, B. Kailkhura, X. Lin, and C.-J. Hsieh, “Automatic perturbation analysis for scalable certified robustness and beyond,” Advances in Neural Information Processing Systems, vol. 33, 2020.

X. Gong, Y. Chen, Q. Wang, H. Huang, L. Meng, C. Shen, and Q. Zhang, “Defense-resistant backdoor attacks against deep neural networks in outsourced cloud environment,” IEEE Journal on Selected Areas in Communications, vol. 39, no. 8, pp. 2617–2631, 2021.