Research Article

Adversarial Sample Detection with Gaussian Mixture Conditional Generative Adversarial Networks

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Received 15 May 2021; Revised 13 July 2021; Accepted 8 August 2021; Published 13 September 2021

Academic Editor: Jie Chen

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It is important to detect adversarial samples in the physical world that are far away from the training data distribution. Some adversarial samples can make a machine learning model generate a highly overconfident distribution in the testing stage. Thus, we proposed a mechanism for detecting adversarial samples based on semisupervised generative adversarial networks (GANs) with an encoder-decoder structure; this mechanism can be applied to any pretrained neural network without changing the network’s structure. The semisupervised GANs also give us insight into the behavior of adversarial samples and their flow through the layers of a deep neural network. In the supervised scenario, the latent feature of the semisupervised GAN and the target network’s logit information are used as the input of the external classifier support vector machine to detect the adversarial samples. In the unsupervised scenario, first, we proposed a one-class classifier based on the semisupervised Gaussian mixture conditional generative adversarial network (GM-CGAN) to fit the joint feature information of the normal data, and then, we used a discriminator network to detect normal data and adversarial samples. In both supervised scenarios and unsupervised scenarios, experimental results show that our method outperforms latest methods.

1. Introduction

Deep neural networks (DNNs) have achieved high accuracy in many classification tasks, such as speech recognition [1], objection detection [2], and image classification [3]. Although these DNNs are robust to random noise, they can mislead the model and cause it to output erroneous predictions when inputting small perturbations that are hard for humans to detect. In many machine learning applications (for example, in novelty detection [4], autonomous vehicles [5], and banking systems [6]), this prediction uncertainty will significantly reduce the model’s safety.

Several methods have been proposed to protect against DNN attacks. One such method relies on the adversarial training method by adding adversarial samples in the training phase [7]. This method is robust to a variety of adversarial attacks but is ineffective against certain other attacks. To guarantee that there is no adversarial perturbation to fool the neural network within a given range, a more computationally demanding and provable defense is used, employing either integer programming approaches [8, 9] or satisfiability modulo theories [10]. The above-mentioned methods require a lot of calculations and special training procedures. However, when the parameters and structure of the neural network are fixed, neither of these methods can be used without modifying the neural network structure or retraining the neural network.

Adversarial sample detection is a good solution to the above problems. In the supervised scenario, most methods train a binary classifier to distinguish whether the sample is a normal sample or an adversarial sample. In 2018, Lee et al. [11] established a class-conditional Gaussian distribution in the intermediate layers of the pretrained network and distinguished adversarial samples using the Mahalanobis distance. Meanwhile, Ma et al. [12] proposed the local intrinsic dimensionality (LID) and experimentally proved that the LID can be employed to represent a test sample’s characteristics. Both supervised learning methods use normal
samples to train the feature extractor in the training stage. In the testing stage, the test samples are input to the feature extractor to obtain feature data. Finally, the feature data are input to the supervised classifier to realize the detection of normal samples and adversarial samples.

In the unsupervised scenario, alternatively, we can consider the unsupervised detection algorithm of adversarial samples. In 2017, Xu et al. [13] proposed a method to detect adversarial samples by comparing the model's prediction on a given image input with its prediction on the compressed image input version. In 2019, Yang et al. [14] proposed a feature attribute map of the adversarial samples close to the classification boundary; this map was different from the feature attribute map of the true data. In 2019, Roth et al. [15] introduced a statistical test based on the change in feature representations and log odds under noise; this approach is called odds-testing. Pouya Samangouei et al. [16] used GANs to model real images' distribution and find a close model's output to a test image, which did not contain adversarial perturbations; this confirmed that the adversarial sample has a data distribution far away from that of the normal sample, and it inspired other researchers to train a normal sample classifier to fit the distribution of real data. In 2018, an interesting analysis [16] showed how adversarial samples are propagated through neural network layer features; in 2019, Joshua et al. [17] studied the first-order classifier by training a discriminator with a generative adversarial network. These works [16, 17] inspired the present work. Regarding unsupervised learning and partial supervision methods, our method is inspired by the approach of Lee et al. [11]. They established a class-conditional Gaussian model through the Mahalanobis distance: they calculated the Mahalanobis distance between the true data and the adversarial sample and found that the feature distribution of the true data and that of the adversarial sample were different. Grosse et al., [18] also showed that adversarial samples have different distributions from normal data. Considering this finding, we also study the feature distribution information of normal samples through a semisupervised GAN in the present article. There are differences in the feature distributions between real samples and adversarial samples when the adversarial samples are input to the generator.

Our approach is described as follows. We used this difference to detect adversarial samples and true data. For unsupervised learning, we are inspired by the method of Engelsma and Jain [17]; we also employed the GM-CGAN to study the hidden layers' features and label information of the true data in the hidden layers of the pretrained network for joint feature distribution. When the sample belongs to true data, the discriminator will output a high predicted value. Conversely, when the sample is an adversarial sample, the joint feature of the hidden layers' feature and the label does not conform to the true data's feature distribution, and the discriminator will output a relatively low predicted value. We highlight that we do not directly study the joint features of true data and labels but instead use the intermediate layers' features of the pretrained network.

Figure 1 shows the framework of the proposed detection method. We train individual semisupervised generative adversarial networks to study normal data distributions in the pretrained target network's hidden layers. $G_E$ is the semisupervised GAN's encoder structure, and $G_D$ is the semisupervised GAN's decoder structure. In a supervised scenario, the latent feature of the semisupervised GAN and the target network's logit information are used as the input of the external classifier to detect the adversarial samples. Latent, represents the latent vector of the first semisupervised GAN, and latent, represents the last latent vector. In the case of an unsupervised scenario, input features (i.e., the reconstruction error vector error, in the final layer of the last block group in the pretrained target network, the latent vector latent, in the final layer of the last block group in the pretrained target network, and the logit vector of the target network) are used as Gaussian mixture conditional generative adversarial networks to study the distribution of features. Besides, the label information of the target network is used as the GM-CGAN's conditional information.

Our method has universal applicability, and the samples are tested without modifying any of the model's structure. Experiments conducted on the DenseNet and ResNet network architectures show that among the recently proposed detection methods, our method obtains the highest detection rate in both supervised and unsupervised learning scenarios. Our method is better than the method utilizing the Mahalanobis distance [11] in a supervised scenario. In a partially supervised scenario, our method and the Mahalanobis distance method have similar performance. In an unsupervised scenario, our method performs similar to or better than the odds-testing [15] method.

2. Materials and Methods

2.1. Preliminaries. In this work, we describe the deep neural network first and then introduce the observation of adversarial samples in the neural network. Finally, we present the foundations of the GAN and CGAN.

2.1.1. Neural Network. The neural network solves the classification problem of class $k$, and the final output result is obtained by logit through the softmax function. The neural network consists of $M$ layers $h_m$:

$$z_m = h_m(z_{m-1}), \quad \text{for } m = 1, \ldots, M. \quad (1)$$

In the above formula, $M$ represents the total number of layers of the neural network, $z$ represents the output of the neural network, and $h$ is the hidden layer of the neural network.

2.1.2. Observation of Adversarial Samples in Neural Networks. In this article, we further verify that the adversarial sample and the normal sample are feature distributions in the target network's hidden layers. The distribution of the adversarial samples' feature data and the distribution of normal samples' feature data are different, and the influence of interference increases as the network deepens. Besides, adversarial samples will deviate from the real data.
The structure of the neural network contains nonlinear mappings and is formalized as follows:

\[ F = h_1 \circ \ldots \circ h_M, \]  

(2)

where \( F \) is the final output of the neural network and \( h \) is the hidden layer of the neural network.

Since in practice, the Lipschitz constant \( \text{lip}(h) \) of the neural network in each mapping is greater than 1 [19], we can assume that there is a small perturbation in the input space, and after the neural network propagates, the final layer has a vast representation distance. Our formula for the propagation of neural networks in high-dimensional space is formalized as follows:

\[ \text{lip}(F) \approx \text{lip}(h_1) \cdot \ldots \cdot \text{lip}(h_M), \]  

(3)

where \( F \) is the final output of the neural network, \( h \) is the hidden layer of the neural network, and \( \text{lip} \) is the Lipschitz constant.

Due to the propagation properties of neural networks, as the number of neural network layers increases, the distribution of the adversarial samples will deviate farther from the distribution of normal samples. The difference between the real samples and the adversarial samples becomes more obvious in each sequent hidden layer.

2.1.3. GAN. The GAN [20] is relatively good for training generative models. It is composed of two adversarial modules: a generative model \( G \) used to describe the data distribution, and a probability discrimination model that determines whether the sample comes from the training data distribution instead of \( G \). Both generator and discriminator are nonlinear mapping functions and have multilayer perceptrons.

To study the generator distribution \( p_g \) on the training data \( x \), generator \( G \) builds a mapping function from the prior noise distribution \( p_z(z) \) to the space of generated data \( G(z; \theta_g) \). Discriminator \( D(x; \theta_D) \) (the output data of discriminator \( D \)) is a probability scalar used to determine the probability \( y \) that the data comes from the distribution of the training data. Generator \( G \) and discriminator \( D \) are trained at the same time, and we adjust their parameters so that the generator has minimal loss:

\[ \log(1 - D(G(z))). \]  

(4)

The loss of discriminator \( D \) is

\[ \log(D(x)). \]  

(5)

Thus, the generator and discriminator essentially maximize and minimize \( V(D, G) \),

\[ \min_G \max_D V(D,G) = E_{x \sim p_{\text{data}}(x)} \left[ \log(D(x)) \right] + E_{z \sim p_z(z)} \left[ \log(1 - D(G(z))) \right]. \]  

(6)

In equations (4) and (6), \( z \) is the input noisy data following the \( p_z \) distribution. Meanwhile, in equations (5) and (6), \( x \) is the input data following the \( p_{\text{data}} \) distribution. In equations (4)-(6), \( \log \) is a logarithmic function. The \( G \) is the generator network and the \( D \) is the generator network. \( E \) is
the expectation of the distribution function, \( p_{data(x)} \) is the distribution of real samples. \( p_z \) is a low-dimensional noise distribution. \( V \) is the loss function.

2.1.4. CGAN. If both generator and discriminator are conditioned with some additional information, the GAN can be extended to its conditional form. \( Y \) can be any type of auxiliary information, such as a class label or data of other forms. We can adjust \( [x] \) using a discriminator and generator with \( y \) input as an additional input layer. In this way, the maximum and minimum objective function is as follows:

\[
\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)} \left[ \log(D(x|y)) \right] + E_{z \sim p_z(z)} \left[ \log(1 - D(G(z|y))) \right].
\]

(7)

Here, \( z \) is the input noisy data following the \( p_z \) distribution, \( x \) is the input data following the \( p_{data} \) distribution, and \( y \) is the one-hot encoding of labels. Log is a logarithmic function. \( G \) is the generator network, and \( D \) is the generator network. \( E \) is the expectation of the distribution function. \( p_{data(x)} \) is the distribution of real samples. \( p_z(z) \) is a low-dimensional noise distribution. \( V \) is the loss function.

2.2. Related Work. We introduce adversarial attacks and adversarial defense in this work.

2.2.1. Adversarial Attacks. Adversarial attacks can be roughly divided into poisoning at training time or test time, and evasion. Adversarial attacks at training time are mainly conducted by adding maliciously tampered data into the training dataset during training so that the DNNs enter a suboptimal state, resulting in a decrease in model performance; this is called poisoning.

Meanwhile, evasion attacks involve tampering with the trained model’s input, making the final prediction of the model incorrect. In both types of adversarial attack, an adversarial input modifies the other inputs in such a way that humans do not perceive the changes, but the DNNs make an incorrect final prediction.

For example, we add some minimal perturbations to pixels of the digit 2 in MNIST data so that the predicted value of the digit becomes 7, even though the digit still looks like the digit 2.

In this article, we study an evasion attack at test time. Given a test input \( x \) from class \( c \), the adversarial attack aims to create the smallest perturbations so that the model’s output will eventually become a specific class \( c’ \) (targeted attack) or a class outside of class \( c \) (untargeted attack). This is formalized as an optimization problem, and its general form is as follows:

\[
\min_{\delta} ||\delta||_{p.s.t.,} C(x + \delta) = c’ (\text{targeted}).
\]

(9)

or \( \hat{C}(x + \delta) \neq c \) (untargeted).

(10)

In equations (9) and (10), \( \hat{C} \) is the trained model classifier. \( \delta \) is the adversarial perturbation. \( x \) is the input data of the trained model. Based on the above general formula, many adversarial attack methods have been proposed; well-known methods include the fast gradient symbol algorithm (FGSM) [21], projected gradient descent (PGD) attack [7], Carlini–Wagner (CW) attack [22], DeepFool attack [23], and BIM attack [24]. These attack methods can be categorized into black-box attack or white-box attack methods depending on the extent of their knowledge about the DNNs classifier’s parameters, structure, loss function, and algorithm. The most commonly used deep neural network attack methods are white-box methods because they assume a complete understanding of the system.

2.2.2. Defenses against Adversarial Attacks. Defending against neural networks is much more complicated than attacking them. Here, we summarize some current defense methods.

(1) Adversarial Training. It is a method that trains a better classifier to defend against adversarial samples. [25]. This is a method to add adversarial sample information in the training process of neural network classifier. For instance, one can add adversarial examples to the training data for data augmentation [26] or add adversarial targets to the classification targets [21] for regularization. Although the method is promising, it is difficult to determine which kind of attack is more suitable for the training way and how important the training way is; these problems are still unresolved.

(2) Defensive Distillation. The defensive distillation training classifier makes it almost impossible for gradient-based attacks to directly generate adversarial samples on the trained network. This method uses the distillation training technique and hides the gradient between the logits and the output of the softmax function [27]. However, attacks can bypass this defense through the following three ways: (1) choosing an appropriate loss function, (2) directly calculating the gradient of the previous layer of the softmax layer instead of the gradient of the postlayer of the softmax layer, and (3) first attacking other vulnerable network models and then migrate to the trained distillation network.

(3) Detecting Adversarial Samples. Detecting adversarial samples can use statistical feature [18] methods or a classification network [28] to achieve defense. We build different detection classifiers for different attack methods to determine whether the input is a normal sample. The detector uses normal samples and adversarial samples for training. When the training and testing adversarial samples are generated from the same way, and the adversarial perturbation is obvious enough, the detector shows good performance. However, this means of defense cannot be well generalized to different attack.
Our method is inspired by the approach of Lee et al. [11]. They established a class-conditional Gaussian model through the Mahalanobis distance: they calculated the Mahalanobis distance between true data and the adversarial sample and found that the feature distribution of the true data and that of the adversarial sample were different. Our method takes advantage of the difference between the adversarial samples and the normal samples in the middle layers of the neural network. In 2019, Joshua et al. [17] studied the first-order classifier by training a discriminator with a generative adversarial network. In our unsupervised method, we use the feature vectors extracted from the middle layer to train the discriminator network. Because our method takes advantage of the difference between the adversarial samples and the normal samples in the middle layer, we capture the weak perturbation of adversarial samples. Thus, our method will have better detection performance than the three types of methods described above.

2.3. Our Approach. In this work, we introduce the semi-supervised GAN’s structure and training method for studying the hidden layers’ feature distribution of the pretrained network first. Then, we present our detection methods under supervised, partially supervised, and unsupervised scenarios.

2.3.1. Semisupervised GAN. Samet Akcay et al. [29] inspired us to use the semisupervised anomaly detection structure. They used an encoder-decoder-encoder structure to study the data distribution of the input image. For simplicity, we used an encoder-decoder structure in the generator part of the semisupervised GAN to analyze the feature distribution of the target network’s hidden layers.

The formal principle behind the semisupervised GAN is as follows. Generator $G$ first reads the intermediate layer feature $x$ of the target network, where $x \in \mathbb{R}^n$, and forward passes it to the encoder network $G_e$. With the use of convolutional layers followed by batch norm and ReLU() activation, $G_e$ downscales $x$ by compressing it to a latent vector, where latent $\in \mathbb{R}^d$ ($d$ represents the best dimension). In our experiment, $d$ is set to 128. The decoder network $G_d$ of generator $G$ is composed of convolution transpose layers, the batch-norm function, and the ReLU() activation function. Finally, the latent vector is input to $G_d$ to reconstruct the intermediate layer feature $\hat{x}$ of the target network. Finally, generator $G$ generates the intermediate layer feature $\hat{x}$ via $\hat{x} = G_d(\text{latent})$, where latent $= G_e(x)$.

1) Adversarial Loss. Because the GAN is unstable during the training phase, we add feature matching loss to the training phase. In the ordinary GAN’s training phase, generator $G$ is updated based on discriminator $D$. Following the work of Salimans et al. [30], feature matching is employed to reduce instability during training. We update this approach based on the internal representation of discriminator $D$. First, we assume that there is an $f$ function of the intermediate layer of discriminator $D$. For the input data $x$ that satisfies the $p_x$ distribution and outputs the intermediate layer features of discriminator $D$, the feature matching loss calculates the $L_2$ distance between the original feature and the generated feature. The form of our formalized adversarial loss $L_{adv}$ is as follows:

$$L_{adv} = E_{x \sim p_x} \| f(x) - E_{x \sim p_x} f(G(x)) \|^2_2$$

(11)

In equation (11), $x$ is the input data; $f$ is the function of the intermediate layer of discriminator $D$, $G$ is the generator network, $D$ is the discriminator network, and $p_x$ is the distribution of real samples. The adversarial loss $L_{adv}$ is the $L_2$ loss. $E$ is the expectation of the distribution function.

2) Contextual Loss. While adversarial loss makes the generated adversarial samples deceive discriminator $D$, there is only one adversarial loss, and the generator cannot be optimized according to the input data’s context information. Punishing the generator by measuring the distance between the input data and the generated data can remedy this problem. Isola et al. [31] showed that the fuzzy results due to L1 loss are less than those due to L2 loss. Therefore, we penalize $G$ by measuring the L1 distance between the original input data and the generated data $\hat{x} = G(x)$. Thus, the contextual loss $L_{con}$ is formalized as follows:

$$L_{con} = E_{x \sim p_x} \| x - G(x) \|_1.$$ 

(12)

In equation (12), $x$ is the input data, $E$ is the expectation of the distribution function, and $p_x$ is the distribution of real samples. The contextual loss $L_{con}$ is the L1 loss.

In this way, the generator encodes normal data but cannot encode adversarial samples because our generator $G$ and discriminator $D$ are optimized for normal data. The loss function we trained is as follows:

$$L = W_{adv} L_{adv} + W_{con} L_{con},$$

(13)

where $W_{adv}$ is the weight coefficient of $L_{adv}$, and $W_{con}$ is the weight coefficient of $L_{con}$. $W_{adv}$ and $W_{con}$ are both positive integers; $W_{adv} = 1$, and $W_{con} = 15$. $L_{adv}$ is the adversarial loss in equation (11). $L_{con}$ is the contextual loss in equation (12). The semisupervised GAN training flow chart is described in Algorithm 1.

2.3.2. Supervised Scenario and Partially Supervised Scenario. We used the semisupervised GAN to study the normal data’s feature distribution information in the hidden layers of the pretrained network. Then, we input the normal data and the adversarial samples into the pretrained network and obtain the corresponding latent features through the semisupervised GAN. Finally, the features are input into the supervised classifier support vector machine to realize supervised classification and partially supervised classification. The supervised scenario and partially supervised scenario training flowchart is described in Algorithm 2.

2.3.3. Unsupervised Scenario. Due to the discrepancy between the feature distributions of the normal data and the adversarial samples in the hidden layers of the pretrained
network, we use the hidden layers’ difference features of the normal data and its label as the joint feature information for training the CGAN and a good discriminator.

The loss function of the target is as follows:

$$
\min_G \max_D V(D,G) = E_{x \sim p_{\text{normal}}(x)}[\log(D(x | y))] + E_{z \sim p_z(z)}[\log(1 - D(G(z | y)))].
$$

(14)

Here, in order to reduce the amount of calculation, \( x \) is the joint feature data that includes the reconstruction error vector in the final layer of the last block group in the pretrained target network, the latent vector in the final layer of the pretrained target network, and the logit vector of the target network.

TRAINING THE CGAN

The normal data \( x \) latent feature is \( \sum_l \text{latent}_l \) and the logit vector of the target network. The adversarial samples \( x_{\text{adv}} \) latent feature is \( \sum_l \text{latent}_l \cdot \text{adv} \) and the logit vector of the target network.

We use the normal data \( x \) latent feature and adversarial samples \( x_{\text{adv}} \) latent feature input the support vector machine classifier. return the evaluation data’s AUROC.

ALGORITHM 2: In the supervised and partially supervised scenario, the final detection classifier is the support vector machine classifier. We used 10% of the test set as training data and 90% as evaluation data.

ALGORITHM 1: We train individual semisupervised generative adversarial networks to study normal data distributions in the pretrained target network’s hidden layers.

3. Results and Discussion

3.1. Experiments. We test our detection method against DeepFool, FGSM, BIM, PGD, and CW adversarial attacks on CIFAR10 [32], CIFAR100 [32], and SVHN [33] datasets. We used the ResNet-34 [3] and DenseNet-BC [34] models. Similar to Lee’s method, we chose to train the semisupervised GAN on the last layer of the basic block of the two neural network models; then, we extracted the hidden layers’ features from the target network. For convenience of calculation, if the feature shape of the dataset in the network’s hidden layers is the same, we used the same semisupervised GAN.

In the supervised and partially supervised scenario, the final detection classifier is the support vector machine classifier; we used 10% of the test set as training data and 90% as evaluation data. In the unsupervised scenario, we used the GM-CGAN as the final detection classifier trained on the training samples that not include adversarial samples and noise samples. Our analyses of reconstruction error and L2 norm are presented in Figures 2–4. When we train the GM-CGAN, we select the input features as the reconstruction error vector in the final layer of the last block group in the pretrained target network, the latent vector in the final layer...
of the last block group in the pretrained target network, and the logit vector of the target network. The GM-CGAN’s conditional information is the label of the output of this neural network model.

The features we input are important for detecting adversarial samples. In the study by Wójcik et al. [19], the reconstruction error vector of the L1 norm was shown to reflect the discrepancy between the given sample and the real sample. The latent feature vector’s norm reflects whether a given sample can be generated on the data manifold. In Figure 2, we can also view the importance of the logit norm. This can reduce the computational complexity and allows us to better capture the difference information. The hyper-parameters of the SVM classifier are fine-tuned.

First, similar to how Wójcik et al. [19] approached the problem, we analyzed the norm and reconstruction error information of the hidden layer’s latent feature vectors generated from the semisupervised GAN (Figures 2 and 3). We also analyzed the joint feature information of the norm and reconstruction error (Figure 4). Finally, we assessed the importance of different hidden layers’ features (Figure 5). Here, due to limited space of article, we only present figures for the ResNet model under attack by five methods, on the CIFAR10 dataset. This analysis puts forward a strong argument that the reconstruction error and the latent norm can fully explain the data manifold, which can help us to detect adversarial samples.

For the sake of fairness, our method and the method of Lee et al. [11] are initialized with the same settings. In the experimental test stage of Lee et al., noisy data and adversarial samples are generated for normal test data. Our semi-supervised GAN obtains latent features, and then, we used these latent features to train the supervised and unsupervised classifiers. We used 10% of the test set as training data and 90% as evaluation data and performed five-fold cross-validation.

3.2. Result. In Figure 2, we visualized the distribution information of normal (green) and adversarial (red) samples through kernel density estimation in 2D space. In the subfigure, $x$-axis represents the L2 norm in the latent vector produced by the generator and $y$-axis represents probability density. These figures are generated for the CIFAR10 dataset, with the ResNet model. The adversarial samples flow through 5 semisupervised GANs and the target network’s logit layer, and hence, there are 6 rows of subfigures. The difference between the real sample and the adversarial sample is obvious in the last few layers of the neural network, especially in the logit layer.

In Figure 3, we visualized the distribution information of normal (green) and adversarial (red) samples through kernel density estimation in 2D space. In the subfigure, $x$-axis represents reconstruction error and $y$-axis represents probability density. These figures are generated for the CIFAR10 dataset, with the ResNet model. The adversarial samples flow through 5 semisupervised GANs, and hence, there are 6 rows of subfigures.

In Figure 4, we visualized the distribution information of normal (green) and adversarial (red) samples through kernel density estimation in 2D space. In the subfigure, $x$-axis represents the L2 norm in the latent vector produced by the generator and $y$-axis represents reconstruction error. These figures are generated for the CIFAR10 dataset, with the ResNet model. The adversarial samples flow through 5 semisupervised GANs, and hence, there are 6 rows of subfigures. Figure 5 presents the AUROC of the threshold-based detector using the latent vector generated from the semisupervised GAN’s generator at different basic blocks of ResNet trained on CIFAR10 dataset and the logit vector of the target network. We measured the detection performance using adversarial samples produced by FGSM, BIM, DeepFool, CWL2, and PGD. We also measured the detection performance using the entire latent vectors generated from the semisupervised GAN’s generator (see the last subfigure, i.e., Feature Ensemble).

To generate the results for the supervised scenarios (Table 1), the final detection classifier is the support vector machine classifier whose input includes all latent vectors. For the partially supervised scenarios (Table 2), the final detection classifier is the support vector machine classifier whose input only includes FGSM samples.

Meanwhile, for the unsupervised scenarios (Table 3), we used the GM-CGAN as a one-class classifier whose input features are the reconstruction error vector, the latent vector in the final layer of the last block group (obtained by the semisupervised GAN), and the logit of the target network. The GM-CGAN’s conditional information is the label of the target network. We train the classifier based on the training data, which does not include any adversarial samples and noisy samples.
Figure 2: Continued.
Figure 2: Continued.
3.3. Discussion. In our experiment, we utilized the PGD-100 attack. In the supervised scenario, our method performed significantly better than that of Lee et al. Our method reduced the preprocessing time for input data and reduced the total amount of calculations. We note that the Mahalanobis distance covariance matrix must be full rank and that it cannot handle problems on nonlinear manifolds. In the deep layers of the neural network, the Mahalanobis distance cannot provide a reliable measure of the distance between the data, which mainly exist in a nonlinear form; ultimately, the Mahalanobis distance is unstable in such situations. The source of this instability is the covariance matrix. In Lee’s method, the distance between data of different network blocks is very small compared with the distance between high-dimensional adversarial data and the real data. Furthermore, Lee’s method cannot reflect the difference between the adversarial data and the real data. In contrast, our semisupervised GAN method maps different network block feature data to low-dimensional space, thereby obtaining more sample feature information. Moreover, it can overcome the drawback of the Mahalanobis distance being unsuitable for the determination of nonlinear data. Considering these key characteristics, it is clear why our method achieved the best results in the supervised classification task.

We highlight that our method improved the detection of DeepFool to above 94.68%.

For the partially supervised scenario, we used the SVM as the final classifier with FGSM samples. Although it did not achieve the same effect as Lee’s method in this scenario, our method still achieved good results. Here, we take the ResNet model and the CIFAR10 dataset as an example (Table 2). For BIM attacks, the detection AUROC dropped from 98.91% to 73.19%; meanwhile, for FGSM attack detection, the AUROC was 99.98%. We argue that there might be a trade-off between performance on a fully supervised scenario (where our method had an AUROC close to 100% in some cases) and an ability to generalize to other attacks. In Figure 4, we find that BIM attacks and FGSM attacks deviate from the real data and have great inconsistencies; this is mainly manifested in the 1st, 7th, and 27th layers of the network. By the same token, the ways in which different attacks deviate from the true data are also different. Therefore, only partial supervision is suitable for FGSM attacks.

For the unsupervised scenario, our method performed better than the odds-testing method [15], except for with the PGD-100 attack. We argue that not all attack differential features are present in the last layer. The PGD attack consists of initializing the search for an adversarial
Figure 3: Continued.
Figure 3: Continued.
example at a random point within the allowed norm ball, then running several iterations of the basic iterative method. The PGD-100 has stronger attack performance because of the basic iterative method. We think the performance feature of PGD’s adversarial samples in the network middle layer is more similar to those of real samples. The input at the end of the network is different from the real one. The PGD-100 can attack deep neural networks, such as ResNet-34 and DenseNet, which contain many features. GM-CGAN contains fewer features and is easier to be attacked by PGD-100. Because GM-CGAN is also a classifier based on neural network, the features in the hidden layers space will also be attacked by PGD. It reduces the defensive performance of GM-CGAN. For example, as shown in Figures 3 and 4, the most obvious difference in the PGD-100 attack is in the 15th layer. Although our method requires multiple forward propagations of neural networks like the odds-testing method, we provide a new idea for detecting adversarial samples: a new one-class classifier. We emphasize that our one-class classifier does not require any noisy data during the training process compared with the odds-testing method, and the training method is simple and easy to operate. Additionally, the number of forward propagations of our method is relatively small. Through Figures 2–4, we find that as the network layer deepens, the data distribution of the adversarial sample deviates farther from the characteristic distribution of the normal data. The L2 norm information of the logit can better reflect this difference than the latent vector’s norm information. Compared with the L2 norm information, the reconstruction error can reveal the distribution discrepancy between the adversarial sample and the normal sample earlier, and the deeper the network layer, the greater the discrepancy. The combined information of the reconstruction error and L2 norm can also reflect this trend. In general, the discrepancy between the distribution of real samples and adversarial samples is more obvious in the last few layers. In Figure 5, we analyzed the detector’s performance with different basic blocks (which have different latent vector characteristics). We also analyzed the performance of the detector after the integration of different basic block features. Like in Figures 2–4, in most instances, the discrepancy is most obvious in the last layer. At the same time, we found that

Figure 3: Analysis of reconstruction errors in different network layers.
Figure 4: Continued.
the logit vector is significant for the detection of adversarial samples. In our supervised and partially supervised experiments, we ensemble the latent feature vectors; we believe that this treatment can provide adaptability to different adversarial attack strategies and lead to good performance.

This method has practical significance. For example, this method can be used in target recognition. Without modifying the original neural network, this method can detect images with adversarial perturbation. For example, if adversarial perturbation is added to a picture of a kitten, it may be recognized as other animals in target recognition.
Table 1: Supervised scenarios for detecting adversarial samples

| Model | Dataset | Method       | FGSM  | BIM   | DeepFool | CW   | PGD   |
|-------|---------|--------------|-------|-------|----------|------|-------|
|       |         |              |       |       |          |      |       |
| DenseNet | CIFAR10 | Mahalanobis  | 99.94 | 99.78 | 83.41    | 87.31| 97.79 |
|        |         | Ours         | 99.99 | 99.98 | 97.46    | 96.11| 99.42 |
|        | CIFAR100| Mahalanobis  | 99.86 | 99.17 | 77.57    | 87.05| 79.24 |
|        |         | Ours         | 100.00| 99.86 | 97.22    | 98.01| 90.35 |
|        | SVHN    | Mahalanobis  | 99.85 | 99.28 | 95.10    | 97.03| 98.41 |
|        |         | Ours         | 99.95 | 99.85 | 99.25    | 98.65| 99.49 |
| ResNet | CIFAR10 | Mahalanobis  | 99.94 | 99.57 | 91.57    | 95.84| 89.81 |
|        |         | Ours         | 99.98 | 99.86 | 98.66    | 97.89| 100.00|
|        | CIFAR100| Mahalanobis  | 99.77 | 96.90 | 85.26    | 91.77| 91.08 |
|        |         | Ours         | 99.92 | 99.11 | 94.68    | 97.21| 99.95 |
|        | SVHN    | Mahalanobis  | 99.62 | 97.15 | 95.73    | 92.15| 92.24 |
|        |         | Ours         | 99.96 | 99.46 | 99.54    | 99.30| 99.98 |

These bold values show that our experimental method is better than the comparison method.

Table 2: Partially supervised scenarios in detecting adversarial samples.

| Model   | Dataset  | Method       | FGSM  | BIM   | DeepFool | CW   | PGD   | Partially unsupervised scenario |
|---------|----------|--------------|-------|-------|----------|------|-------|--------------------------------|
| DenseNet     | CIFAR10 | Mahalanobis  | 99.94 | 99.51 | 83.42    | 87.95| 81.84 |
|           |         | Ours         | 99.99 | 99.06 | 98.06    | 95.75| 84.79 |
|           | CIFAR100| Mahalanobis  | 99.86 | 98.27 | 75.63    | 86.20| 39.32 |
|           |         | Ours         | 100.00| 89.86 | 83.10    | 79.07| 40.32 |
|           | SVHN    | Mahalanobis  | 99.85 | 99.12 | 93.47    | 96.95| 81.40 |
|           |         | Ours         | 99.95 | 99.00 | 98.71    | 98.16| 81.45 |
| ResNet     | CIFAR10 | Mahalanobis  | 99.94 | 98.91 | 78.06    | 93.90| 100.00|
|           |         | Ours         | 99.98 | 73.19 | 96.79    | 95.71| 100.00|
|           | CIFAR100| Mahalanobis  | 99.77 | 96.38 | 81.95    | 90.96| 100.00|
|           |         | Ours         | 99.92 | 81.18 | 83.32    | 86.63| 100.00|
|           | SVHN    | Mahalanobis  | 99.62 | 95.39 | 72.20    | 86.73| 99.92 |
|           |         | Ours         | 99.96 | 74.89 | 95.97    | 89.65| 99.96 |

These bold values show that our experimental method is better than the comparison method.
This method can be used to detect kitten images with anti-interference. This method can prevent the recognition image from making mistakes.

4. Conclusions

Our article intends to discover the adversarial samples in training data in order to prevent the generation of the highly overconfident distribution in the test phase. The proposed method designs a semisupervised generative adversarial network that is applied to the output of the hidden layers in a neural network to detect the variation of the adversarial samples without modifying the structure of the neural network. In the supervised scenario, the latent feature of the semisupervised GAN and the target network's logit information are used as the input of the external classifier support vector machine to detect the adversarial samples. In the unsupervised scenario, first we proposed a one-class classifier based on the semisupervised Gaussian mixture conditional generative adversarial network (GM-CGAN) to fit the joint feature information of the normal data and then we used a discriminator network to detect normal data and adversarial samples. The novel contribution is that the output of hidden layers of a neural network is analyzed without modifying the neural network.

Data Availability

The [DATA TYPE] data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by Science and Technology Project of State Grid Zhejiang Electric Power Co., Ltd.

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