INCREASING-MARGIN ADVERSARIAL (IMA) TRAINING TO IMPROVE ADVERSARIAL ROBUSTNESS OF NEURAL NETWORKS

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ABSTRACT

Deep neural network, including convolutional neural network, is known to be vulnerable to adversarial attacks, which may lead to disastrous consequences in medical applications. Adversarial samples are usually generated by attack algorithms and can also be induced by white noises, and therefore the threats are real. In this study, we propose a novel training method, named Increasing Margin Adversarial (IMA) Training, to improve DNN robustness against adversarial noises. During training, the IMA method increases the margins of training samples by moving the decision boundaries of the DNN model far away from the training samples to improve robustness. The IMA method is evaluated on four publicly available datasets (including a COVID-19 CT image dataset) under strong 100-PGD white-box adversarial attacks, and the results show that the proposed method significantly improved classification accuracy on noisy data while keeping a relatively high accuracy on clean data. We hope our approach may facilitate the development of robust DNN applications, especially in the medical field.

1 INTRODUCTION

Deep neural network (DNN), especially convolutional neural network (CNN), has become the first choice for automated image analysis due to its superior performance. However, recent studies have shown that DNNs are not robust to a special type of noise, called adversarial noise. Adversarial noise was first discovered by (Szegedy et al., 2013) and then explained by (Goodfellow et al., 2014). Adversarial noises can significantly affect robustness of DNNs for a wide range of image classification applications (Akhtar & Mian, 2018), such as handwritten digits recognition (Graese et al., 2016), human face recognition (Mirjalili & Ross, 2017), and even traffic sign detection (Eykholt et al., 2018). DNN-based image segmentation can also be affected by adversarial noises because image segmentation is often realized by pixel classification.

The COVID-19 pandemic has infected millions of people and caused the death of about 1 million people as of today (WHO, 2020). A large scale study in China shows that CT had higher sensitivity for the diagnosis of COVID-19 as compared with initial reverse-transcription polymerase chain reaction (RT-PCR) from swab samples (Ai et al., 2020). As reviewed in (Shi et al., 2020), many DNN models for COVID-19 diagnosis from CT images have been developed and achieved very high classification accuracy. However, none of these studies (Shi et al., 2020) considered DNN robustness against adversarial noises. We modified a Resnet-18 model (He et al., 2016) and trained it on a public COVID-19 CT image dataset (Soares et al., 2020), and then the model robustness is tested (details in section 3.3). Fig. 1 shows a CT image (denoted by x) of a lung that was infected by COVID-19 and correctly classified as infected. After adding a small amount of noise δ to the image x, the noisy image $x + \delta$ is classified as uninfected. On the test set, although the model achieved $\geq 95\%$ accuracy on original clean images, its accuracy dropped to zero on the noise level of 0.03. This non-robust model clearly cannot be used in real clinical applications. It may be argued that adversarial noises are created by algorithms and therefore may not exist in the real world unless some bad people want to hack the system to achieve personal gain at the expense of public health. However, on the COVID-19 dataset, we found that 2.75% of the noisy samples with uniform white noises on the noise level of 0.05, can cause the DNN model to make wrong classifications, which

shows that white-noise-induced adversarial samples can exist. For medical applications, 2.75% is not a negligible number, and it is worth developing methods to improve DNN adversarial robustness.

There are mainly two categories of adversarial attacks: white-box attack and black-box attack. For a white-box attack, the attacker knows everything about the DNN to be attacked. For a black-box attack, the attacker only can use the DNN as a black-box (i.e. send an input to the DNN and get an output from the DNN, not knowing anything else). From the perspective of defense, we should consider the worst-case scenario: white-box attack. People have explored many ideas to improve robustness, but many of them have been shown to be ineffective (Uesato et al., 2018) (Tramer et al., 2020). A general and effective strategy is adversarial training (Goodfellow et al., 2014) (Madry et al., 2017)(Ding et al., 2019a), and the basic idea is to use adversarial attack algorithms to generate noisy samples and add those samples to the training set, which basically is a special data augmentation strategy. Through adversarial training, the DNN model can learn from the noisy samples and become robust to noises. Adversarial training is straightforward but computationally expensive. Thus, one needs to make sure that the generated noisy samples can indeed help to improve robustness: samples with too much noise can harm performance while samples with too little noise may have no effect at all. Generative adversarial training has been directly applied to improve robustness; however, it can only defend against black-box attack (Wang & Yu, 2019).

In this paper, we propose a novel method, Increasing-Margin Adversarial (IMA) Training, to improve robustness of deep neural networks for classification tasks. Our method aims to increase margins of training samples by moving decision boundaries far away from the samples to improve robustness. We evaluated our method on four datasets with 100-PGD white-box attack and the results show that our proposed method can achieve a significant improvement in DNN robustness against adversarial noises.

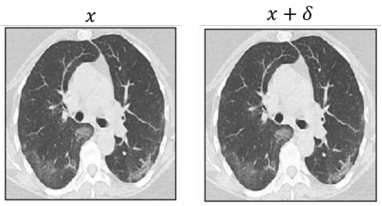

Figure 1: An example of clean and noisy images.

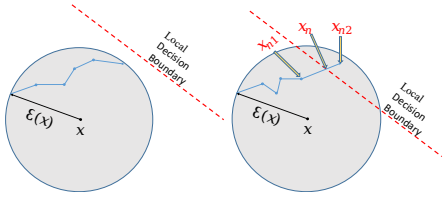

Figure 2: Left: case-0 in BPGD; Right: case-1 in BPGD. Please zoom in for better visualization.

2 METHODOLOGY

2.1 ADVERSARIAL ATTACK AND NEURAL NETWORK ROBUSTNESS

To evaluate the robustness of different adversarial training methods, we use projected gradient descent (PGD) (Madry et al., 2017)(Kurakin et al., 2016) to generate adversarial noises, which is widely used for method evaluation (Uesato et al., 2018) (Tramer et al., 2020). For the convenience of the reader, we briefly describe PGD: Let x denote an input sample and y be the true class label. Let $J(x)$ denote the scalar objective function of PGD, which could be the cross-entropy loss function or other classification loss functions. Let δ denote the adversarial noise, and its magnitude is ε which is measured by the vector Lp norm of δ, i.e., $\varepsilon = ||\delta||_p$, where p is inf or 2 usually. PGD adds noises to x iteratively:

$$x_{(i)} = clip\left(x_{(i-1)} + \eta \cdot h\left(J'\left(x_{(i-1)}\right)\right)\right) \tag{1}$$

where η is step size, $J'(x) = \frac{\partial J}{\partial x}$, and i is iteration index. $x_{(0)} = x + \xi$, where ξ is random noise with $||\xi||_p \leq \varepsilon$. $||\ ||_p$ denotes the vector p-norm. The clip operation in Eq.(1) ensures that $||x_{(i)} - x||_p \leq \varepsilon$ (called ε-ball). If x is an image, the clip operation also ensures that pixel values stay within the feasible range (e.g. 0 to 1). If L-inf norm is used, $h(J')$ is the sign function; and if L2 norm is used, then $h(J')$ normalizes J' by its L2 norm. The total adversarial noise is $\delta = x_{(N_{PGD})} - x$, and N_{PGD} is the number of iterations. η is usually set to $\alpha \cdot \varepsilon / N_{PGD}$, and therefore the algorithm may sweep the ε-ball α times ($\alpha \geq 1$) within N_{PGD} iterations. By adding

the adversarial noise δ to the input x, the objective function $J(x+\delta)$ will be significantly larger than $J(x)$, leading to wrong classification of the noisy sample $x+\delta$.

It is easy to understand the robustness issue through Eq.(1) and Fig. 1. Given a trained classifier, if a sample x is very close to the decision boundary of the classifier, then one could add a small noise δ to x such that $x+\delta$ goes across the decision boundary and is wrongly-classified. As shown in section 3, using cross-entropy loss and clean data for training, the decision boundaries of the trained classifier will often be very close to the samples; as a result, the accuracy can drop to zero upon very small noises. To improve robustness, vanilla adversarial training (Goodfellow et al., 2014)(Kurakin et al., 2016) based on PGD can be used: given the maximum noise level $\varepsilon = \varepsilon_{max}$, generate a noisy sample $x_\varepsilon = PGD(x, y, \varepsilon)$ for every clean sample x in training set; use the clean samples and noisy samples together to train the model. The loss function is given in (Goodfellow et al., 2014):

$$L_{adv} = (L_{ce}(x, y) + L_{ce}(x_\varepsilon, y))/2 \tag{2}$$

In practice, the loss is accumulated over each mini-batch. L_{ce} is the cross-entropy loss. As shown in section 3, the vanilla adversarial training is very sensitive to the user-defined noise level ε_{max}.

2.2 Increasing-Margin Adversarial (IMA) Training

We developed a novel method, Increasing-Margin Adversarial (IMA) training, to enhance DNN classifier robustness. As its name indicates, IMA is a type of adversarial training: it generates noisy samples and trains a DNN model on clean and noisy samples. IMA algorithms are significantly different from the other adversarial training algorithms.

IMA training includes two alternating sub-processes: Algorithm 1 to compute loss and update the DNN model, and Algorithm 2 to update margin estimation. In Algorithm 1, by minimizing the loss on clean and noisy data, the model will reach a balance between robustness and accuracy on clean data. In Algorithm 2, the sample margins are updated after each epoch. These estimated margins are used to generate noisy samples for training the model in the next epoch.

Algorithm 1 compute loss and update model in an epoch

Input: : $S = (x, y)$ is the training set, containing pairs of clean sample x and true label y. f is the DNN model and $\hat{y} = f(x)$. $\mathcal{E}$ is an array containing the estimated margins of individual training samples. β is a scalar coefficient. In a batch, X contains samples and Y contains class labels.
Output: updated model f after this training epoch
Process:
for Batch data X and Y in S **do**
  Run model f to classify the samples and divide the samples into two groups, wrongly-classified X_0, Y_0 and correctly-classified X_1, Y_1 where $X = X_0 \cup X_1$ and $Y = Y_0 \cup Y_1$
  Get noisy samples $X_n = BPGD(X_1, Y_1, \mathcal{E}(X_1))$ and classify them $\hat{Y}_n = f(X_n) \cdot \mathcal{E}(X_1)$ is a sub-array of $\mathcal{E}$, containing the estimated margins of samples in X_1. $BPGD$ is described in Algorithm 3.
  Compute the loss L:
  $L_0 = cross_entropy(f(X_0), Y_0)$ (take sum)
  $L_1 = cross_entropy(f(X_1), Y_1)$ (take sum)
  $L_2 = cross_entropy(f(X_n), Y_1)$ (take sum)
  $L = ((1-\beta) \cdot (L_0 + L_1) + \beta \cdot L_2)/batch_size$
  Back-propagate from L and update the model f
end for

Our IMA method tries to generate noisy samples on decision boundaries as much as possible: adding too much noise to a training sample may lead to low accuracy on clean samples, but adding too little noise may have no effect on robustness. Since the distance between a training sample and a decision boundary is different for different training samples, the noises added to the training samples have different magnitudes (i.e. vector norms). The rationale of doing so is discussed in section 2.3. Here, the margin of a sample is the minimum distance between the sample and the decision boundaries. It is difficult to compute the exact margin for a sample in a high dimension space, and therefore we can only estimate it.

Algorithm 2 update margin estimation after an epoch

Input: $S = (x, y)$ is the training set. f is the DNN model and $\hat{y} = f(x)$. $\mathcal{E}$ is an array of the estimated margins of training samples. $\mathcal{E}(x)$ is the estimated margin of x. Δ_ε is margin expansion step size. ε_{max} is maximum noise level.

Output: updated $\mathcal{E}$

Process:

for each sample x and y in S **do**
  Classify the sample $\hat{y} = f(x)$
  if x is wrongly-classified ($\hat{y}$ is not y) **then**
    Update $\mathcal{E}(x) = \Delta_\varepsilon$ (re-initialize)
  else if x is correctly-classified ($\hat{y}\ is\ y$) **then**
    Get noisy sample $x_n = BPGD(x, y, \mathcal{E}(x))$
    if x_n is on decision boundary (not None) **then**
      Update $\mathcal{E}(x) = ||x - x_n||_p$ (refine/shrink)
    else
      Update $\mathcal{E}(x) = \mathcal{E}(x) + \Delta_\varepsilon$ (expand)
    end if
  end if
end for
Clip every element of $\mathcal{E}$ into the range of Δ_ε to ε_{max}

Note: Every $\mathcal{E}(x)$ is initialized to be Δ_ε which can be set to ε_{max} divided by the number of adversarial training epochs. The algorithm runs in mini-batches.

Algorithm 3 (BPGD): generate noisy samples

Input: : a sample x with class label y, the estimated margin ε of x, and the model $f \cdot N_{PGD}$ is the number of iterations in PGD. N_{binary} is the number of iterations in binary search.

Output: $x_n = BPGD(x, y, \varepsilon)$

Process:

Run the standard $PGD(x, y, \varepsilon)$ and obtain a sequence of noisy samples (N_{PGD} samples)
Classify those noisy samples using the model f
if all of the noisy samples are correctly-classified (case-0 in Fig.2) **then**
  return None (x_n is None and will be ignored)
else
  (case-1 in Fig.2) Find x_{n1} and x_{n2}, two adjacent samples in the sequence. x_{n1} is correctly-classified and x_{n2} is wrongly-classified. Thus, x_{n1} and x_{n2} are close to the decision boundary.
  Run binary search along the straight-line segment between x_{n1} and x_{n2} in order to find x_n on the decision boundary (Fig.3)
  return x_n
end if

Note: it is unnecessary to store the whole sequence. The algorithm runs in mini-batches.

We developed Algorithm 3, named BPGD, to find noisy samples on decision boundaries. At the very beginning of the IMA training process, the margins of the training samples are initialized to a small number equal to margin expansion step size in Algorithm 2. Intuitively, during IMA training, the margin of a training sample keeps increasing as if a ball is expanding (the ball center is the sample x, and the radius is the margin $\mathcal{E}(x)$; it is called ε-ball), until the ball of the sample x collides with the ball of another sample x' in a different class. When the two balls collide and therefore a local decision boundary is formed, Algorithm 2 will prevent them from further expansion by refining/shrinking margins (Fig. 4). In section 2.3, we will show that an equilibrium state may exist (Fig. 5) under which the margins of the samples are maximized.

2.3 THE EQUILIBRIUM STATE

We can show that on certain conditions, an equilibrium state (Fig. 5-Left) exists under which the margins of the samples are maximized. To simplify the discussion, we assume there are three classes and three decision boundaries between classes (Fig. 5-Right). The softmax output of the neural

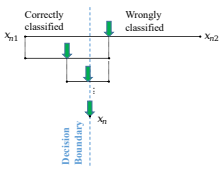

Figure 3: Binary search in BPGD.

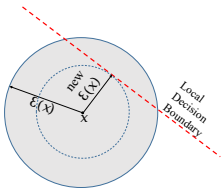

Figure 4: Shrink Margin.

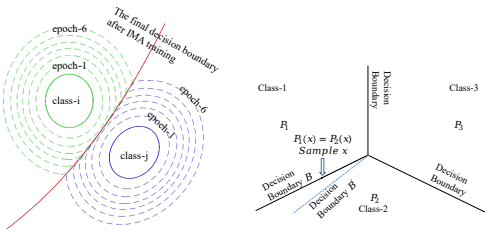

Figure 5: Left: Equilibrium State; Right: Three-class Scenario.

network model f has three components: P_1, P_2 and P_3 corresponding to the three classes. If a point (i.e. a sample) x is on the decision boundary B_{ij} between class-i (c_i) and class-j (c_j), then $P_i(x) = P_j(x)$. The mathematical expectation of the cross-entropy loss of the noisy samples (L_2 in Algorithm 1) is:

$$E = \mathbf{E}_{X_n \in c_1}\left(-log\left(P_1\left(X_n\right)\right)\right) + \mathbf{E}_{X_n \in c_2}\left(-log\left(P_2\left(X_n\right)\right)\right) + \mathbf{E}_{X_n \in c_3}\left(-log\left(P_3\left(X_n\right)\right)\right) \quad (3)$$

The IMA method puts the noisy samples on the decision boundaries, thus:

$$\mathbf{E}_{X_n \in c_1}\left(-log\left(P_1\left(X_n\right)\right)\right) = \mathbf{E}_{X_n \in c_1, B_{12}}\left(-log\left(P_1\left(X_n\right)\right)\right) + \mathbf{E}_{X_n \in c_1, B_{13}}\left(-log\left(P_1\left(X_n\right)\right)\right) \quad (4)$$

$$\mathbf{E}_{X_n \in c_2}\left(-log\left(P_2\left(X_n\right)\right)\right) = \mathbf{E}_{X_n \in c_2, B_{12}}\left(-log\left(P_2\left(X_n\right)\right)\right) + \mathbf{E}_{X_n \in c_2, B_{23}}\left(-log\left(P_2\left(X_n\right)\right)\right) \quad (5)$$

$$\mathbf{E}_{X_n \in c_3}\left(-log\left(P_3\left(X_n\right)\right)\right) = \mathbf{E}_{X_n \in c_3, B_{13}}\left(-log\left(P_3\left(X_n\right)\right)\right) + \mathbf{E}_{X_n \in c_3, B_{23}}\left(-log\left(P_3\left(X_n\right)\right)\right) \quad (6)$$

If the noisy samples (random variables) $X_n \in c_i$ and $X_n \in c_j$ have the same spatial distribution on the decision boundary B_{ij} between the two classes, Eq.(3) can be simplified to

$$E = E_{X_n \in\, B_{12}} + E_{X_n \in\, B_{23}} + E_{X_n \in\, B_{13}} \quad (7)$$

where

$$\begin{aligned} E_{X_n \in\, B_{ij}} &= \mathbf{E}_{X_n \in\, B_{ij}}\left(-log\left(P_i\left(X_n\right)\right) - log\left(P_j\left(X_n\right)\right)\right) \\ &= \mathbf{E}_{X_n \in\, B_{ij}}\left(-log\left(P_i\left(X_n\right) P_j\left(X_n\right)\right)\right) \\ &\geq \mathbf{E}_{X_n \in\, B_{ij}}\left(-log\left(\frac{P_i\left(X_n\right) + P_j\left(X_n\right)}{2}\right)^2\right) \end{aligned} \quad (8)$$

E reaches the minimum when $P_i(X_n) = P_j(X_n)$.

The analysis shows that the loss of noisy samples will increase if the decision boundaries of the model f change a little bit from the current state. Thus, when the loss $(L_0 + L_1)$ on clean data is minimized and noisy samples are on the decision boundaries, an equilibrium is reached under the assumption that noisy samples have the same spatial distribution on the decision boundaries between classes. This analysis provides the rationale that our IMA method puts the noisy samples on decision boundaries as much as possible, which is significantly different from the theory of the MMA method (Ding et al., 2019a). If the assumption does not hold, an equilibrium may still be reached (when L is minimized) and the decision boundaries will be determined by sample spatial distribution, which may not be desired solution. Nevertheless, the experiment results show that sample margins can be increased significantly, compared to those trained only on clean data.

3 Experiment

We applied the IMA method for four DNNs on four datasets. For every dataset, β in Algorithm 1 is 0.5 because robustness and accuracy are equally important. In Algorithm 3, N_{PGD} is 20, N_{binary} is 10, and there is no repeat. α in PGD is 4. Larger N_{PGD} and N_{binary} may lead to better convergence of the algorithms but more computing-time. Pytorch (Paszke et al., 2017) is used for model implementation. Nvidia V100 and Titan V GPUs are used for model training and testing.

To describe the DNNs, we use "COV (a, b, c, d, e)" to represent a convolution layer with "a" input channels, "b" output channels, kernel size of "c", stride of "d" and padding of "e"; "Linear (f, g)" to denote a linear layer with input size of "f" and output size of "g"; "IN" to denote instance normalization; "LN" to denote layer normalization, and "LR" to denote leaky ReLU.

To obtain the baseline performance, each DNN was trained with cross-entropy loss on clean data, and the trained model is denoted by "ce". To evaluate the performance, we compare our method with the other three adversarial training methods, including: (1) 20-PGD (N_{PGD}=20 and α=4) based vanilla adversarial training with noise level ε, denoted by "adv ε"; (2) tradeoff-inspired adversarial defense via surrogate-loss minimization, named TRADES in (Zhang et al., 2019); (3) adversarial training for direct input space margin maximization, named MMA in (Ding et al., 2019a). MMA is a state of art method, and TRADES was state of art at the time of its publication.

To make the comparison as fair as possible, the number of iterations and step size of TRADES are the same as those of the 20-PGD; and the number of PGD-iterations in MMA is 20. We used PGD to evaluate the robustness of the methods, which is widely used for method evaluation (Liao et al., 2018)(Uesato et al., 2018). The number of PGD iterations is 100 to ensure a strong attack, and it is called 100-PGD. To further enhance the attack during model testing, each 100-PGD rans twice, using MarginalLoss and CrossEntropyLoss respectively, which is implemented in (Ding et al., 2019b)https://github.com/BorealisAI/advertorch .

3.1 Evaluation on Moons dataset

The Moons dataset is available in sk-learn (Pedregosa et al., 2011). There are two classes of 2D points in the dataset. The training set has 20000 samples, the validation set has 2000 samples, and the test set has 2000 samples. The neural network structure is Linear(2, 32)-LR-Linear(32, 64)-LN-LR-Linear(64, 128)-LN-LR-Linear(128, 2). The purpose of this evaluation is to visualize the decision boundaries of the models trained by different adversarial training methods. For every method, we set the number of training epochs to 30, maximum noise level to 0.3, and batch-size to 128; Adam optimizer was used with default parameters. To measure robustness on the test set, adversarial samples on different noise levels (defined by L-inf norm) are generated by the 100-PGD. The results of decision boundaries and accuracy scores are shown in Fig. 6. The accuracy scores

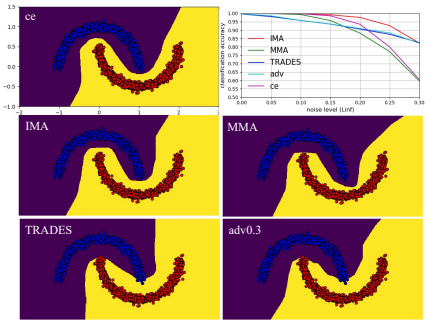

Figure 6: Results on Moons dataset.

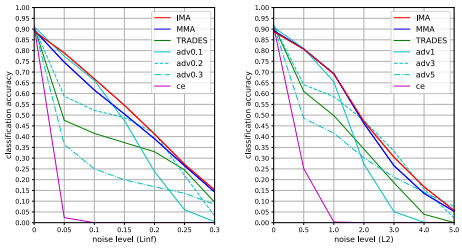

Figure 7: Results on Fashion-MNIST (L-inf and L2 norm in 100-PGD).

are also reported in Table 1 in the appendix. Our method IMA is better than the other methods, and its decision boundary is close to the "middle line" of the two classes. The results of TRADES and adv0.3 are very similar: the decision boundary is far away from most of the red dots. MMA is better than TRADES and adv0.3 when the noise level is less than 0.15, and then it becomes worse with larger noises. Surprisingly, "ce" (model trained with cross-entropy loss and clean data) has very good robustness when the noise level is less than 0.15.

3.2 Evaluation on Fashion-MNIST and SVHN datasets

We used Fashion-MNIST dataset instead of MNIST which is too easy. The dataset contains 28×28 grayscale images in 10 classes (shirts, shoes, etc.). The network structure is COV(1, 64, 5, 2, 2)-LR-COV(64, 128, 5, 2, 2)-IN-LR-COV (128, 256, 5, 2, 2)-IN-LR-COV (256, 512, 4, 1, 0)-Flatten-LN-LR-Linear(512, 10). For every method, we set the number of training epochs to 60, maximum noise level to 0.3 for IMA, MMA and TRADES, and batch-size to 128. Adam optimizer was used with default parameters. Besides adversarial training, we did not use any other data-augmentation (e.g. crop, etc.). The results on the test set are shown in Fig. 7 and reported in Table 2 and Table 3 in the appendix.

We also used SVHN dataset which contains 32×32 color images of $0 \sim 9$ digits. The network structure is COV(3, 32, 3, 1, 1)-LR-COV(32, 32, 3, 2, 1)-IN-LR-COV(32, 64, 3, 1, 1)-IN-LR-Conv2d(64, 64, 3, 2, 1)-IN-LR-COV(64, 128, 3, 1, 1)-IN-LR-Conv2d(128, 128, 3, 2, 1)-IN-LR-COV(128, 256, 4, 1, 0)-Flatten-LN-LR-Linear(256, 10). Besides adversarial training, we did not use any other data-augmentation. Training parameters (e.g. epochs) are the same as those for Fashion-MNIST. The results on the test set are shown in Fig. 8 and reported in Table 4 and Table 5 in the appendix.

Form the results shown in Fig. 7 and Fig. 8 on the two datasets, it can be seen that "ce" had the worst performance on noisy samples, "adv ε" is very sensitive to the maximum noise level ε for training, and TRADES did not perform well on L-inf norm-based tests. Compared to "ce", accuracy of every adversarial training method on clean data is slightly lower, which shows the sign of tradeoff between robustness and accuracy on clean data.

Recall that IMA significantly outperformed the other methods on the Moons dataset, which demonstrates its strong potential. On Fashion-MNIST and SVHN datasets, IMA also significantly outperformed TRADES and "adv ε". However, IMA is only slightly better than MMA on Fashion-MNIST and on-par with MMA on SVHN. The non-ideal performance of IMA is hightly likely caused by data scarcity in high dimensional space, so that the ideal equilibrium cannot be reached. To further improve its performance, generative adversarial training could be used to generate more clean samples to fill the "holes" of the space, which will be our future work. Nevertheless, our method IMA is at least on-par with MMA method which is start-of-art.

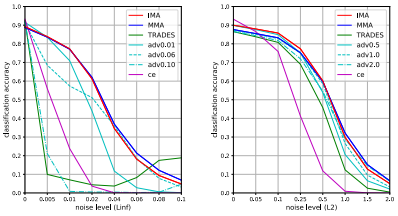

Figure 8: Results on SVHN (L-inf and L2 norm in 100-PGD).

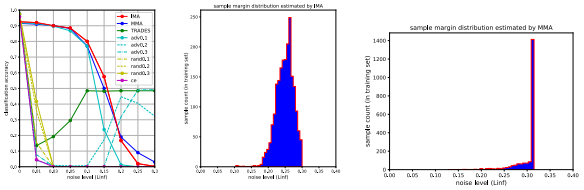

Figure 9: Results on COVID-19 CT: accuracies (left), IMA margins estimation (middle) and MMA margins estimation(right). Comparing with the estimation of IMA, MMA significantly overestimated the margins.

3.3 Application of COVID-19 detection from CT images

We used a public COVID-19 CT image dataset (Soares et al., 2020), which is collected from patients in hospitals from Sao Paulo, Brazil. It contains 1252 CT scans (2D images) that are positive for COVID-19 infection and 1230 CT scans (2D images) for patients non-infected by COVID-19, 2482 CT scans in total. From infected cases, we randomly selected 200 samples for testing, 30 for validation, and 1022 for training. From the uninfected cases, we randomly selected 200 for testing, 30 for validation and 1000 for training. Each image is resized to 224×224. Since there is no pixel segmentation mask in the dataset, we can only perform classification for COVID-19 detection on the image level.

We modified the output layer of the Resnet-18 model (He et al., 2016) for the binary classification task: uninfected (label 0) vs infected (label 1), and we also replaced batch normalization with instance normalization because it is known that batch normalization is not stable for small batch-size (Wu & He, 2018). As shown in the previous studies (Shi et al., 2020), infected regions in the images have a special pattern called ground-glass opacity.

For every method, we set the number of training epochs to 100, and maximum noise level to 0.3 for IMA, MMA and TRADES, and batch-size to 32. Adam optimizer was used with default parameters. For "ce", weight decay of 0.01 is applied with Adam (i.e. AdamW with default parameters). To measure robustness on the test set, adversarial samples on different noise levels (L-inf norm) are generated by the 100-PGD. We choose L-inf over L2 norm because L-inf norm can be used to control the maximum amplitude of noises on individual pixels, which resembles random white noises from

a uniform distribution. We also tested the effect of adding uniform white noises to the images, and the trained model is denoted by "rand ε" where ε is the maximum noise level/amplitude. "rand ε" can be considered a weak form of adversarial training, analog to "adv ε". The results on the test set are shown in Fig.9 and reported in Table 6 in the appendix. Examples of clean and noisy images are shown in Fig. 10 (see in Appendix).

The results show that IMA has the strongest overall performance, and MMA is slightly better than IMA when noise level is larger than 0.2. As shown in Fig. 10, when noise level is larger than 0.1, the noisy images look significantly different from the clean images, and those noisy images cannot be from a well-functioning CT machine and may even look like images of infection. Thus, a model robust to noises less than the level of 0.2 is good enough for this application. Also, from Fig. 9 (right), we can see that most of the estimated margins of MMA were larger than 0.3, which means most of the samples should have been free of influence of noises of magnitude less than 0.3. However, if this were true, the accuracy of MMA in Fig. 9 (left) at noise of 0.3 should not have been significantly different from that of "adv0.3". The results show that MMA significantly overestimated the margins of samples, because that MMA does not consider the equilibrium (Fig.5) between classes.

From section 1 and 2, it can be seen that the vanilla adversarial training ("adv ε") is quite good when the maximum noise level ε for training is chosen "properly". The question arises: what is the proper ε of "adv ε"? A straightforward way to find a good ϵ would be running grid-research and evaluating the performance on the validation set. However, the grid-research is impractical because adversarial training is computationally expensive and time-consuming, compared to training with cross-entropy loss on clean data. It turns out that the sample margin distribution ($\mathcal{E}$ in Algorithm 1) estimated by our method IMA indicates a good $\varepsilon = 0.1$ (Fig. 9). For this application, "adv0.1" is as competitive as other advanced methods and has a less computational cost. Although adversarial training may reduce accuracy on clean data, for this application, one can tweak the classification threshold to increase the sensitivity to infection, which is often desired.

The results also show that adding random noises to the input can improve classification accuracy on clean samples (from 0.9575 of "ce" to 0.9775 of "rand0.1"). However, random noise-based data augmentation ("rand0.1", "rand0.2" and "rand0.3") has little effect on adversarial robustness for this application, which is easy to explain: not every noise (vector) is in the direction that can drive the input across the decision boundary.

4 Conclusion

In this study, we proposed a novel Increasing-Margin Adversarial (IMA) training method to improve the robustness of DNN for classification tasks and applied it for the application of COVID-19 detection from CT images. Our method aims to increase the margins of the training samples to improve DNN robustness against adversarial attacks. The experiment results show that our method significantly improved DNN classification accuracy on noisy data while keeping a relatively high accuracy on clean data, and its performance is at least on-par with the start-of-art MMA method. We also show that the vanilla adversarial training with a properly chosen ε is as competitive as other advanced methods for the COVID-19 detection application, and our method IMA can provide a good ε for it from the sample margin distribution. We hope our approach may facilitate the development of robust DNNs, especially in the medical field.

Note: (1) we will release the code when the paper is accepted. (2) all figures are in high resolution, please zoom in.

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A APPENDIX

We encountered a problem when we were trying to evaluate IMA and MMA on cifar10.

MMA(Ding et al., 2019a) was evaluated on cifar10 with standard data augmentation (e.g. crop). Without standard data augmentation, it is impossible to achieve a classification accuracy of $> 90\%$ on clean data.

However, standard data augmentation imposes two challenges:

(1) standard data augmentation produces a random set of augmented images, and the randomness may affect robustness

(2) both IMA and MMA need to record the margin of each sample. Since the augmented images are generated online, then it is impossible to assign an ID to each augmented image. The way of MMA handling this issue is not ideal: it assigns the same ID to image x and its augmented version x_aug. In fact, x and x_aug have different margins and thus need different IDs in the margin data array. The solution could be to generate a large number of images from standard data augmentation and save those images to hard-drive before training. This solution needs a huge amount of storage and computing power (the margin of every sample needs to be expanded), which our humble research lab currently does not have.

Thus, we leave the evaluate on cifar10 (and other datasets that need standard data augmentation) to our future investigation. Our current experiments have empirically verified our theory and demonstrated the effectiveness of IMA on four datasets including a COVID-19 CT dataset.

B APPENDIX

It seems that adversarial noises are created by algorithms (e.g. PGD) and therefore it is only a security issue caused by hackers. In fact, random imaging noises could also be "adversarial" noises leading to wrong classifications. We did an additional test and found out that 2.75% of the noisy samples with uniform white noises on the level of 0.05, can cause the model "ce" to make wrong classifications. 2.75% is not a negligible number for this application. We note that CT imaging noises can be better described by Poisson distribution (Wang et al., 2008). However, without the hardware parameters of the CT machine, it is impossible to simulate Poisson noises. Nevertheless, adversarial robustness should be the built-in property of a model for this application, and all of the DNN models in the previous COVID-19 studies (Shi et al., 2020) should be checked and enhanced for adversarial robustness before deploying those models in clinics and hospitals.

C APPENDIX

Table 1: Results on Moons dataset (L-inf norm-defined noise level)

noise	0.0	0.05	0.1	0.15	0.2	0.25	0.3
IMA	1.0	0.999	0.9975	0.9915	0.9755	0.927	0.823
MMA	1.0	0.9985	0.993	0.957	0.882	0.772	0.597
TRADES	0.996	0.9805	0.9575	0.936	0.906	0.875	0.8255
adv	0.9975	0.985	0.957	0.9365	0.9095	0.883	0.822
ce	1.0	1.0	0.9975	0.9855	0.935	0.7995	0.606

Table 2: Results on Fashion-MNIST dataset (L-inf norm-defined noise level)

noise	0.0	0.05	0.1	0.15	0.2	0.25	0.3
IMA	0.89	0.789	0.6688	0.5457	0.4121	0.2715	0.1521
MMA	0.8955	0.746	0.6166	0.5051	0.3902	0.2644	0.1425
TRADES	0.9116	0.4759	0.4151	0.3722	0.3298	0.2453	0.0949
adv0.1	0.9112	0.7739	0.6613	0.4743	0.2376	0.0602	0.0046
adv0.2	0.9101	0.5879	0.5218	0.4885	0.4164	0.2199	0.0313
adv0.3	0.9132	0.3637	0.2506	0.1992	0.1671	0.1364	0.0854
ce	0.9117	0.0236	0.0	0.0	0.0	0.0	0.0

Table 3: Results on Fashion-MNIST dataset (L2 norm-defined noise level)

noise	0.0	0.5	1.0	2.0	3.0	4.0	5.0
IMA	0.8881	0.8069	0.6914	0.4711	0.3046	0.1666	0.0567
MMA	0.8926	0.807	0.6927	0.4617	0.2651	0.1361	0.0526
DDN	0.8666	0.789	0.6989	0.5066	0.3409	0.1965	0.0781
TRADES	0.9176	0.6103	0.4977	0.3425	0.1857	0.039	0.0008
adv1	0.9086	0.8096	0.6549	0.2726	0.0513	0.0015	0.0
adv3	0.9172	0.641	0.5859	0.4754	0.3325	0.1558	0.0229
adv5	0.9148	0.4851	0.4161	0.3011	0.2121	0.1419	0.075
ce	0.9117	0.2512	0.0033	0.0	0.0	0.0	0.0

Table 4: Results on SVHN dataset (L-inf norm-defined noise level)

noise	0.0	0.005	0.01	0.02	0.04	0.06	0.08	0.1
IMA	0.8919	0.8387	0.7731	0.6123	0.3461	0.1818	0.0938	0.0481
MMA	0.887	0.8357	0.771	0.6204	0.3693	0.2139	0.1216	0.0688
TRADES	0.9243	0.0995	0.0705	0.044	0.0371	0.0827	0.1748	0.1885
adv0.01	0.9152	0.8352	0.7095	0.4401	0.1174	0.0281	0.0062	0.0017
adv0.06	0.9105	0.6851	0.5737	0.5115	0.3599	0.1852	0.0784	0.0318
adv0.10	0.9209	0.2112	0.0086	0.0052	0.0048	0.0022	0.004	0.0472
ce	0.932	0.56	0.2384	0.0368	0.001	0.0	0.0	0.0

Table 5: Results on SVHN dataset (L2 norm-defined noise level)

noise	0.0	0.05	0.1	0.25	0.5	1.0	1.5	2.0
IMA	0.8995	0.8797	0.8576	0.7731	0.6012	0.2982	0.128	0.05
MMA	0.8765	0.8548	0.8322	0.7518	0.5974	0.3215	0.1519	0.0654
DDN	0.8649	0.8432	0.8184	0.7396	0.5852	0.3183	0.153	0.0669
TRADES	0.8652	0.8377	0.8076	0.6903	0.4581	0.1238	0.0256	0.0047
adv0.5	0.8986	0.876	0.849	0.7508	0.539	0.2062	0.0654	0.0208
adv1.0	0.873	0.8513	0.8284	0.7504	0.5857	0.2654	0.0955	0.0326
adv2.0	0.8663	0.8436	0.8175	0.7195	0.5458	0.2883	0.1454	0.0631
ce	0.932	0.8656	0.7588	0.4125	0.1185	0.0092	0.0006	0.0

Table 6: Results on COVID-19 CT image dataset (L-inf norm-defined noise level)

noise	0.0	0.01	0.03	0.05	0.1	0.15	0.2	0.25	0.3
IMA	0.925	0.92	0.9	0.885	0.8	0.575	0.1675	0.02	0.0025
MMA	0.915	0.91	0.9	0.8825	0.77	0.5	0.19	0.09	0.03
TRADES	0.975	0.135	0.1925	0.295	0.485	0.4825	0.485	0.485	0.485
adv0.1	0.9175	0.915	0.8975	0.8675	0.77	0.2375	0.0125	0.0	0.0
adv0.2	0.975	0.04	0.01	0.005	0.0075	0.1725	0.4475	0.405	0.3225
adv0.3	0.975	0.0775	0.0025	0.0025	0.0	0.0025	0.3175	0.49	0.4925
rand0.1	0.9775	0.155	0.0	0.0	0.0	0.0	0.0	0.0	0.0
rand0.2	0.965	0.3575	0.0	0.0	0.0	0.0	0.0	0.0	0.0
rand0.3	0.9725	0.4175	0.0	0.0	0.0	0.0	0.0	0.0	0.0
ce	0.9575	0.045	0.0	0.0	0.0	0.0	0.0	0.0	0.0

D APPENDIX

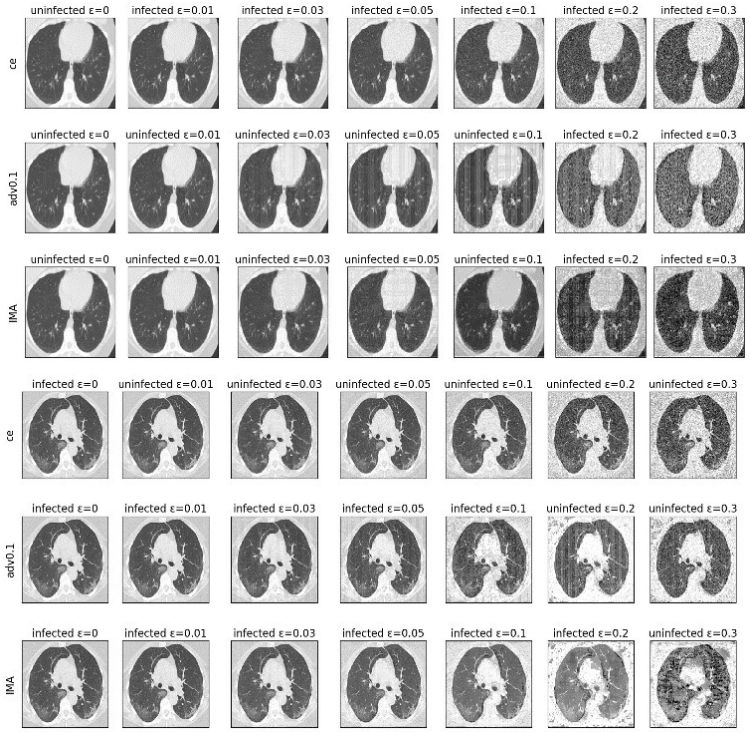

Figure 10: Each row shows a clean image and noisy images associated with a training method. The title of each image shows the predicted class label and the noise level. The clean images are correctly classified.