REINFORCING THE ROBUSTNESS OF A DEEP NEURAL NETWORK TO ADVERSARIAL EXAMPLES BY USING COLOR QUANTIZATION OF TRAINING IMAGE DATA

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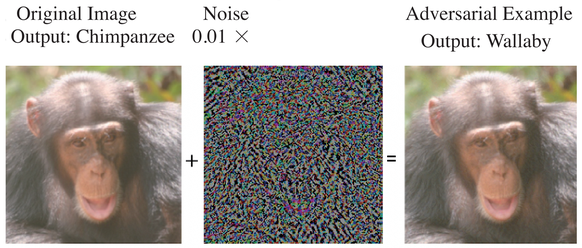
Introduction

Adversarial Example:
• Image classification using CNN is vulnerable to Adversarial Examples with small perturbation
• Adversarial Example is a possible threat to CNN used in the real-world (such as self-driving car and face-recognition).

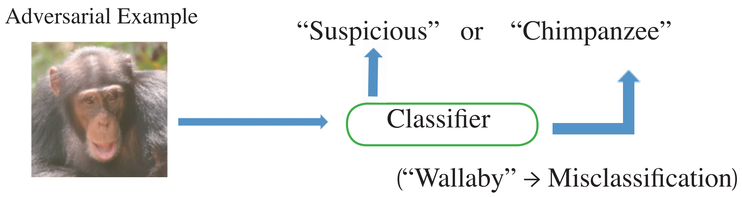


Black-Box Attack: (⇄ White-Box Attack)
• Attackers can generate Adversarial Example without knowing the parameters of the target models because of Transferability
• Transferability: Adversarial Examples for one model tend to induce misclassification through other models as well

Problem:
Detection of Adversarial Example (especially Black-Box Attack) or robustness to Adversarial Example is needed

Contribution

• Loss Mazimization (through color quantization of training data)
• We generated an ensemble of models which can classify Adversarial Examples correctly or reject them as undecidable

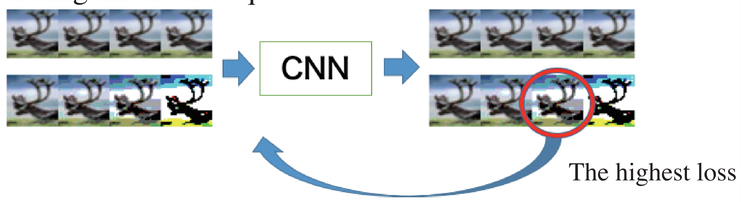


Proposed Method

Color Quantization:
Adversarial noise contains small features
→ Training data are quantized so that models learn only conspicuous features and become insensitive to small features

(TQ means test data are quantized as well for comparison)

Loss Maximization (LM):
Recent works show training by high-loss adversarial examples can generate more robust CNN
→ The loss is maximized immediately before backpropagation by selecting the level of quantization



Ensemble (En):
ResNet-20, VGG-16 and DenseNet trained using LM
• Majority rule (MR): Only if two or three models output the same inference, the image is accepted and the ensenble outputs it
• Unanimous rule (UR): Only if three models output the same inference, the image is accepted

Settings

Dataset: Cifar10 (10, 000 images as test data)
Attack Method: FGSM + Black Box (Attacker know VGG16 trained by the original images)
Comparative Method: Adversarial Training (ResNet-20 trainied using Adversarial Examples with noise which size is 8/255 or 2/255)

Results

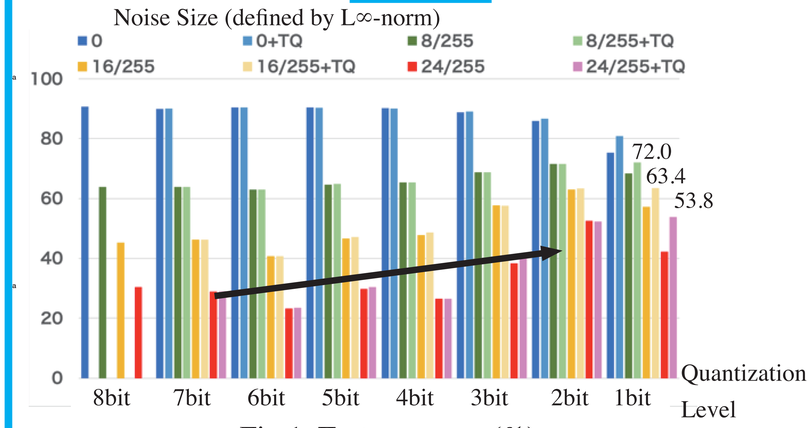


Fig 1. Test accuracy (%)

Table 1. Test accuracy (%) . The values in parentheses show the numbers of accepted data. F-AT means Adversarial Trainig.

Method	Noise Size			
	0	8/255	16/255	24/255
ResNet 8bit	90.7	63.9	45.2	30.4
VGG 8bit	91.2	64.6	57.0	45.7
DenseNet 8bit	92.3	64.8	49.1	29.5
F-AT 8/255	81.3	77.7	70.5	61.4
F-AT 2/255	88.3	80.6	71.1	56.6
LM-ResNet	86.0	74.7	65.1	54.3
LM-VGG	86.7	75.3	68.0	63.0
LM-Dense	87.1	75.8	65.3	50.7
MR-En	94.5(9850)	66.9(9273)	57.6(8976)	38.7(8819)
UR-En	**98.0**(8654)	79.5(6898)	72.7(5253)	41.7(4174)
LM-MR-En	90.0(9736)	78.5(9556)	70.4(9414)	62.5(9129)
LM-UR-En	95.9(8090)	**88.0**(7561)	**82.4**(6966)	**74.5**(5750)

Conclusion

• LM improves the robustness compared with simple quantization.
• The ensemble with LM increases the accuracy of the accepted examples to a better level than F-AT.