### SaliencyMix: A Saliency Guided Data Augmentation Strategy for Better Regularization

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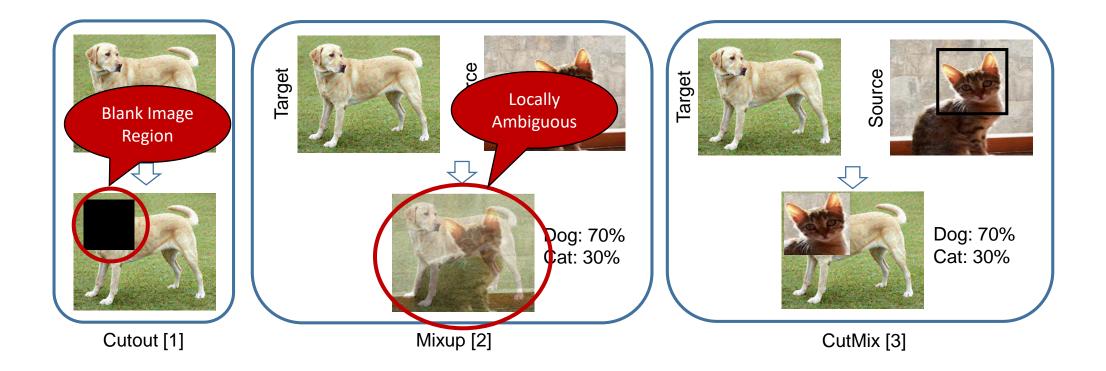
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# **Advanced Data Augmentation Techniques**



- Better regularization technique helps to improve model robustness and performance
- Recently, several effective data augmentation strategies have been proposed

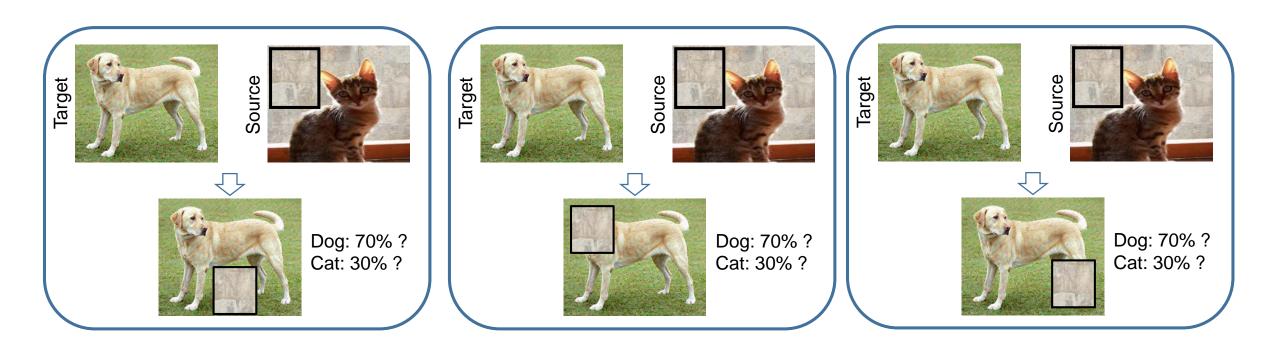




### **Motivation**



- Limitation of CutMix [3]
  - Random selection of the source patch may not always represent the source object



Guides the model to learn

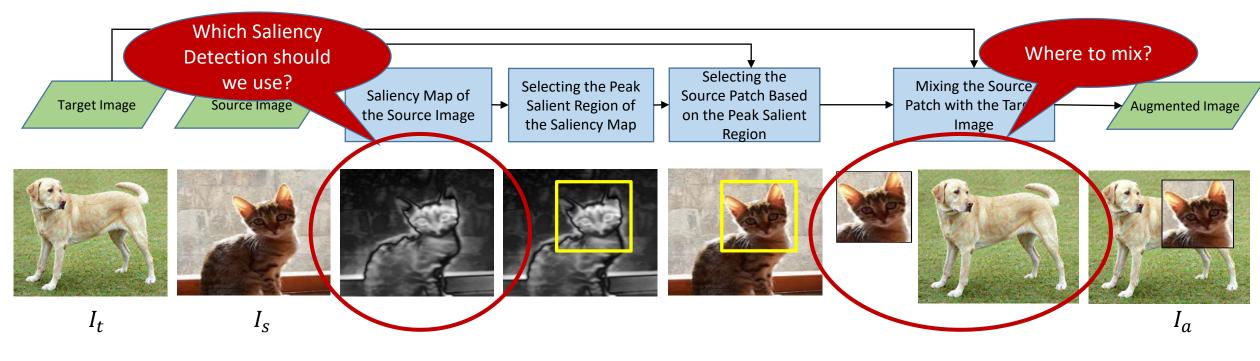
as Cat feature !!!

May mislead the classifier?

Proposed Method

# Our Approach: SaliencyMix

- Proposed approach
  - 1. Extract the Saliency map [4] of the source image
  - 2. Select and cut the most salient region of the source image
  - 3. Then mix the source patch with the target image based on a mixing ration  $\lambda$



Augmented Image  $I_a = M \odot I_s + M' \odot I_t$ 

Augmented Label  $y_a = \lambda y_t + (1 - \lambda)y_s$ 

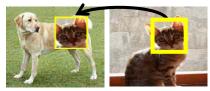
Classification Error (%)

# **Our Approach: SaliencyMix**

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- Effect of various Saliency Detection methods
- Several strategy of **source patch** selection and mixing

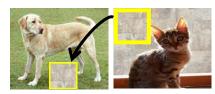












CIFAR10 CIFAR10 Tiny ImageNet Tiny ImageNet 5.0 [9] 5 4 [5]  $\geq$ [9] 4 4.5 4.5 45 40 4.0 40 4.0I I 35 1 3.5 Ŧ 3.5 35 30 Non-Sal to Non-Sal Soto - Montabone & Soto 3.0 Non-Sal to Non-Sal Frequency Tuned Spectral Residual Frequency Tuned 3.0 30 **Spectral Residual Center to Center** Center to Center 25 2.5 25 2.5 Non-Sal to Sal ø Sal to Non-Sal Non-Sal to Sal 20 Sal to Non-Sal 2.0 20 2.0 Montabone Sal to Corr Sal to Corr Sal to Sal Baseline 15 Sal to Sal - Baseline 1.5 1.5 15 BASNet BASNet 10 1.0 10 1.0 0.5 5 0.5 5 0.0 0.0 37.63 45.05 38.56 36.03 38.27 36.05 43.37 44.12 44.53 3.0 37.10 36.79 4.20 4.45 4.72 3.94 3.87 <u> 3</u>.65 A.23 4.18 A.34 N.43 Source and Target Patch Mixing Style Saliency Detection Method Source and Target Patch Mixing Style Saliency Detection Method (c) (d)

Introduction

**Proposed Method** 

**Experimental Result** 

Conclusion



# **Experimental Result**



### **Image Classification**

#### CIFAR dataset

Manuan	TOP-1 ERROR (%)					
Method	CIFAR-10	CIFAR-10+	CIFAR-100	CIFAR-100+		
RESNET-18 (BASELINE)	$10.63 \pm 0.26$	$4.72 \pm 0.21$	$36.68 \pm 0.57$	$22.46 \pm 0.31$		
RESNET-18 + CUTOUT	$9.31 \pm 0.18$	$3.99 \pm 0.13$	$34.98 \pm 0.29$	$21.96 \pm 0.24$		
RESNET-18 + CUTMIX	$9.44 \pm 0.34$	$3.78 \pm 0.12$	$34.42 \pm 0.27$	$19.42 \pm 0.23$		
ResNet-18 + SaliencyMix	$7.59 {\pm} 0.22$	$3.65 {\pm} 0.10$	$28.73 {\pm} 0.13$	$19.29 {\pm} 0.21$		
RESNET-50 (BASELINE)	$12.14 \pm 0.95$	$4.98 \pm 0.14$	$36.48 {\pm} 0.50$	$21.58 \pm 0.43$		
ResNet-50 + Cutout	$8.84 {\pm} 0.77$	$3.86 {\pm} 0.25$	$32.97 \pm 0.74$	$21.38 \pm 0.69$		
RESNET-50 + CUTMIX	$9.16 \pm 0.38$	$3.61 \pm 0.13$	$31.65 \pm 0.61$	$18.72 \pm 0.23$		
ResNet-50 + SaliencyMix	$6.81 {\pm} 0.30$	$3.46 {\pm} 0.08$	$24.89 {\pm} 0.39$	$18.57 {\pm} 0.29$		
WIDERESNET-28-10 (BASELINE)	$6.97 \pm 0.22$	$3.87 \pm 0.08$	$26.06 \pm 0.22$	$18.80 {\pm} 0.08$		
WIDERESNET-28-10 + CUTOUT	$5.54 {\pm} 0.08$	$3.08 \pm 0.16$	$23.94{\pm}0.15$	$18.41 \pm 0.27$		
WIDERESNET-28-10 + AUTOAUGMENT	-	$2.60 {\pm} 0.10$	-	$17.10 \pm 0.30$		
WIDERESNET-28-10 + PUZZLEMIX (200 EPOCHS)	-	-	-	16.23		
WIDERESNET-28-10 + CUTMIX	$5.18 \pm 0.20$	$2.87 \pm 0.16$	$23.21 \pm 0.20$	$16.66 \pm 0.20$		
WIDERESNET-28-10 + SALIENCYMIX	$4.04 {\pm} 0.13$	$2.76 \pm 0.07$	$19.45{\pm}0.32$	$16.56 \pm 0.17$		

#### ImageNet dataset

Метнор	TOP-1	TOP-5	
METHOD	Error (%)	Error (%)	
RESNET-50 (BASELINE)	23.68	7.05	
ResNet-50 + Cutout	22.93	6.66	
ResNet-50 + StochasticDepth	22.46	6.27	
ResNet-50 + Mixup	22.58	6.40	
ResNet-50 + Manifold Mixup	22.50	6.21	
ResNet-50 + AutoAugment	22.40	6.20	
ResNet-50 + DropBlock	21.87	5.98	
ResNet-50 + CutMix	21.40	5.92	
RESNET-50 + PUZZLEMIX	21.24	5.71	
ResNet-50 + SaliencyMix	21.26	5.76	
ResNet-101 (BASELINE)	21.87	6.29	
ResNet-101 + Cutout	20.72	5.51	
ResNet-101 + Mixup	20.52	5.28	
ResNet-101 + Cutmix	20.17	5.24	
ResNet-101 + SaliencyMix	20.09	5.15	



#### Transfer Learning on Object Detection Task

BAC	KBONE NETWORK	IMAGENET Cls. Err. Top-1 (%)	DETECTION (F-RCNN) (MAP)
RES	NET-50 (BASELINE)	23.68	76.71 (+0.00)
CUT	OUT-TRAINED	22.93	77.17 (+0.46)
MIX	UP-TRAINED	22.58	77.98 (+1.27)
CUT	MIX-TRAINED	21.40	78.31 (+1.60)
SAL	IENCYMIX-TRAINED	21.26	78.48 (+1.77)

SaliencyMix trained model offers **1.77** % performance **improvement** 

#### Adversarial Robustness

	BASELINE	CUTOUT	MIXUP	CUTMIX	SALIENCYMIX
ACC. (%)	8.2	11.5	24.4	31.0	32.96

SaliencyMix trained model shows **better robustness** 

#### Computational Complexity

	BASELINE	CUTOUT	MIXUP	CUTMIX	SALIENCYMIX
TIME (HOUR)	0.83	0.84	0.87	0.89	0.91

*c* Computational burden slightly **increased** due to saliency detection



# Conclusion



- SaliencyMix is an effective data augmentation technique
  - Offers the CNN with greater regularization ability
  - o Improves the model performance
    - Classification
      - WideResNet: Best known top-1 error of 2:76% and 16:56% on CIFAR-10 and CIFAR-100, respectively
      - F ResNet-50: Best known top-1 error of 21.26% on ImageNet
      - F ResNet-101: Best known top-1 error of **20.09%** on ImageNet
    - Object Detection
      - SaliencyMix trained model improves detection performance by +1.77 mAP
    - Robustness against adversarial attack
      - SaliencyMix trained model achieves 1:96% accuracy improvement on adversarially perturbed ImageNet validation set





#### References

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Introduction

Motivation

**Proposed Method** 

**Experimental Result**