

Advanced Data Augmentation Approaches: A Comprehensive Survey and Future directions

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Abstract—Deep learning (DL) algorithms have shown significant performance in various computer vision tasks. However, having limited labelled data lead to a network overfitting problem, where network performance is bad on unseen data as compared to training data. Consequently, it limits performance improvement. To cope with this problem, various techniques have been proposed such as dropout, normalization and advanced data augmentation. Among these, data augmentation, which aims to enlarge the dataset size by including sample diversity, has been a hot topic in recent times. In this article, we focus on advanced data augmentation techniques, we provide a background of data augmentation, a novel and comprehensive taxonomy of reviewed data augmentation techniques, and the strengths and weaknesses (wherever possible) of each technique. We also provide comprehensive results of the data augmentation effect on three popular computer vision tasks, such as image classification, object detection and semantic segmentation. For results reproducibility, we compiled available codes of all data augmentation techniques. Finally, we discuss the challenges and difficulties, and possible future direction for the research community. We believe, this survey provides several benefits i) readers will understand the data augmentation working mechanism to fix

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overfitting problems ii) results will save the searching time of the researcher for comparison purposes. iii) Codes of the mentioned data augmentation techniques are available at ¹ iv) Future work will spark interest in research community.

Index Terms—Big data, Computer vision, Data Augmentation, Deep learning, Image classification, Object detection, Semantic segmentation, Survey Data Augmentation

I. INTRODUCTION & MOTIVATION

Deep learning models have been very popular and made immense progress in computer vision (CV) tasks such as image classification [11], [48], [60], [68], [70], [71], [103], [110], object detection [40], [47], and image segmentation [74], [79], [81], [86]. All this advancement has been accelerated by different deep neural network architectures, powerful computation resources, a large amount of accessible data, and mature deep learning libraries. Among the deep learning models, Convolution Neural Networks (CNNs) have performed well on computer vision tasks. CNNs apply the convolution operation with the input image and kernel to learn different features in an image. The initial layers of CNN learn the low-level features (i.e edges, lines, etc) while the deep layers learn more structured complex features. The success of CNN has caught the attention to apply it for computer vision tasks. Along with CNN, the Vision Transformers (ViT) [28] are also

¹<https://github.com/kmr2017/Advanced-Data-augmentation-codes>

getting popular and have been widely used in deep learning for computer vision tasks. Although these algorithms are popular and have shown excellent performance in deep learning, they require a lot of data to learn the correct features and avoid overfitting problem [104]. Overfitting is when a model is performing well on training data but is not performing on the test (unseen) data, as shown and explained in figure 1. However, data is not always available in large quantities due to various reasons such as privacy issues (e.g., medical imaging analysis) or the need for tedious human labeling (object detection, image segmentation) etc [108]. Another reason is, it is always tedious, time-consuming and expensive to label data in the case of an availability of unlabeled data [71]. Even in the availability of huge datasets such as imageNet, data augmentation can still help to reduce overfitting effect. It happens because, with a standard training process, the model learns only the important regions (for example head of a dog). But it is also necessary for the model to learn other less important features to be more generalized [146]. The CNNs trained on the small set of data often lead to overfitting. Another concern is the adversarial attacks [50], [88], [152], where the noisy perturbation is added to the input image to fool the CNNs and consequently degrade DNNs accuracy. This modification caused by perturbation is invisible to the human eyes but makes the network fail to identify the correct features in an image.

To address these problems, data augmentation is mostly applied. It is not only useful in computer vision tasks, but also helpful in number of domains such as audio [3], [12], [65], [72], [92], [95], [111], [124] and text domains [6], [33], [84], [109] as well. In this survey, we focus only the computer vision domain.

Regularization is a technique that generalizes well the model from architectural and data perspectives. There are several forms of regularization such as Dropout [117], Batch normalization [56], transfer learning [107], [137], pre-training [30], data augmentation [154], human-in-the-loop for data augmentation [10] and many others [108]. Data augmentation is the form of regularization explicitly [69], [110], [154]. Technically, it enlarges the dataset by changing the sample view or flavour [154] to give a diverse view. Other mentioned techniques do not work directly on data like data augmentation as the data is the main cause of any problem for training. If it has an overfitting issue or is biased, it will be propagated to the model as well. Carefully performing data augmentation is the key challenge as it is discussed in section IV. Data augmentation is performed on assumption that more information can be extracted from the real dataset. But this assumption is not true in real world scenario.

Generally, data augmentation solves two key problems. i) the problem of lack of data or limited data, consequently it leads to problem of overfitting. To solve the overfitting, data augmentation makes the model more generalized based on scenario(s). This can be achieved by feeding the various possible scenarios of an image. This indicates more information is extracted indirectly from the original dataset. ii) Labeling, the original

dataset has a label for each sample. Augmenting each sample, the label is assigned to the augmented sample as that of the original sample. In some augmentations, the label information is not preserved such as in Mixup data augmentation, labels are also mixed to augment a label.

There are numerous surveys on data augmentation. Wang et al. [98] explores and compares several traditional data augmentations for image classification tasks only. In another work, Wang et al. [130] review available data augmentation approaches for facial data. This work is only limited to face recognition. Khosla et al. [61] discuss warping and oversampling-based data augmentation approaches. No taxonomy, no literature review and no evaluation of the methods are discussed. Shorten et al. [108] provide a very detailed work with different aspects of data augmentation, but they did not provide an evaluation of the data augmentation for different CV tasks and they did not include state-of-the-art (SOTA) augmentation methods such as cutmix and grid mask etc. Previously the discussed surveys have been two years old and in the last the years, there have been proposed several data augmentation techniques, so it is a dire need for a survey. Recently Yang et al. [142] provides a detailed survey with results of several computer vision tasks. Very limited results are compiled and SOTA data augmentation methods are not covered. Another recently work [141] by Xu, discusses the data augmentation that is model-based and model-free and, proposes novel taxonomy. But this work fails to provide the evaluation of the data augmentation and discusses very limited data augmentations. There are the number of the data augmentation based on generative adversarial network (GAN) [118], [145], but we do not cover GAN-based data augmentations in this work, as GAN is itslef vast topic and GAN-based techniques are very huge in number Interestingly, none of the mentioned works provides extensive evaluations of SOTA data augmentation and available code compilation based on the proposed taxonomy for result reproducibility. To fill these mentioned gaps, our survey makes the following contributions:

- Presents novel Data augmentation taxonomy.
- Explains SOTA augmentation approaches with visualization.
- Presents SOTA augmentation evaluation for several tasks.
- Compiles the available codes of data augmentations following the proposed taxonomy for results reproducibility.
- This survey discusses data augmentation challenges and future directions
- This survey provides open research questions

The above contributions provide the following benefits:

- A better understanding of data augmentation working mechanism to fix the overfitting problem.
- Our comprehensive analysis and comparison between the existing data augmentation techniques will save researchers' time searching this field.
- facilitate result reproducibility by providing the source code for the different data augmentation techniques in-

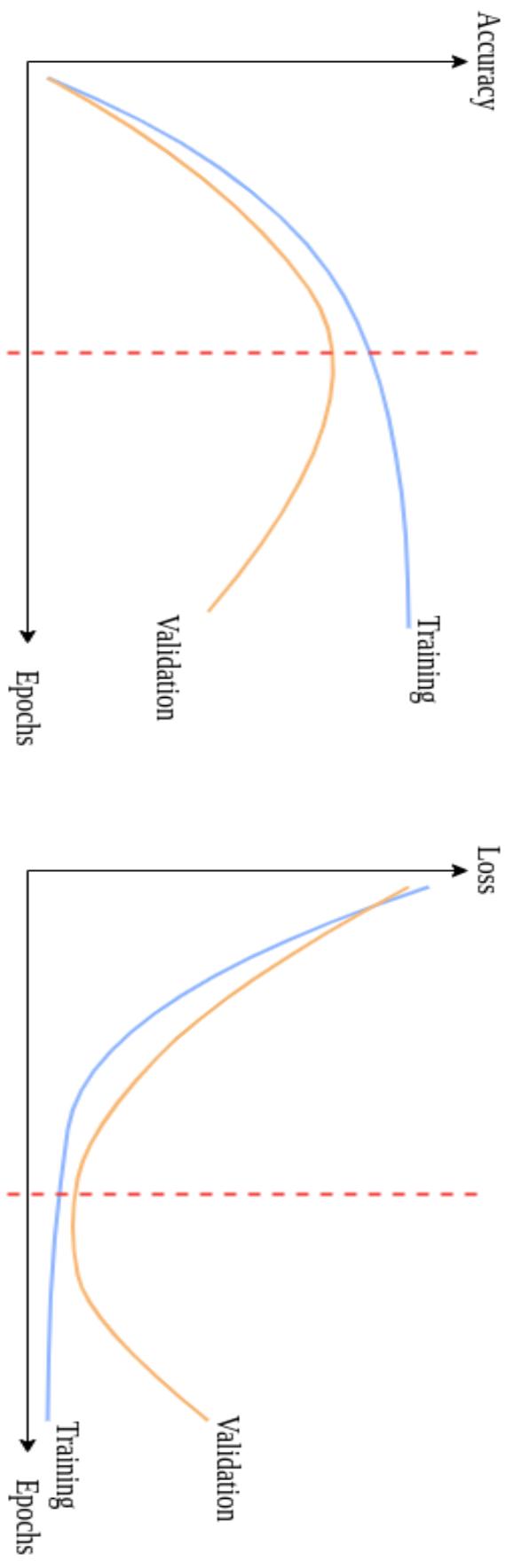


Fig. 1. Overfitting problem: On the left side, overfitting is explained in terms of accuracy, after the inflation point (red dotted line), the training accuracy is increasing but validation accuracy is decreasing. On the right side, alternatively in terms of loss, training loss is decreasing but validation loss is increasing after the red dotted line. The figure is taken from the source ³<https://www.baeldung.com/cs/ml-underfitting-overfitting>

vestigated.

- Future work will spark interest in the research community.

II. TAXONOMY AND BACKGROUND

In this section, we discuss the proposed taxonomy as shown in the figure 2, first data augmentation is classified into two branches, i) basic data augmentations ii) Advanced data augmentations. Then these two are classified further based on operations. Background and explanation of each augmentation are discussed below taxonomically:

A. Basic Data Augmentation Methods

This section describes basic data augmentation methods and classifies the augmentation techniques.

1) **Image Manipulation:** Image manipulation refers to the changes made in an image with respect to its position or color. The positional manipulation is made by adjusting the position of the pixels while color manipulations are made by altering the pixel values of the image. Image manipulation is further divided into two main categories. Each of them is discussed below.

Geometric Data Augmentation: Geometric augmentation refers to the changes made with respect to the image geometry. Geometry refers to position, shifting at certain angle etc. This technique alters the position of pixel values in image. e.g. Rotation, Translation, and Shearing. Basic geometric augmentations are shown in figure 3.

- (i) **Rotation :** Rotation data augmentation where image is rotated between 0 and 360 degree. Degree of rotation is a hyperparameter, it should be chosen wisely. Like in case MNIST we can not rotate 180 rotations, i.e. rotation 6 digit by 180 degree, it will be 9. So it won't make sense. It depends on the dataset.
- (ii) **Translation :** It is another geometric type data augmentation, which shifts the image in upward, downward, right or left direction to give diverse view. The demonstration is shown in the second of the figure 3.

(iii) **Shearing :**

Word ‘shear’ means to pervert an image along an axis. Shearing is a data augmentation technique that shifts one part of the image to one direction, while the other part is in the reverse direction. Technically, it is divided into two categories, x shear and y shear. In x shear, the top part of the image is shifted in one direction and the bottom is shifted in the totally opposite direction. In y shear, the left part of the image is shifted in one direction and the right part is shifted in the reverse direction.

2) **Non-Geometric Data Augmentations:** This category focuses on the visual appearance of the image rather than its geometrical shape. Noise injection, flipping, cropping, resizing, and color space manipulation is examples of non-geometric augmentation techniques. Some examples of non-geometric data augmentations are shown in figure 4. A few classical approaches are discussed below.

(i) **Flipping :** it is a kind of data augmentation technique that flips the image either horizontally or vertically, it has shown positive results on the most popular datasets such as cifar10, cifar100 [67] and many more.

(ii) **Cropping and resizing :** Cropping is another data augmentation technique that is used as a preprocessing augmentation. Either random cropping or central cropping is used as data augmentation. This technique decreases the size of the image then resizing is performed to match the original size of the image, while the labels of the image are not smoothed.

(iii) **Noise Injection :** Injection noise is another technique of data augmentation, that helps neural networks to learn robust features and is quite helpful in defending against adversarial attacks. Nine datasets from the UCI repository have shown impressive results (Reference from [108]).

(iv) **Color Space:** Images having dimensions of $H \times W \times C$ (where H, w and C represent the height, width and channels, respectively) consist of three channels R, G and B. Manipulating each channel values separately in order to control brightness is another way of data augmentation, sometimes it is also referred as photometric augmentation. This augmentation is useful for avoiding the model to be biased toward lightning conditions. The Simplest way of performing color space augmentation is to isolate any channel and add 2 channels filled with any random value or 0 or 255. Color space is used in photo editing applications i.e. to control the brightness or darkness [108].

(v) **Jitter:** It is another data augmentation technique, that randomly changes the brightness, contrast and saturation and hue of the image. These four are the hyperparameters and their range (min-max) should be chosen carefully. For example, if we increase the brightness of X-Ray images for lung disease detection, it will whiten and mix the lung in X-ray and won't help disease diagnosis. (examples will be shown).

(vi) **Kernel Filters:** it is another data augmentation technique that sharpens or blurs the image. It starts first, we slide the window of size $n \times n$ kernel/matrix of gaussian blur filter or edge filter. Gaussian blur filter blurs the image and the edge filter sharpens the edge of the image either horizontally or vertically.

3) *Image Erasing Data Augmentations:*

a) **Cutout:** It randomly erases the sub region and fills with 0 or 255 in an image during training. It shows the impressive performance on very popular datasets [27]. The demonstration of cutout is shown in figure 16.

b) **Random erasing:** It [154] randomly erases the sub region in the image like a cutout. But it also randomly determines to mask out or not and also determines the aspect ratio and size of the masked region. Random erasing demonstration for different tasks is shown in figure 5.

c) **Hide-and-Seek:** The key idea of hide-and-seek data augmentation [114] is to divide the image into uniformly squares of random size and randomly remove a random

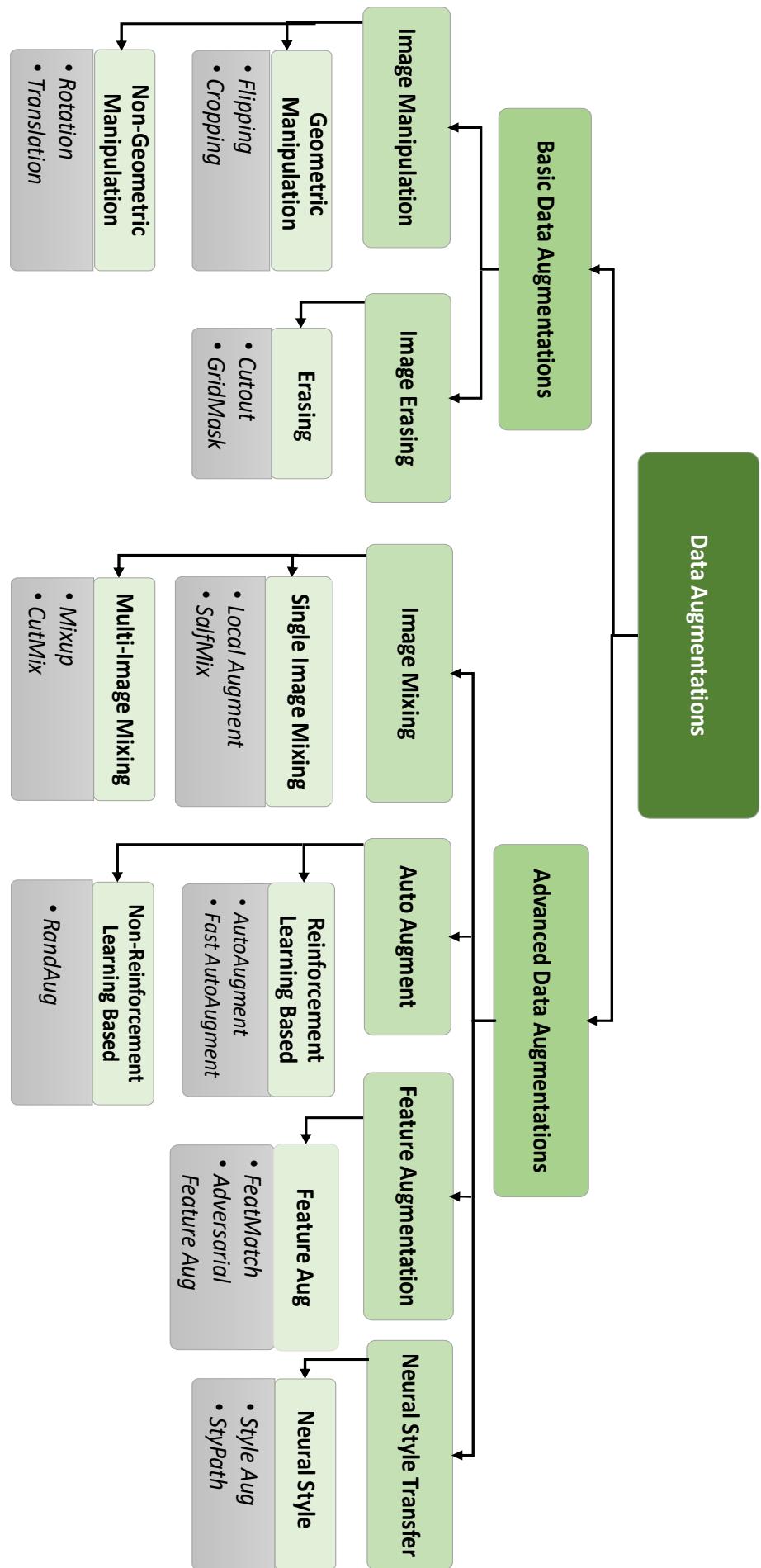


Fig. 2. Proposed image data augmentation taxonomy

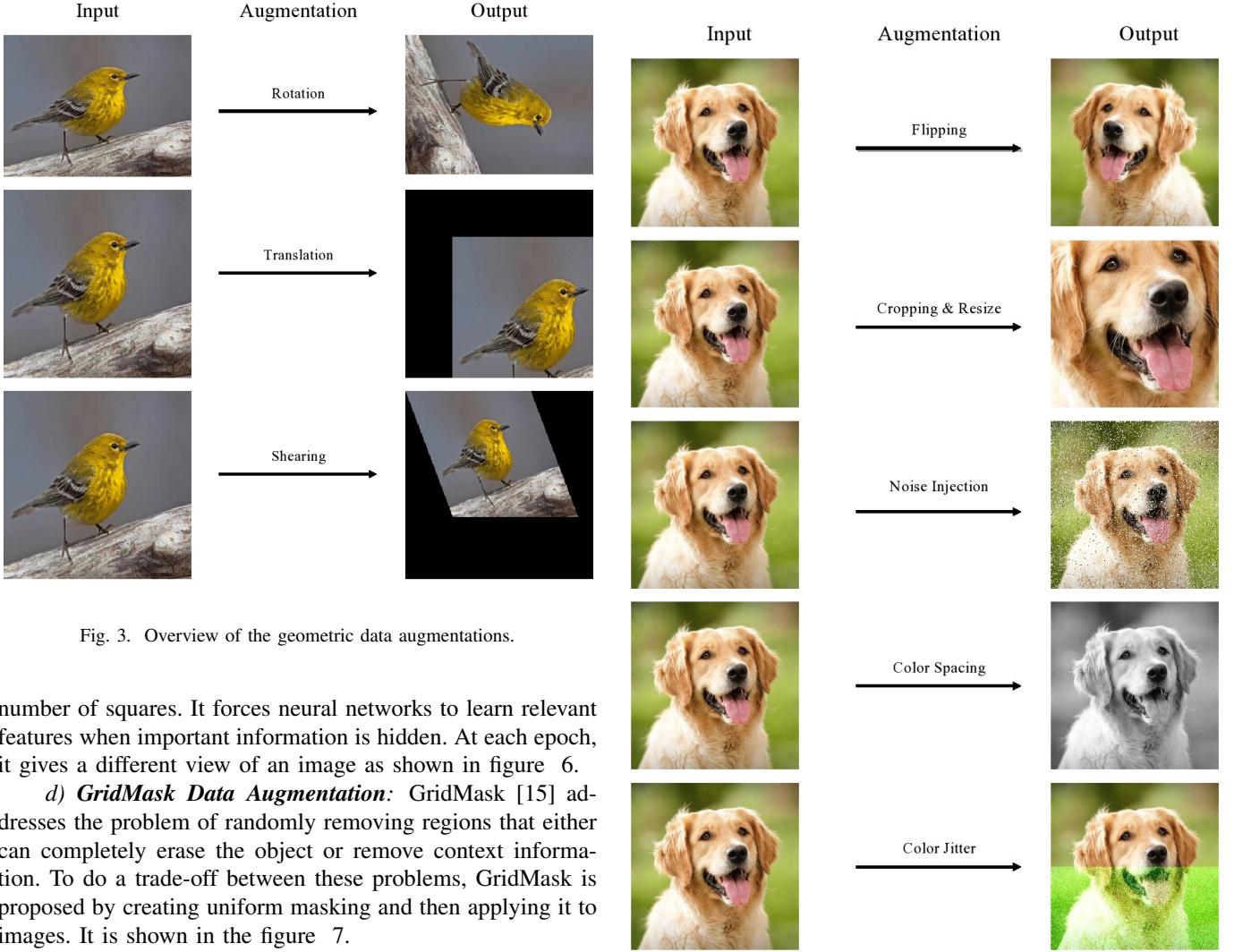


Fig. 3. Overview of the geometric data augmentations.

number of squares. It forces neural networks to learn relevant features when important information is hidden. At each epoch, it gives a different view of an image as shown in figure 6.

d) GridMask Data Augmentation: GridMask [15] addresses the problem of randomly removing regions that either can completely erase the object or remove context information. To do a trade-off between these problems, GridMask is proposed by creating uniform masking and then applying it to images. It is shown in the figure 7.

B. Image Mixing Data Augmentations

Image mixing data augmentation has been a hot topic for the last few years. Image mixing data augmentation is about mixing image(s) with others or the same image(s). In this work, we classify the image mixing data augmentation into two categories:

- Single image mixing
- Non-single image mixing

• Single Image Mixing Data Augmentations

The single image mixing technique uses only one image and plays around with it from different strategic points of view. Recently there has been a lot of work done on single-image augmentation, such as LocalAugment, SelfAugmentation, SalfMix, etc. The description of each SOTA single image mixing data augmentation has been discussed below.

(i) **Local Augment:** This paper [64] proposes a local augment, that divides image into patches and applies different kinds of data augmentation on each with the aim of potentially changing bias properties but generating significant local features, as shown in the figure below.

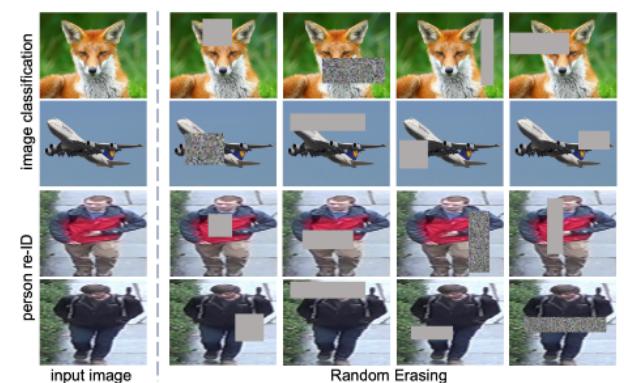


Fig. 5. Random erasing examples for different tasks. Figure source is [154]

Method	Accuracies			
	CIFAR10	CIFAR10+	CIFAR100	CIFAR100+
ResNet-18 (Baseline)	89.37	95.28	63.32	77.54
ResNet-18 + CutOut	90.69	96.25	65.02	80.58
ResNet-18 + Random Erasing	95.28	95.32	-	-
ResNet-18 + CutMix	90.56	96.22	65.58	80.58
ResNet-18 + SaliencyMix	92.41	96.35	71.27	80.71
ResNet-18 + GridMask	95.28	96.54	-	-
ResNet-50 (Baseline)	87.86	95.02	63.52	78.42
ResNet-50 + CutOut	91.16	96.14	67.03	78.62
ResNet-50 + CutMix	90.84	96.39	68.35	81.28
ResNet-50 + SaliencyMix	93.19	96.54	75.11	81.43
WideResNet-28-10 (Baseline) [125]	93.03	96.13	73.94	81.20
WideResNet-28-10 + CutOut [27]	94.46	96.92	76.06	81.59
WideResNet-28-10 + Random Erasing	96.2	96.92	81.59	82.27
WideResNet-28-10 + GridMask	96.13	97.24	-	-
WideResNet-28-10 + CutMix	94.82	97.13	76.79	83.34
WideResNet-28-10 + PuzzleMix	-	-	-	83.77
WideResNet-28-10 + SaliencyMix	95.96	97.24	80.55	83.44

Note: + sign after dataset name show that traditional data augmentation methods have been used

TABLE I

BASELINE PERFORMANCE COMPARISON OF VARIOUS AUGMENTATION ON CIFAR10 AND CIFAR100 DATASETS.

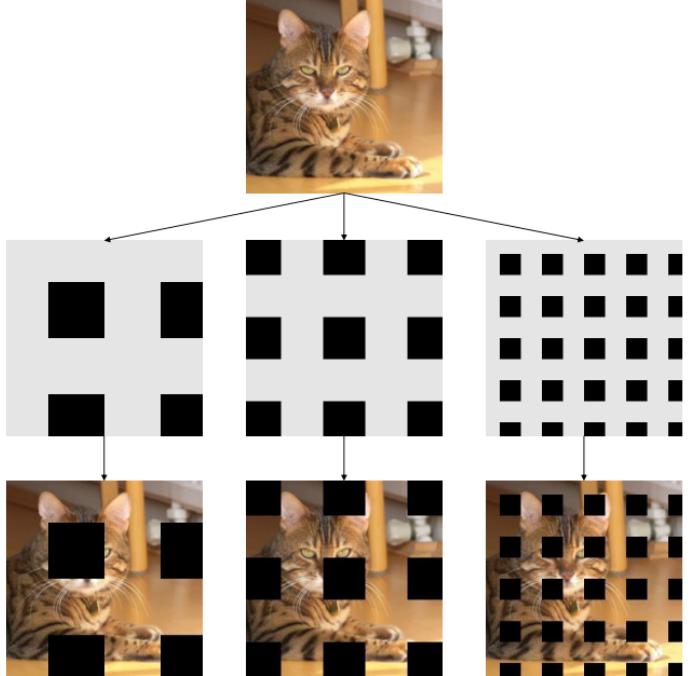
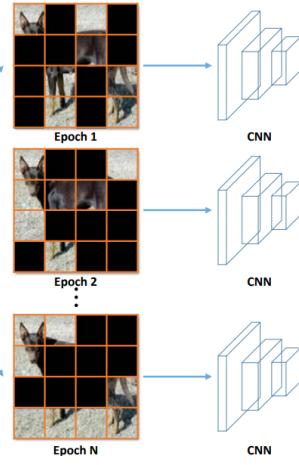
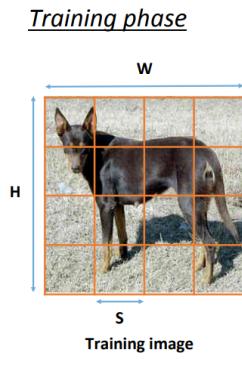


Fig. 6. An example of Hide-and-Seek augmentation, image is taken from [114]

Though this augmentation does not main global structure but provides very diverse features of images, that are essential for neural networks to learn local features in a more generalised way. The visual representation is shown in figure 8 and 9.

- (ii) **Self Augmentation:** This paper [106] proposes the self-augmentation, where a random region of an image is cropped and pasted randomly in the image, improves the generalization capability in few-shot learning. The process demonstrated in the figure 10.
- (iii) **SelfMix:** This paper [20] focuses on whether it is possible to generalize neural networks based on single-image mixed augmentation? For that purpose, it proposes SelfMix, the first salient part of the image is found to decide which part should be removed and which

Fig. 7. This figure shows the procedure of GridMask augmentation. They produce a mask and then multiply it with the input image, the image is taken from [15].

- portion should be duplicated. Most salient regions are cropped and placed into non-salient regions. This process is defined and compared with other techniques in the figure 11.
- (iv) **KeepAugment** KeepAugment [41] is introduced to prevent distribution shift which degrades the performance of neural networks. KeepAugment's idea is to increase

Augmentation	CIFAR-10		CIFAR-100		ImageNet	
	Accuracy (%)	Model	Accuracy (%)	Model	Accuracy (%)	Model
Cutout [27]	97.04	WRN-28-10	81.59	WRN-28-10	77.1	ResNet-50
Random Erasing [154]	96.92	WRN-28-10	82.27	WRN-28-10	-	-
Hide-and-Seek [114]	95.53	ResNet-110	78.13	ResNet-110	77.20	ResNet-50
GridMask [15]	97.24	WRN-28-10	-	-	77.9	ResNet-50
LocalAugment [64]	-	-	95.92	WRN-22-10	76.87	ResNet-50
SaltMix [20]	96.62	PreActResNet-101	80.11	PreActResNet-101	-	-
KeepAugment [41]	97.8	ResNet-28-10	-	-	80.3	ResNet-101
Cut-Thumbnail [140]	97.8	ResNet-56	95.94	WRN-28-10	79.21	ResNet-50
MixUp [147]	97.3	WRN-28-10	82.5	WRN-28-10	77.9	ResNet-50
CutMix [146]	97.10	WRN-28-10	83.40	WRN-28-10	78.6	ResNet-50
SaliencyMix [125]	97.24	WRN-28-10	83.44	WRN-28-10	78.74	ResNet-50
PuzzleMix [63]	-	-	84.05	WRN-28-10	77.51	ResNet-50
FMix [45]	98.64	Pyramid	83.95	Dense	77.70	ResNet-101
MixMo [101]	96.38	WRN-28-10	82.40	WRN-28-10	-	-
StyleMix [52]	96.44	PyramidNet-200	85.83	PyramidNet-200	77.29	PyramidNet-200
RandomMix [85]	98.02	WRN-28-10	84.84	WRN-28-10	77.88	WRN-28-10
MixMatch [9]	95.05	WRN-28-10	74.12	WRN-28-10	-	-
ReMixMatch [8]	94.71	WRN-28-2	-	-	-	-
FixMatch [115]	95.69	WRN-28-2	77.04	WRN-28-2	-	-
AugMix [49]	-	-	-	-	77.6	ResNet-50
Improved Mixed-Example [120]	96.02	ResNet-18	80.3	ResNet-18	-	-
RICAP [122]	97.18	WRN-28-10	82.56	ResNet-28-10	78.62	WRN-50-2
ResizeMix [100]	97.60	WRN-28-10	84.31	WRN-28-10	79.00	ResNet-50
AutoAugment [23]	97.40	WRN-28-10	82.90	WRN-28-10	83.50	AmoebaNet-C
Fast AutoAugment [82]	98.00	SS(26 2x96d)	85.10	SS(26 2x96d)	80.60	ResNet-200
Faster AutoAugment [46]	98.00	SS(26 2 x 112d)	84.40	SS(26 2x96d)	75.90	ResNet-50
Local Patch AutoAugment [83]	98.10	SS(26 2 x 112d)	85.90	SS(26 2x96d)	81.00	ResNet-200
RandAugment [24]	98.50	PyramidNet	83.30	WRN-28-10	85.00	EfficientNet-B7

TABLE II

PERFORMANCE COMPARISON OF THE VARIOUS IMAGE ERASING AND IMAGE MIXING AUGMENTATIONS FOR IMAGE CLASSIFICATION PROBLEMS. WRN STANDS FOR WIDERESNET AND SS FOR SHAKE-SHAKE.

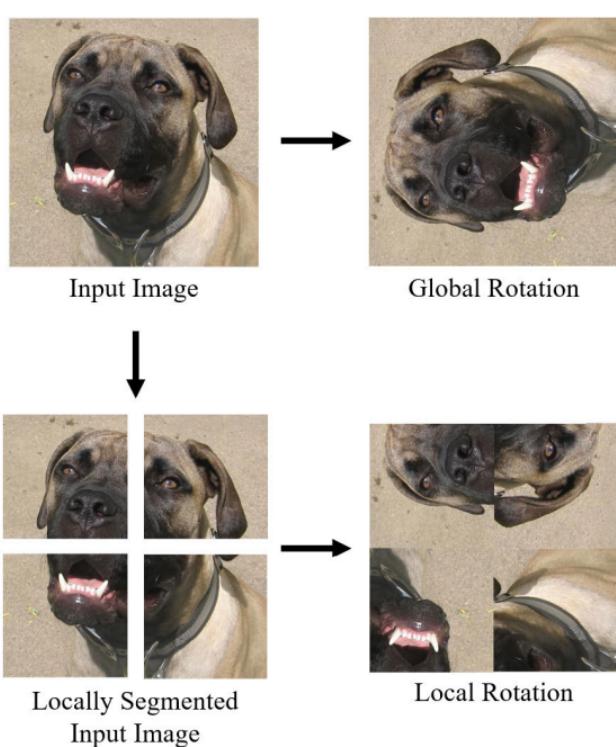


Fig. 8. An example of Global and Local Rotation Image, example is taken from [64].

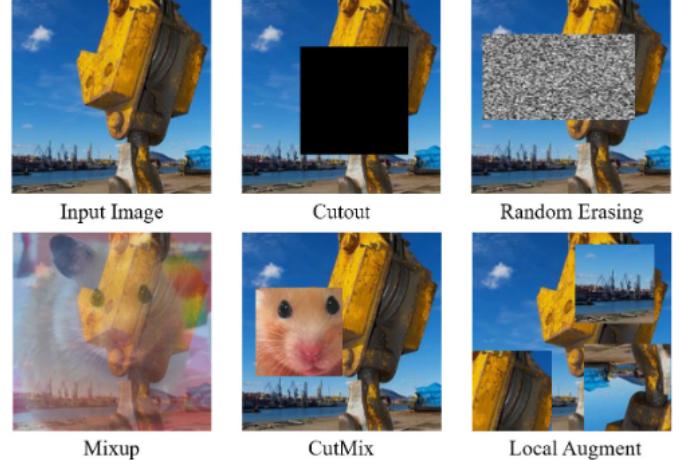


Fig. 9. Comparison of LocalAugment with CutOut, MixUp etc, example is taken from [64].

fidelity by preserving the salient features of the image and augmenting the non-salient region. Preserved features further allow for increased diversity without shifting the distribution. Keep augment is shown in the figure 12.

(v) **You Only Cut Once** You Only Cut Once (YOCO) [44] is introduced with the aim of recognizing objects from partial information and improving the diversity of augmentation that encourage neural networks to perform

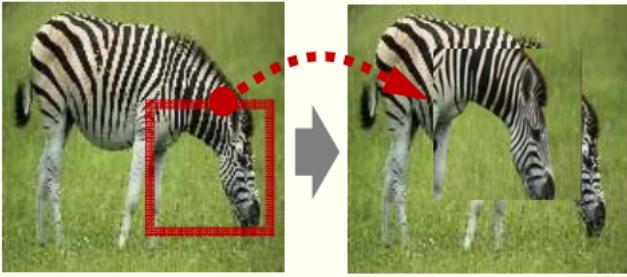


Fig. 10. An example of self augmentation, image is taken from [106]

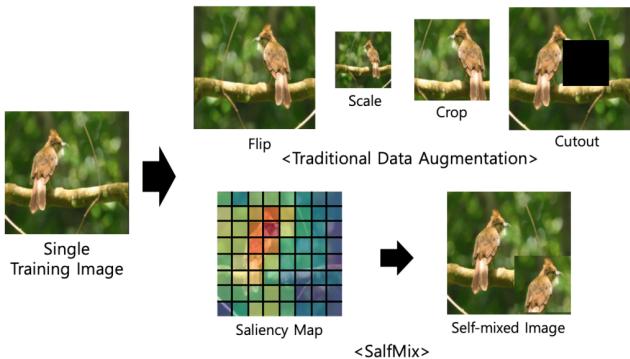


Fig. 11. Conceptual comparison between SalfMix method and other single image-based data augmentation methods, example is taken from [20].

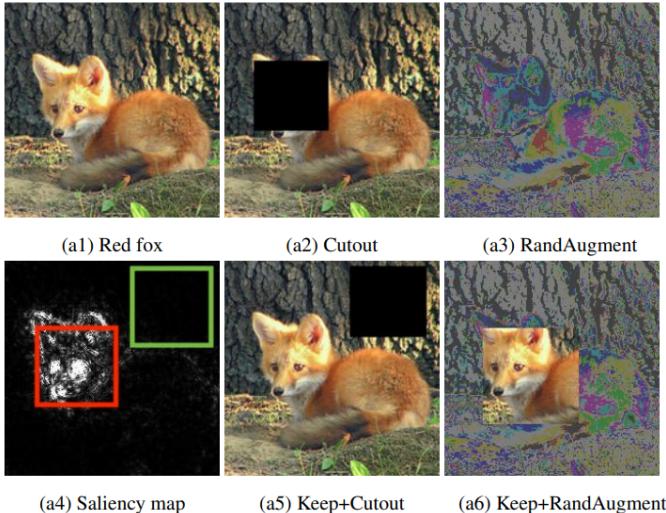


Fig. 12. This image shows the example of KeepAugment with other augmentations, courtesy [41].

better. YOCO makes two pieces of image and augmentation is applied one each piece, then each piece is concatenated for an image and YOCO shows impressive performance and compared with SOTA augmentations, sometimes it outperforms them. It is easy to implement, has no parameters, and is easy to use. The YOCO augmentation process is shown in the figure 13.



Fig. 13. An example of YOCO augmentation, image is taken from [44].

(vi) **Cut-Thumbnail** : Cut-Thumbnail [140] is a novel data augmentation, that resizes the image to a certain small size and then randomly replaces the random region of the image with the resized image, aiming to alleviate the shape bias of the network. The advantage of Cut-thumbnail is, that it not only preserves the original image but also keeps it global in the small resized image. On ImageNet, it shows impressive performance using resnet50. Overall, the cut-thumbnail process and its comparison are shown in figure 15 and figure 14, respectively.

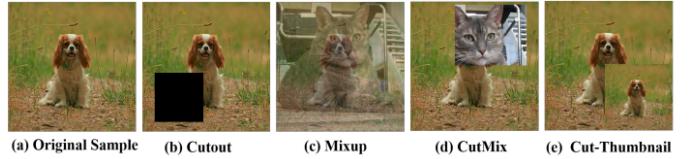


Fig. 14. Comparison between existing data augmentation methods with Cut-Thumbnail, example is from [140].

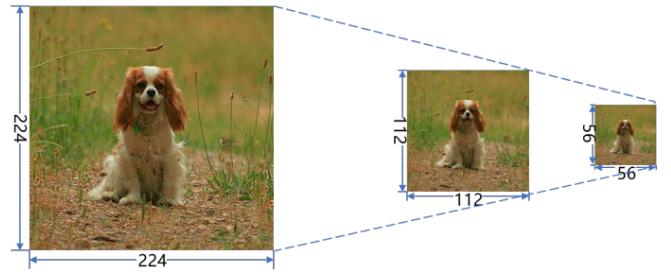


Fig. 15. This image shows an example of reduced images that is called thumbnails. After reducing the image to a certain size 112x112 or 56x56, The dog is still recognizable even though lots of local details are lost, courtesy [140].

• Non-Single Image Mixing Data Augmentations

Non-Single image mixing data augmentation uses more than one image and applies different mixing strategies. Recently, many researchers explored a lot of non-single image mixing strategies and still, it is a very attentive topic for many researchers. Recently work has included Mixup, CutMix,

SaliencyMix, and many more. Each of the relevant non-single image mixing data augmentation techniques is discussed below.

- (i) **Mixup:** It blends any random two images based on the blending factor (alpha) and the corresponding labels of these images are also mixed in the same way. Mixup data augmentation [147] sustainable improved the performance not only in terms of accuracy but also in terms of robustness. Experiments on ImageNet-2012, CIFAR-10, CIFAR-100, Google commands and UCI datasets showed impressive results on SOTA methods. As it is compared and shown in the figure 16.
- (ii) **CutMix :** It [146] tackles the issues of information loss and region dropout issue. It is inspired by cutout [27], where any random region is filled with 0 or 255, while in cutmix instead of filling the random region with 0 or 255, the region is filled with a patch from another image. Correspondingly their labels are also mixed proportionally to the number of pixels mixed. (as shown in figure 16)



Fig. 16. Overview of the Mixup, Cutout, and CutMix, example is from [146].

- (iii) **SaliencyMix :** It [125] basically addresses the problem of cutmix and argues that filling a random region of the image with a patch from another won't guarantee that patch has rich information and thereby mixing labels of unguaranteed patches leads the model to learn unnecessary information about the patch. To deal with that issue, saliencyMix first selects the salient part of the image and pastes it to a random region or salient or non-salient of another image. (as shown in figure 17 and figure 18)

Target Image	Source Image	Augmented Image

Mixed label for randomly mixed images Dog - 80% & Cat 20% ? Dog - 80% & Cat 20% ?

Fig. 17. An example of SaliencyMix augmentation, image is taken from [125].

- (iv) **Puzzle Mix :** This article [63] proposes a puzzle mix data augmentation technique that focuses on using explicitly salient information and basic statistics of image wisely with the aim of breaking misled supervision of neural networks over existing data augmentations. Furthermore, the demonstration is shown and compared with relevant methods in the figure 19.
- (v) **SnapMix:** The article [53] proposes the Semantically Proportional Mixing (SnapMix) that utilises class activation

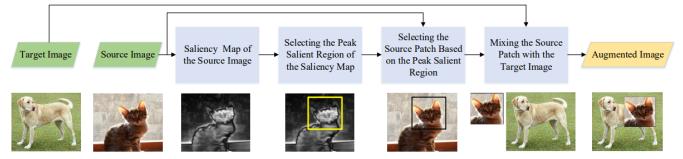


Fig. 18. This image shows the proposed SaliencyMix data augmentation procedure, courtesy [125]

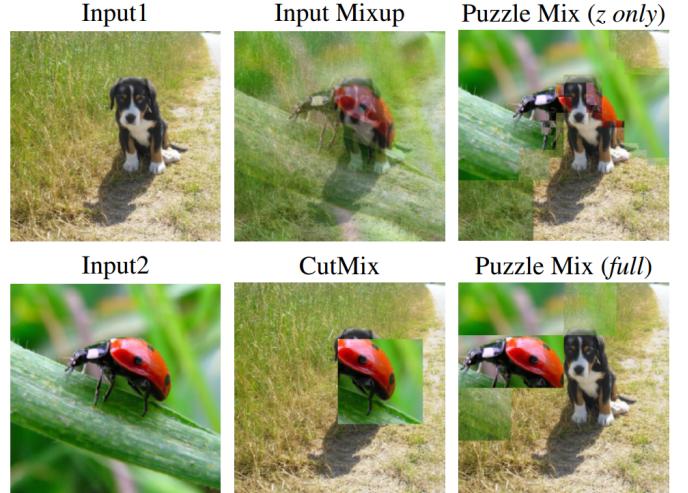


Fig. 19. A visual comparison of the mixup methods. Puzzle Mix ensures to contain sufficient target class information while preserving the local statistics of each in, example is from [63].

tion map (CAM) to reduce the label noise level. SnapMix creates the target label considering the actual salient pixel taking part in the augmented image, which ensures semantic correspondence between the augmented image and mixed labels. The overall process is demonstrated and compared with closely matching augmentations in the figure 20.

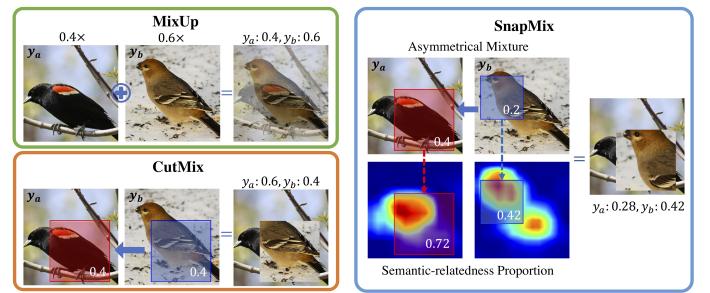


Fig. 20. A visual Comparison of Mixup, CutMix, and SnapMix. The figure gives an example where SnapMix's generated label is visually more consistent with the mixed image's semantic structure comparing to CutMix and Mixup, courtesy [53].

- (vi) **FMix:** This article proposes the FMix [45], a kind of mixed sample data augmentation (MSDA), utilises the random binary masks. These random binary masks are acquired by applying a threshold to low-frequency images

that are obtained from Fourier space. Once the mask is obtained, one colour region is applied on input one and another colour region is applied on another input. The overall process is shown in figure 21:



Fig. 21. Example masks and mixed images from CIFAR-10 for FMix, example is from [45].

(vii) **MixMo** : This paper [101] focuses on the learning of multi-input multi-output via subnetwork. Main motivation of the paper is to replace direct hidden summing operations with more solid mechanisms. For that purpose, it proposes MixMo, which embeds M inputs into shared space, mixes them and passes them to a further layer for classification. Moreover, the overall process is demonstrated in figure 22:

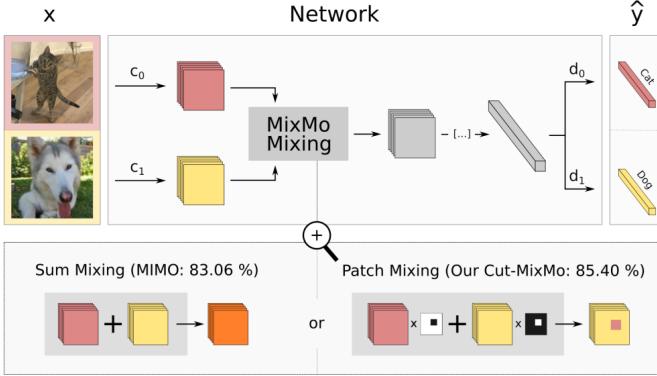


Fig. 22. This image shows the overview of MixMo augmentation, image is taken from [101].

(viii) **StyleMix** : This paper [52] targets previous approaches problems, they don't differentiate between content and style features. To remedy this, this problem proposes two approaches styleMix and StyleCutMix, this is the first work that separately deals with content and style features of images very carefully and it showed impressive performance on a popular benchmark datasets. The overall process is defined and compared with SOTA approaches in the figure 23:

(ix) **RANDOMMMIX** : This paper [85] improves generalization capability by proposing randomMix, which randomly selects mix augmentation from a set of augmentations and applies it to images, enabling the model to look at diverse

	Input 1	Input 2		
Method	Mixup	StyleMix	CutMix	
Content label	Parrot 0.5 Panda 0.5	Parrot 0.4 Panda 0.6	Parrot 0.2 Panda 0.8	Parrot 0.2 Panda 0.8
Style label	X Parrot 0.8 Panda 0.2	Panda 0.2 X Parrot 0.6 Panda 0.4		

Fig. 23. A Visual comparison of StyleMix [52] and StyleCutMix with Mixup [147] and CutMix [146], example is from [52].

samples. This method showed impressive results over SOTA image mixing methods. The overall demonstration is shown in the figure 24:

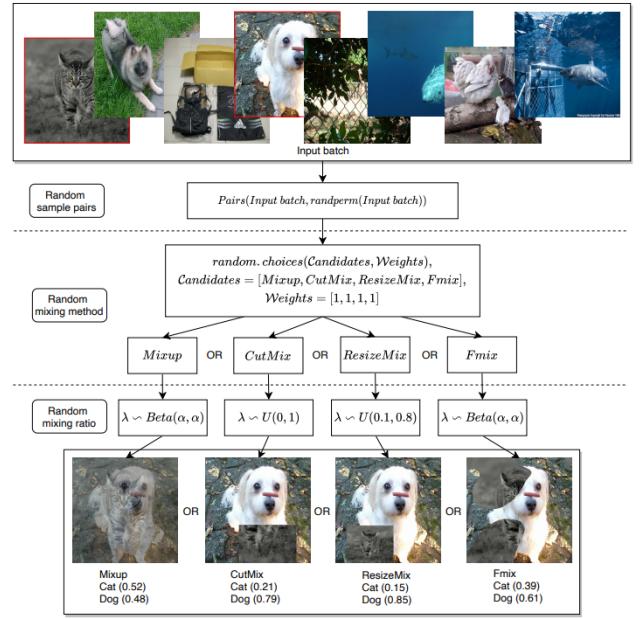


Fig. 24. An illustrative example of RandomMix, image is taken from [85].

- (x) **MixMatch** : Data augmentation technique is very useful in semi-supervised learning. MixMatch [9] augments single image K time and passes all K number of images to a classifier, averages their prediction and finally, their predictions are sharpened by adjusting their distribution temperature term. (as shown in the figure 25)
- (xi) **REMXMATCH** : This work [8] is an extension of mix match and makes prior work efficient by introducing distribution alignment and augmentation anchoring.



Fig. 25. Diagram of the label guessing process used in MixMatch, courtesy [9].

Distribution alignment tasks are to make the marginal distribution of predictions on unlabeled data close to the marginal distribution of ground truth and encourage the marginal distribution of predictions on unlabeled data to be close to the marginal distribution of ground truth labels. Augmentation anchoring feeds multiple strongly augmented versions of an input into the model and encourages each output to be close to the prediction for a weakly-augmented version of the same input. It is shown in figure 26.

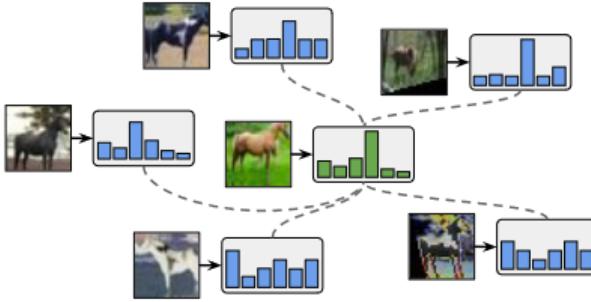


Fig. 26. Anchoring augmentation. It makes predictions on strong augmentations of the same image (blue) using the forecast for a weakly enhanced image (green, centre), courtesy [8].

- (xii) **FixMatch :** Fixmatch [115] also alleviates the performance of semi-supervised learning (SSL), the model is trained on limited labeled data then the trained model is used to assign the label to unlabeled data. Fixmatch first assigned pseudo labels to unlabeled images having a probability higher than a certain threshold. The model is forced to make predictions on a strong augmented version of the unlabeled image to match its prediction with the pseudo label using cross-entropy loss. (Overall process is shown in the figure 27)
- (xiii) **AugMix :** Augmix [49] is a simple and effective data augmentation that reduces the gap between the distribution of training and test (unseen) data. M operations are performed with a corresponding random magnitude of augmentation and at the end, all those images are merged to produce a new image that widely explores the semantically equivalent input space around an image. As shown in the figure below, three operations are performed separately in three branches and further operations are also performed for diversity purposes. Finally, all images

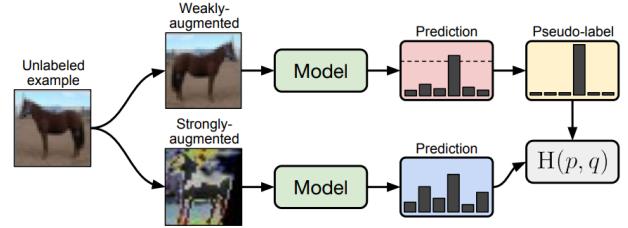


Fig. 27. This image shows the procedure of FixMatch, image is taken from [115].

are mixed to generate a new image. It is very useful for robustness. It is shown in figure 28.

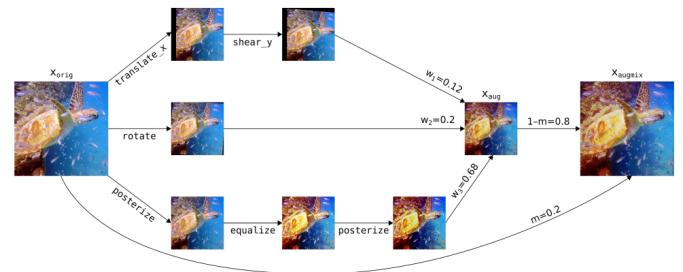


Fig. 28. An overall procedure of AugMix augmentation [49], example is from [49].

- (xiv) **Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation :** This method [37] simply copies and pastes the instances of one image to another image. It shows promising results and is very easy to implement. As shown in the figure below, two images' instances are pasted to each other on different scales. It is visually shown in figure 29.



Fig. 29. Image augmentation performed by simple Copy-Paste [37] method, courtesy [37].

- (xv) **Improved Mixed-Example Data Augmentation:** These days state-of-the-art non-label preserving data augmentation techniques have shown promising results using linear combinations of the two examples. This paper [120] explores research questions: i) Why do these methods work? ii) By proposing new augmentations, is this linearity important? It is shown in figure 30.

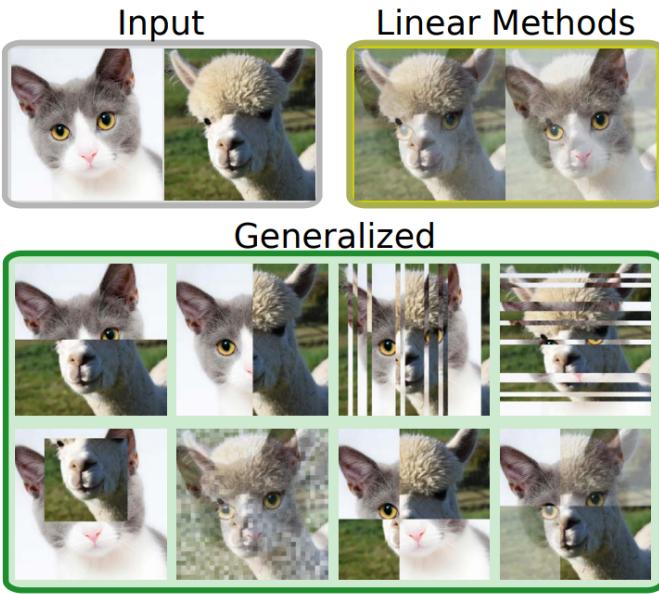


Fig. 30. A visual comparison of linear methods and generalized augmentation performed by Improved Mixed-Example, image is taken from [120].

(xvi) **RICAP :** Random image cropping and patching (RICAP) [122] is a new data augmentation technique that cuts and mixes four images rather than two images, and the labels of the images are also mixed. It shows impressive performance on popular datasets i.e. CIFAR10 , CIFAR100, and imageNet. For more detail, RICAP is shown in the figure 31.

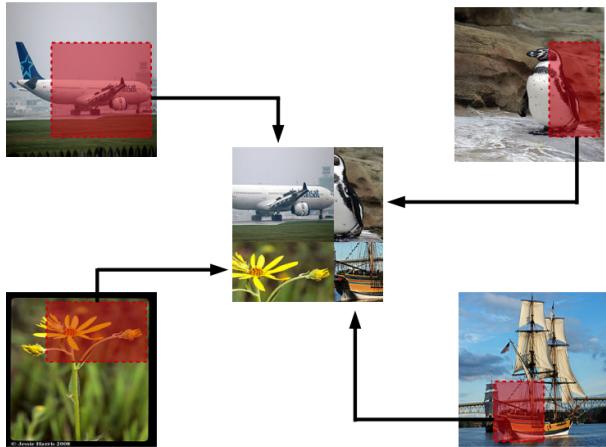


Fig. 31. A conceptual explanation of the RICAP data augmentation, the example is from [122].

(xvii) **Rethinking Data Augmentation for Image Super-resolution: A Comprehensive Analysis and a New Strategy :** This paper [143] explores and analyses existing data augmentation techniques for super-resolution and proposes another data augmentation technique for

super-solution, named cutblur that cuts high-resolution image patches and pastes to corresponding low-resolution images and vice-versa. Cutblur shows impressive performance on super-resolution. Furthermore, the process is illustrated in the figure 32 and 33.

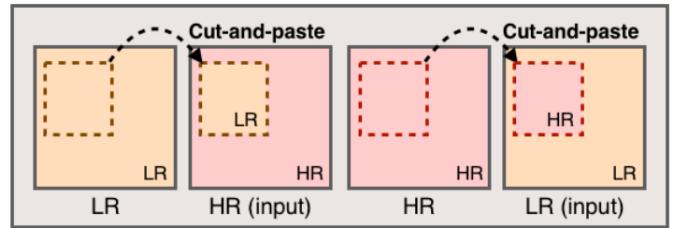


Fig. 32. An Schematic illustration of CutBlur operation, image is taken from [143].



Fig. 33. A visual comparison between High resolution, low resolution and CutBlur, courtesy [143].

(xviii) **ResizeMix: Mixing Data with Preserved Object Information and True Labels :** The ResizeMix [100] method directly cuts and pastes the source data in 4 different ways to target the image. 4 different ways including salient part, non-part, random part or resize source image to patch, as shown in the figure 34. It addresses two questions:

- How to obtain a patch from the source image?
- where to paste the patch from the source image in the target image?

Furthermore, it was found that saliency information is not important to promote mixing data augmentation. ResizeMix is shown in the figure 34.

(xix) **ClassMix: Segmentation-Based Data Augmentation for Semi-Supervised Learning :** This research work [93] proposed novel data augmentation for semi-supervised semantic segmentation with inspiration, traditional data augmentation is not effective for semantic segmentation as they are for image classification. Proposed data augmentation named ClassMix, which augments the training sample by mixing unlabeled samples, by exploiting network prediction while considering object boundaries. The proposed approach showed significant performance on two common datasets for semi-supervised semantic segmentation. The overall process is shown in the figure 35.

(xx) **Context Decoupling Augmentation for Weakly Supervised Semantic Segmentation :** This article [119]

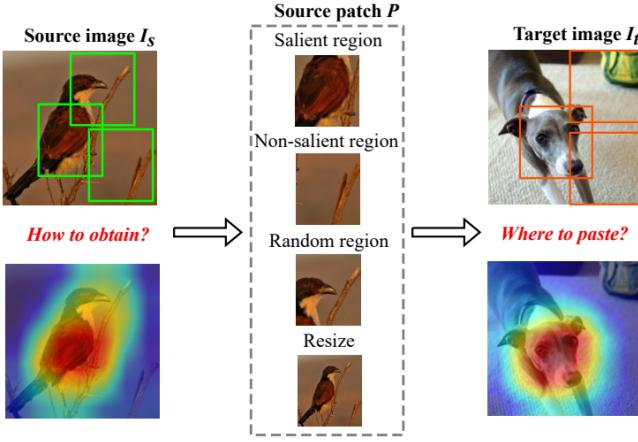


Fig. 34. A visual representation of different cropping manners from the source image and different pasting manners to the target image, image is taken from [100].

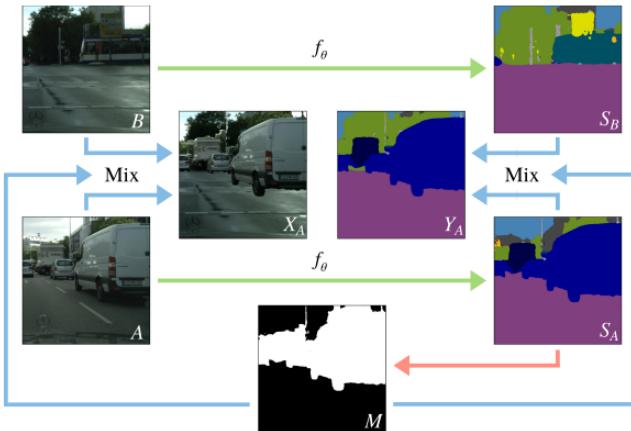


Fig. 35. In a visual representation classMix augmentation, two images are sampled then based on the predictions of each image a binary mask is created. The mask is then used to mix the images and their predictions, the image is taken from [93].

addresses the problem of traditional data techniques for WSSS, increasing the same contextual data semantic samples does not add much value in object differentiation, e.g. image classification, “cat” recognition is due to the cat itself and also its surrounding context, that discourages model to focus only on the cat. To break this, this article proposed a novel data augmentation named Context Decoupling Augmentation, to make it diverse where the specific object appears and guide the network to break the dependencies between object and contextual information. In this, the way it also provides augmentation and the network focus to object instance rather than object instance and contextual information. A comparison of traditional data augmentation and Context Decoupling Augmentation is shown below in the figure 36.

(xxi) ObjectAug: Object-level Data Augmentation for Se-

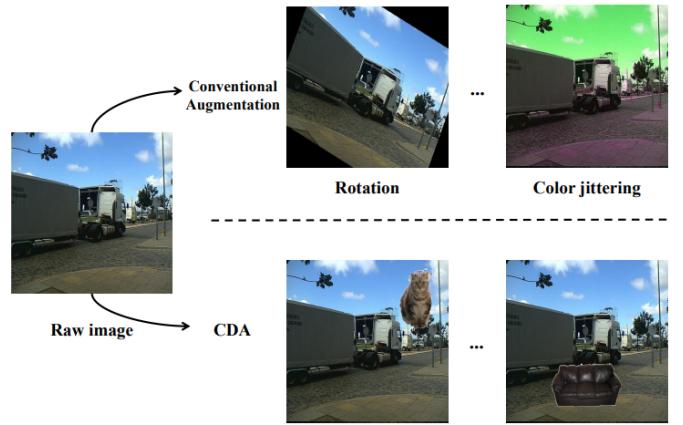


Fig. 36. A visual representation of the difference between the conventional augmentation approach and context decoupling augmentation (CDA), image is taken from [119].

mantic Image Segmentation : This article [148] addresses the problem of mixing image-level data augmentation strategies, which failed to operate for segmentation since at object and background are coupled as boundaries of objects are not augmented due to their fixed semantic bond with the background. To mitigate this problem, this article proposes a novel approach named ObjectAug, object-level augmentation for semantic segmentation. First, it separates object(s) and backgrounds from an image with the help of semantic labels then each object is augmented using popular data augmentation techniques such as flipping and rotating. Pixel changes due to these data augmentations are restored using image inpainting. In the end, the object(s) and background are coupled to create an augmented image. Experimental results suggest that ObjectAug has shown effective performance improvement for segmentation tasks. Furthermore, ObjectAug is shown in the figure 37.

C. Advance Data Augmentation Methods

AutoAugment: The goal of this technique is to find the data augmentation policies from training data. It solves the problem of finding the best augmentation policy as a discrete search problem. It consists of a search algorithm and a search space. It is divided into two parts.

- Reinforcement learning data augmentation
- Non-Reinforcement learning data augmentation

1) **Reinforcement Learning data augmentations:** Reinforcement learning data augmentation technique generalize and improve the performance of deep networks in an environment.

- (i) AutoAugment : This work [23] automatically finds the best data augmentation rather than manual data augmentation. To address this limitation, this article proposes autoaugment, where search space is designed and has policies consisting of many sub-policies. Each subpolicy has two parameters one is image processing function and

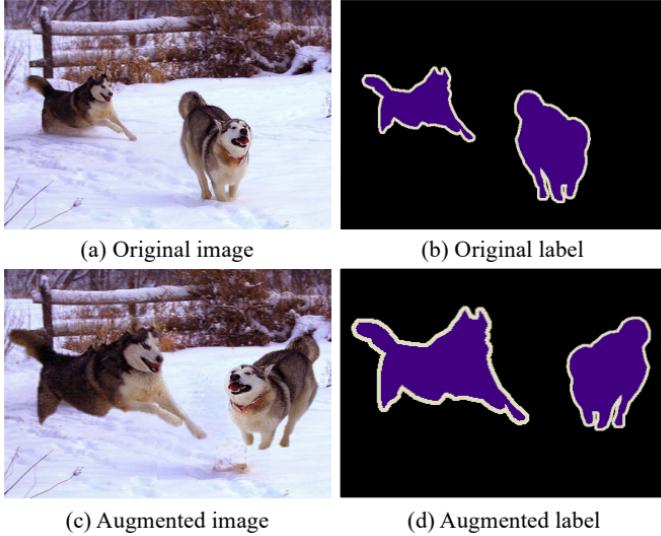


Fig. 37. ObjectAug can perform various augmentation methods for each object to boost the performance of semantic segmentation. The left husky is scaled and shifted, while the right one is flipped and shifted. Thus, the boundaries between objects are extensively augmented to boost their performance, the example is from [148].

the second one is the probability with magnitude. These subpolicies are found using reinforcement learning as a search algorithm. The overall process is shown in the figure 38.

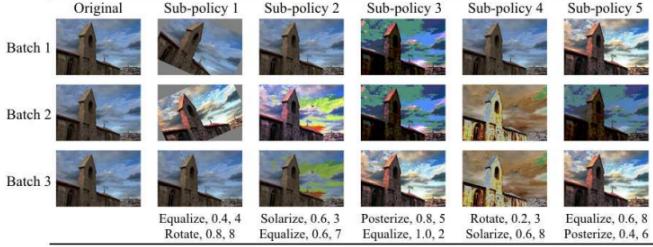


Fig. 38. A visual overview of the sub-policies from ImageNet using AutoAugment, example is from [23].

- (ii) **Fast AutoAugment :** Fast Autoaugment [82] addresses the problem of autoaugment, it takes a lot of time to find the optimal data augmentation strategy. To end this, fast auto augment finds more optimal data augmentations using an efficient search strategy based on density matching. It reduces the higher order of training time compared to auto augment. The overall procedure is shown in figure 39.
- (iii) **Faster AutoAugment:** This article proposes a faster autoaugment [46] policy intending to find effective data augmentation policies very efficiently. Faster autoaugment is based on a differentiable augmentation searching policy and additionally, it not only estimates gradients for many transformation operations having discrete parameters but also provides a mechanism for choosing operations efficiently. Moreover, it introduces a training

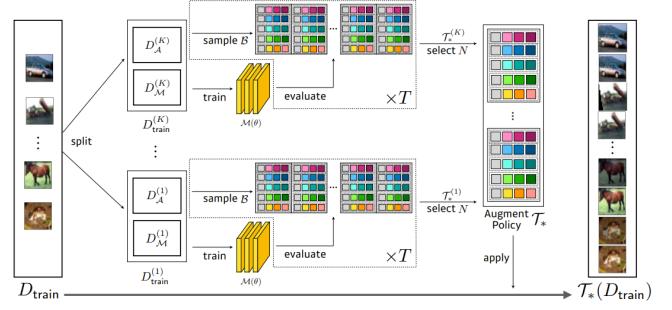


Fig. 39. An overall procedure of augmentation search by Fast AutoAugment algorithm, courtesy [82].

objective function with aim of minimising the distance between original and augmented distribution, that is also differentiable. Parameters of augmentations are updated during backpropagation. The Overall process is defined in figure 40:

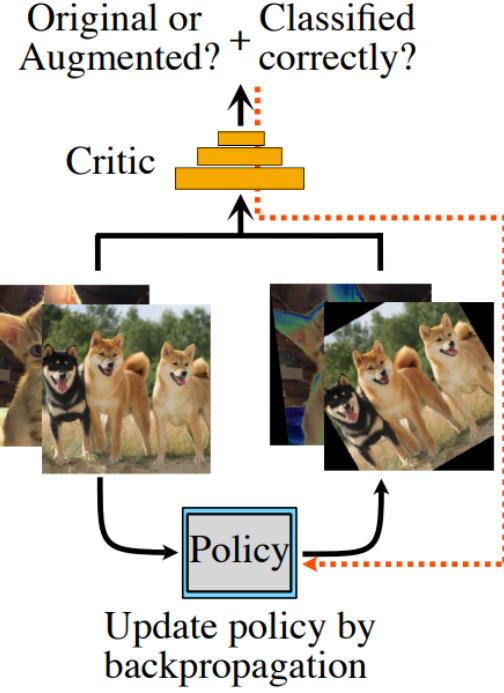


Fig. 40. An Overview of the Faster AutoAugment augmentation, image is taken from [46].

- (iv) **Reinforcement Learning with Augmented Data:** This paper proposes Reinforcement Learning with Augmented Data (RAD) [76], easily pluggable and enhances the performance of RL algorithms by targeting two issues i) learning data efficiency ii) generalisation capability for new environments. Furthermore, it shows traditional data augmentation techniques enable RL algorithms to outperform complex SOTA tasks for pixel-based control and state-based control. Overall process is defined in

figure 41:

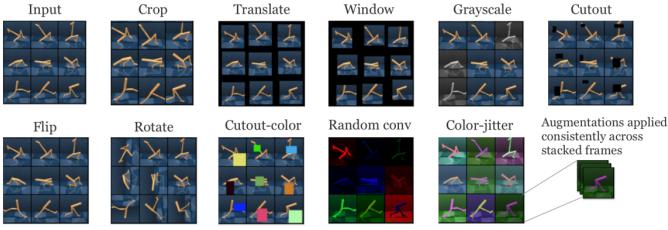


Fig. 41. An overview of different augmentation investigated in RAD, example is from [76].

(v) **LOCAL PATCH AUTOAUGMENT WITH MULTI-AGENT COLLABORATION:** This is the first paper [83] that finds data augmentation policy for patch level using reinforcement learning, named multi-agent reinforcement learning (MARL). MARL starts by dividing images into patches and jointly finds optimal data augmentation policy for each patch. It shows competitive results on SOTA benchmarks. MARL is compared and differentiated with other augmentation. Overall process is defined in figure 42:

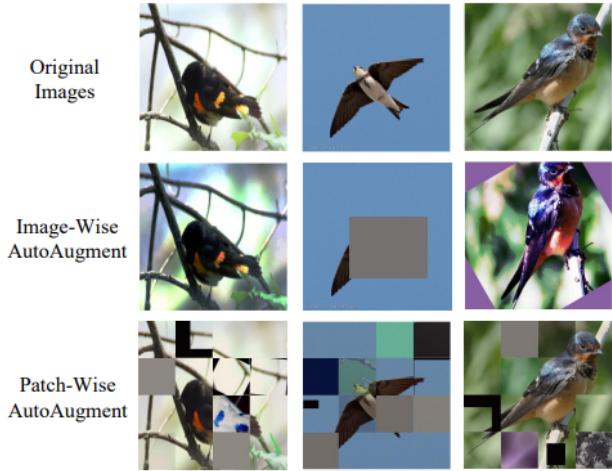


Fig. 42. An Illustration of different automated augmentation policies, courtesy [83].

(vi) **Learning Data Augmentation Strategies for Object Detection:** This work [155] proposes to use autoaugment that learns the best policies for object detection. It finds the best value and then compares it with the value of architecture. It addresses two key issues of augmentation for object detection,

- Classification learned policies can not directly be applied for detection tasks, and it adds more complexity to deal with bounding boxes in a case if geometric augmentations are applied.
- Most research thinks it adds much less value compared to designing new network architecture so gets less

attention but augmentation for object detection should be selected carefully.

Some sub-policies for this data augmentation are shown below.

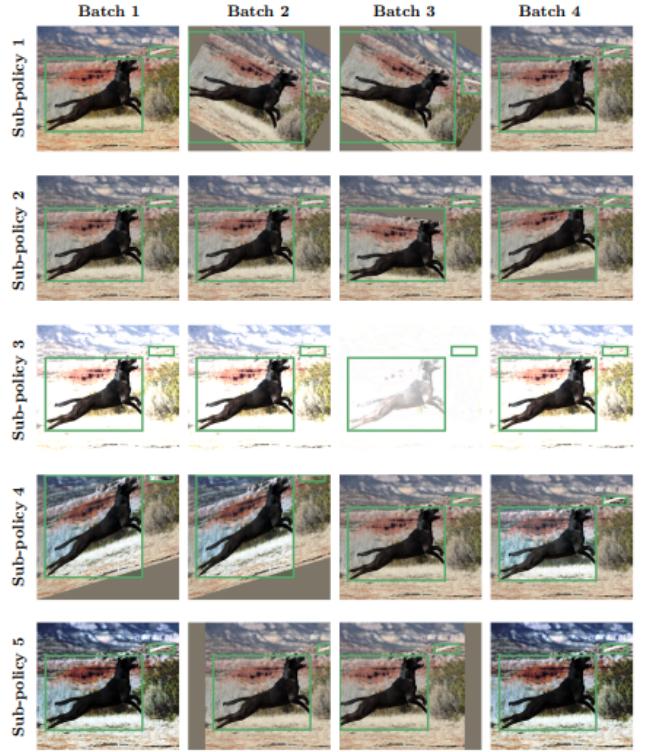


Fig. 43. Different data augmentation sub-policies explored, image is taken from, [155]. The sub-policies details are given below.

- Sub-policy 1. (Color, 0.2, 8), (Rotate, 0.8, 10)
- Sub-policy 2. (BBox_Only_ShearY, 0.8, 5)
- Sub-policy 3. (SolarizeAdd, 0.6, 8), (Brightness, 0.8, 10)
- Sub-policy 4. (ShearY, 0.6, 10), (BBox_Only_Equalize, 0.6, 8)
- Sub-policy 5. (Equalize, 0.6, 10), (TranslateX, 0.2, 2)

- Scale-aware Automatic Augmentation for Object Detection:** This work [18] proposes a new data augmentation for object detection named scale aware autoAug, first, it defines a search space where image level and box level data augmentation are prepared for scale invariance, secondly, this work also proposes a new search metric named Pareto scale balance for search augmentation effectively and efficiently. Some examples of data augmentation are shown in figure 44.
- ADA: Adversarial Data Augmentation for Object Detection:** Data augmentation for object detection has improved performance but it is difficult to understand whether these augmentations are optimal or not. This



Fig. 44. Example of scale-aware search space which includes image level and box-level augmentation, the example is from, [18].

article [7] provides a systematic way to find optimal adversarial perturbation of data augmentation from an object detection perspective, that is based on game-theoretic interpretation aka Nash equilibrium of data. Nash equilibrium provides the optimal bounding box predictor and optimal design for data augmentation. Optimal adversarial perturbation refers to the worst perturbation of ground truth, that forces the box predictor to learn from the most difficult distribution of samples. An example is shown in figure 45.

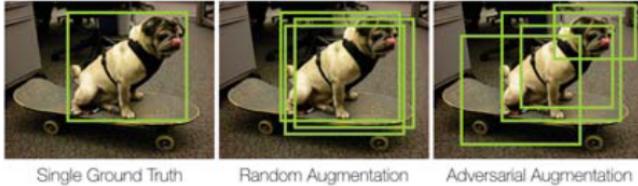


Fig. 45. Annotation distribution types. Adversarial augmentation chooses bounding boxes that are as distinct from the truth as possible while yet containing crucial object characteristics. The example is from, [7].

(ix) **Deep CNN Ensemble with Data Augmentation for Object Detection:** This article [42] proposes a new variant of the R-CNN model with two core modifications in training and evaluation. First, it uses several different CNN models as ensembler in R-CNN, secondly, it smartly augments PASCAL VOC training examples with Microsoft COCO data by selecting a subset from Microsoft COCO datasets that are consistent with PASCAL VOC. Consequently, the dataset size is enlarged and improves the performance. The schematic diagram is shown in the figure 46.

(x) **Robust and Accurate Object Detection via Adversarial Learning:** This [16] first shows classifier performance gain from different data augmentations when fine-tuned to object detection tasks disappears and performance in terms of accuracy and robustness is not improving. The article provides a unique way of exploring adversarial samples that helps to improve performance. To do so, it augments the example during the fine-tuning stage for

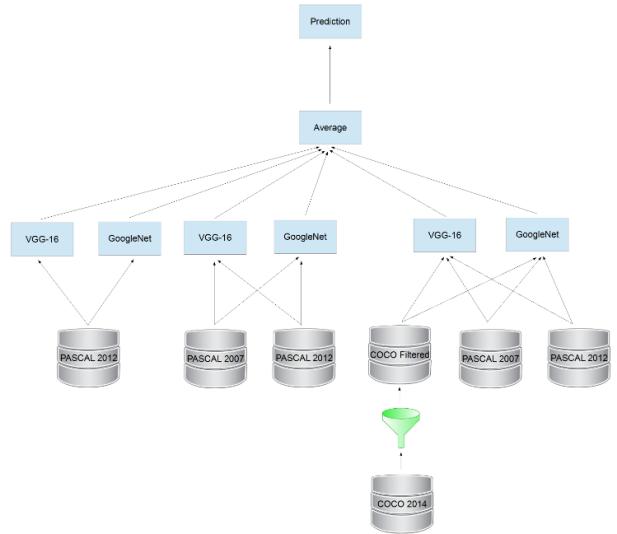


Fig. 46. The proposed schematic diagram. Example is from, [42].

object detectors by exploring adversarial samples, which is considered model-dependent data augmentation. First, it picks the stronger adversarial sample from detector classification and localization layers and these change with the detector to ensure augmentation policy remains consistent. It showed significant performance gain in terms of accuracy and robustness on different object detection tasks.

(xi) **Perspective Transformation Data Augmentation for Object Detection:** This article [129] proposes a new data augmentation for objection detection named perspective transformation that generates new images captured at different angles. Thus, it mimics images as if they are taken at a certain angle where the camera can not capture those images. This method showed effectiveness on several object detection datasets. An example of the proposed data augmentation is shown in the figure below.

(xii) **Deep Adversarial Data Augmentation for Extremely Low Data Regimes:** This article [149] addresses the issue of extremely low data regimes: labeled data is at a very low. To deal with that problem, it proposes a deep adversarial data augmentation (DADA), where data augmentation is formulated as a problem of training class conditional and supervised GAN. Furthermore, it also introduces new discriminator loss with aim of fitting data augmentation were real and augmented samples are forced to participate equally and be consistent in finding decision boundaries.

2) *Non-Reinforcement Learning data augmentations:*
dummy text here

(i) **RandAugment:** Previous optimal augmentation finding uses reinforcement or some complex learning strategy that takes a lot of time to find. RandAugment augmentation [24] removes obstacles of a separate searching phase, which makes training more complex and conse-

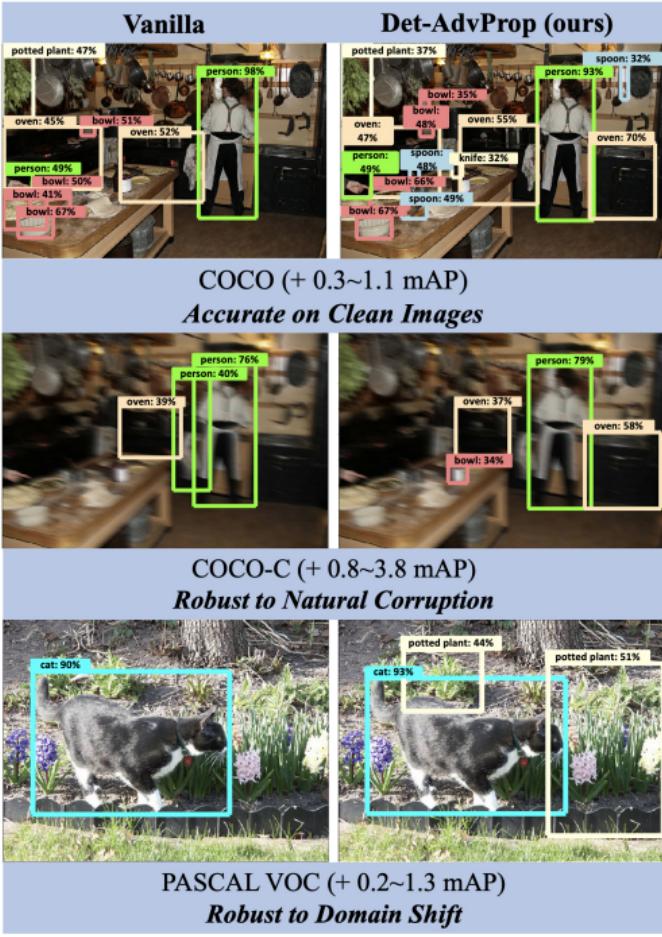


Fig. 47. Overview of Robust and Accurate Object detection via adversarial learning. In the top image, it improves object detector accuracy on clean images. In middle, improves the detector’s robustness against natural corruption, and at the bottom, it improves the robustness against cross-dataset domain shift. The image is taken from, [18].

quently adds computational cost overhead. To break this, randaugment random applies N data augmentations with M magnitude of all augmentations. Some visualisation is demonstrated in the figure 48:

3) **Neural Style Transfer:** It is another category of data augmentation, which can transfer the artist style of one image to another without changing semantics at a high level. It brings more variety to the training set. The main objective of this neural style transfer is to generate a third image from two images, where one image provides texture content and another provides high-level semantic content.

(i) **STaDA: Style Transfer as Data Augmentation :** This work [153] thoroughly evaluated different SOTA neural style transfer algorithms as data augmentation for image classification tasks. It shows significant performance gain on Caltech 101 and Caltech 256 datasets. Furthermore, it also combines neural style transfer algorithms with conventional data augmentation methods. A sample of this augmentation is shown in figure 49.

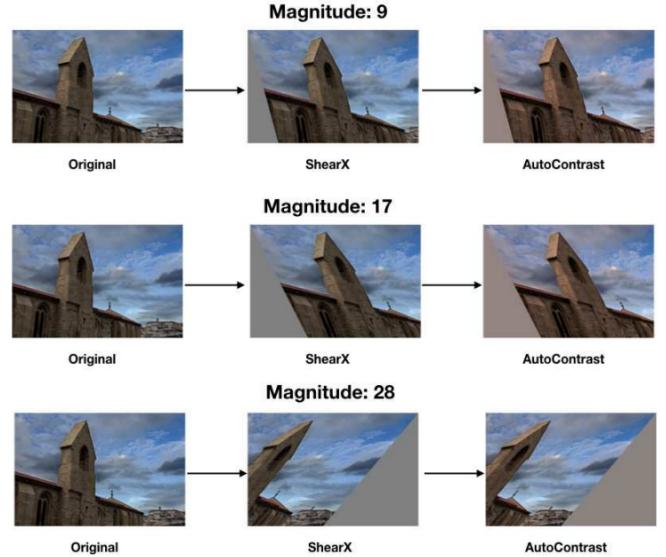


Fig. 48. Example images augmented by RandAugment, image is taken from [24].



Fig. 49. Overview of the original image and two stylized images by STaDA. Image is taken from, [153].

(ii) **Neural Style Transfer as Data Augmentation for Improving COVID-19 Diagnosis Classification :** This work [51] shows the effectiveness of a cycle generative adversarial network (GAN), which is mostly used for neural style transfer, augments COVID-19 negative x-ray image to convert into positive COVID image to balance the dataset and also to increase the diversity of the dataset. It shows that augmenting the images with Cycle GAN can improve performance over several different CNN architectures. A sample of this augmentation is shown in figure 50.

(iii) **Style Augmentation: Data Augmentation via Style Randomization:** This work [59] proposed a novel data augmentation named style augmentation (SA) based on style neural transfer. SA randomizes the color, contrast, and texture while maintaining the shape and semantic content during the training. This is done by picking an arbitrary style transfer network for randomizing the style and by getting the target style from multivariate normal distribution embedding. It improves performance in three different tasks: classification, regression, and

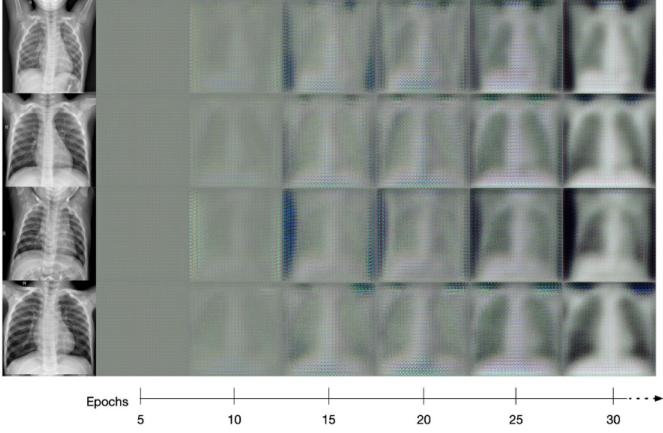


Fig. 50. Overview of generating synthetic covid images from the healthy category. As the no of epochs grows the quality of the synthetic images improves. Example is from [51].

domain adaptation. The style augmentation sample is shown in figure 51.



Fig. 51. Overview of Style augmentation applied to an image. The shape is preserved but the style, including color, texture, and contrast is randomized. Image is from [59].

- (iv) **StyPath: Style-Transfer Data Augmentation for Robust Histology Image Classification:** This paper [22] proposes a novel pipeline for Antibody Mediated Rejection (AMR) classification in kidneys based on StyPath data augmentation. StyPath is data augmentation that transfers style intending to reduce bias. The proposed augmentation is much faster than SOTA augmentations for AMR classification. Some samples are shown in figure 52.
- (v) **A Neural Algorithm of Artistic Style :** This work [36] introduces an artificial system (AS) based on Deep neural network that generates artistic images of high perceptual quality. AS creates neural embedding and then AS uses the embedding to separate the style and content of the image and then recombines the content and style of target images to generate the artistic image. The sample is shown in figure 53

4) Feature space data augmentations: Feature data augmentation is another category of data augmentation, where first images are first transformed into embedding or representation then data augmentation is performed on the embedding of the image. Recently a few works have been done in this area, we selectively highlight the work in a precise way.

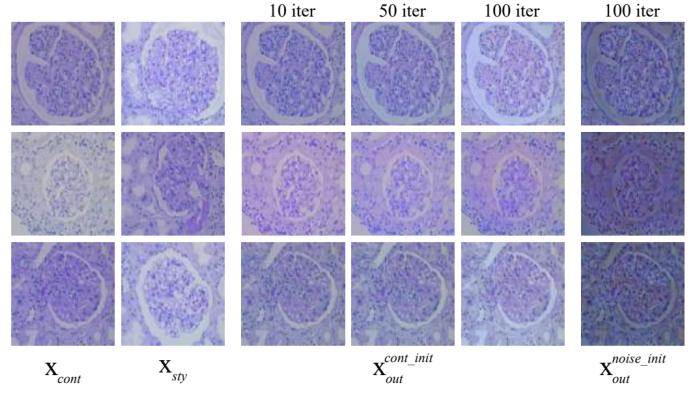


Fig. 52. Comparison of content and random initialization. Authors observe that output images initialized as noise appeared distorted and discolored and failed to retain the content fidelaty. Image is from [22].



Fig. 53. Overview of the styled image by neural algorithm. Image is from [36].

- (i) **Dataset Augmentation in Feature Space :** This work [26] first used encoder-decoder to learn representation, then on representation apply different transformations such as adding noise, interpolating, or extrapolating. The proposed method has shown performance improvement on both static and sequential data.

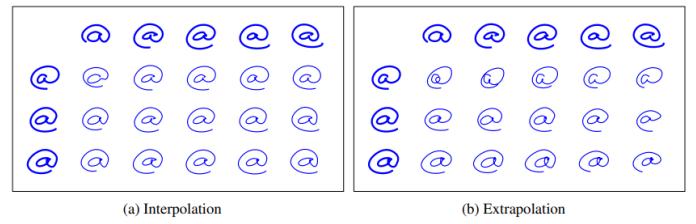


Fig. 54. Overview of interpolation and extrapolation between handwritten characters. Original characters are shown in bold. Image is taken from [26].

- (ii) **Feature Space Augmentation for Long-Tailed Data :** This paper [21] proposed the novel data augmentation in feature space to address the long-tailed issue and uplift the under-represented class samples. The proposed approach first separates class-specific features into generic and specific features with the help of class activation maps. Under-represented class samples are generated by injecting class-specific features of under-represented classes with class-generic features from other confusing

classes. This enables diverse data and also deals with the problem of under-represented class samples. It has shown SOTA performance on different datasets. As it is demonstrated in figure 55.

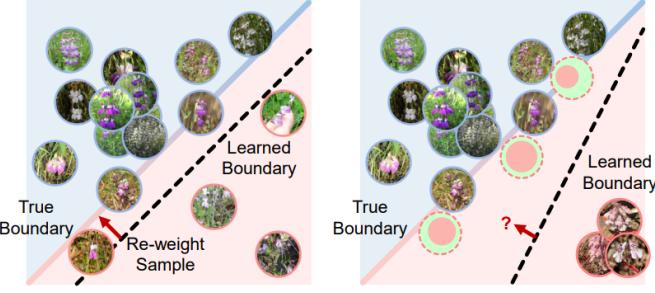


Fig. 55. Left: limited but well-spread data. Right: Without sufficient data. Image is taken from [21].

(iii) Adversarial Feature Augmentation for Unsupervised Domain Adaptation:

Domain Adaptation: Generative Adversarial Networks (GANs) showed promising results in unsupervised domain adaptation to learn target domain features indistinguishable from the source domain. This work [127] extends GAN to force features extractor to be domain-invariant ii) To train it via data augmentation in feature space, named feature augmentation. This work explores data augmentation at the feature level with GAN.

(iv) Understanding data augmentation for classification: when to warp?

: This paper [138] investigates the data augmentation advantages on image space and feature space during training. It proposed two approaches i) data warping which generates extra samples in image space using data augmentations and ii) synthetic oversampling, which generates samples in feature space. It also suggests that it is possible to apply general data augmentation techniques in feature space if reasonable data augmentations for data are known.

(v) FeatMatch: Feature-Based Augmentation for Semi-Supervised Learning :

This work [73] presents a novel approach of data augmentation in features space for SSL inspired by an image-based SSL method that uses a combination of augmentations of the images and consistency regularization. Image-based SSL methods are restricted to only conventional data augmentation. To break this end, the feature-based SSL method produced diverse features from complex data augmentations. One key point is, these advanced data augmentations exploit the information from both intra-class and inter-class representations extracted via clustering. The proposed method only showed significant performance gain on min-Imagenet such as an absolute 17.44% gain on miniImageNet, but also showed robustness on samples that are out-of-distribution. Moreover, the difference between image-level and feature-level augmentation and consistency is shown in figure 56.

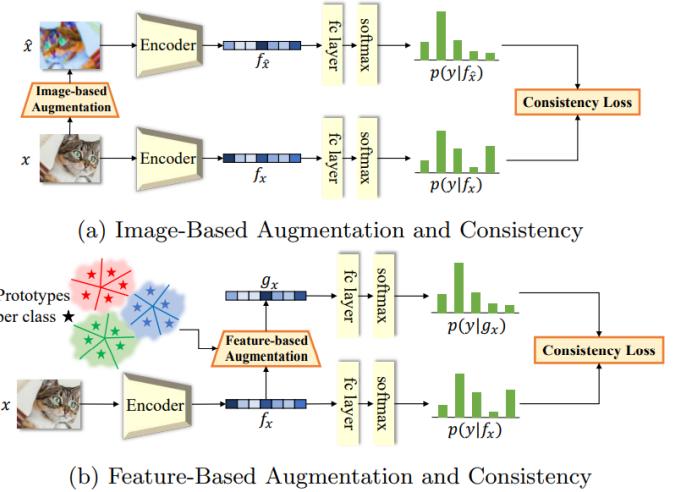


Fig. 56. An overview of FeatMatch augmentation applied on images and features. Image is taken from [21].

III. RESULTS

In this section, we provide the detailed result for various CV tasks such as image classification, object detection, and semantic segmentation. The main purpose is to show the effect of the data augmentation in CV different tasks and to do so, we compile results from various SOTA data augmentation works.

A. Image Classification

In this section, we present the result of several SOTA data augmentation methods for supervised learning and semi-supervised learning. Both are discussed below:

1) *supervised learning results:* Supervised learning is, we have data on a large quantity that is wholly labeled. We train NN on that data. In this section, we compare and compile the results from several SOTA data augmentation methods and put them in two different tables as shown in table II-A3d and table II. In table II-A3d results, + sign shows traditional data augmentations such as flipping, rotating and cropping, have been used along with SOTA augmentation method. The used datasets are CIFAR10, CIFAR100 and ImageNet, and the used networks are wideresnet flavours, pyramid network flavours and several popular resnet flavours. All the classification results are reported in accuracy, the higher is the best. As it is noticed from table II-A3d and table II that each data augmentation has significantly improved the accuracy.

2) *Semi-supervised learning:* Semi-supervised learning (SSL) is when we have limited labeled data but unlabeled data is available on large scale. Labeling the unlabeled data is tedious, time-consuming and cost [71], [139]. To avoid these issues, SSL is used. There are several techniques of SSL, but recently data augmentation is employed with the limited labeled data to increase the diversity of the data. Data augmentation with SSL has increased the performance on different datasets and NN architectures. The used dataset are CIFAR10, CIFAR100, SVHN and Mini-ImageNet. Several

SSL techniques are used. We compile the results from many SOTA SSL methods with data augmentation and present in this work. The effect of the data augmentation has also been shown with the different number of samples in SSL as shown in table III, table IV and table V.

B. Object detection

In this section, we discuss the effectiveness of various image data augmentation techniques on the frequently used COCO2017, PASCAL VOC, VOC 2007, and VOC 2012 datasets, which are commonly used for object detection tasks. We compile results from various SOTA data augmentation methods and put them in three different tables as shown in the table III-B, VII, and VIII. FRCN along with synthetic data gives the best mAP accuracy on VOC 2007 dataset as shown in Table VII. Several classical and automatic data augmentation methods have shown the promising performance on different state-of-the-art models on PASCAL VOC dataset as shown in table III-B. The DetAdvProp achieves the highest score on every model and mAP, AP50 and AP75 metrics on PASCAL VOC 2012 dataset, outperforming AutoAugment [23] as shown in the table VIII. The performance is reported in average precision (AP). AP50 and AP75 are the average precision with 50% and 75% threshold, respectively.

C. Semantic Segmentation

This subsection includes semantic segmentation results on PASCAL VOC and CITYSCAPES datasets, most frequently used in several research papers. In the table (IX) and table (X), we compiled the effectiveness of validation set results on the different datasets (mIoU) with data augmentation on semantic segmentation models; the best results of performance (mIoU) accuracy on the Cityscape dataset as shown in table (ix) and best results of performance (mIoU) accuracy on Pascal VOC datasets are shown in table (x). We found performance gains on a few metrics with several semantic segmentation models: deeplabv3+ [144], DeepLab-v2 [93], Xception-65 [144], ExFuse [150] and Eff-L2 [156]. All semantic segmentation models have been found to perform better when data augmentation techniques are used. Traditional data augmentation methods are rotation, scaling, flipping and shifting [148].

IV. DISCUSSION AND FUTURE DIRECTIONS

A. Current approaches

It is proven that if we provide more data to the model, it improves model performance [43], [121]. A few current tendencies are discussed by Xu et al. [141]. Among these, one way is to collect the data and label it manually, but it is not an efficient way to do this. Another efficient way is to apply data augmentation, the more data augmentations we apply, the more performance improves to a certain extent. Currently, image mixing methods and autoaugment methods are successful for image classification tasks, scale aware based auto augment methods are showing promising results in detection tasks and semantic segmentation tasks. But these data augmentation

performances can vary with the number of data augmentation applied, as it is known that the combined data augmentation methods show better performance than single one [97], [142].

B. Theoretical aspects

There is no theoretical support available to explain why specific augmentation is improving performance and which sample(s) should be augmented, as the same aspect has been discussed by Yang et al [142] and Shorten et al [108]. Like in random erasing, we randomly erase the region of the image - sometime may erase discriminating features, and the erased image makes no sense to a human. But the reason behind performance improvement is still unknown, which is another open challenge. Most of the time, we find the optimal parameters of the augmentation through an extensive number of experiments or we choose data augmentation based on our experience. But there should be a mechanism for choosing the data augmentation with theoretical support considering model architecture and dataset size. Researching the theoretical aspect is another challenge open for the research community.

C. Optimal number of samples generation

It is a known fact, as we increase data size, it improves the performance [43], [108], [121], [142] but it is not a case - increasing the number of samples will not improve performance after a certain number of samples [70]. What is the optimal number of samples to be generated, depending on the model architecture and dataset size, is another aspect to be explored. Currently, researchers perform many experiments to find the optimal number of sample generation [70]. But it is not feasible way as it requires time and computational cost. Can we devise a mechanism to find an optimal number of samples, which is an open research challenge?

D. Selection of data augmentation based on model architecture and dataset

Data augmentation selection depends on the nature of the dataset and model architecture. Like on MNIST [25] dataset, geometric transformations are not safe such as rotation on 6 and 9 digits will no longer preserve the label information. For densely parameterized CNN, it is easy to overfit on weakly augmented datasets, and for shallow parameterized CNN, it may break generalization capability with data augmentation. It suggests, while selecting the data augmentation, the nature of the dataset and model architecture should be taken into account. It is not an easy problem to solve. Currently, numerous experiments are performed to find model architecture and suitable data augmentation for a specific dataset. Devising a systematic approach to select the data augmentation based on dataset and model architecture is another open challenge.

E. Augmentations for spaces

Most of the data augmentation has been explored on the image level - data space. Very few research works have explored data on feature level - feature space. Challenges here arise, in which space should we apply data augmentation, data

TABLE III
COMPARISON ON CIFAR-10 AND SVHN. NUMBER REPRESENTS ERROR RATES ACROSS THREE RUNS.

Method	CIFAR-10				SVHN			
	40 labels	250 labels	1,000 labels	4,000 labels	40 labels	250 labels	1,000 labels	4,000 labels
VAT [91]	-	36.03 \pm 2.82	18.64 \pm 0.40	11.05 \pm 0.31	-	8.41 \pm 1.01	5.98 \pm 0.21	4.20 \pm 0.15
Mean Teacher [123]	-	47.32 \pm 4.71	17.32 \pm 4.00	10.36 \pm 0.25	-	6.45 \pm 2.43	3.75 \pm 1.10	3.39 \pm 0.11
MixMatch [9]	47.54 \pm 11.50	11.08 \pm 0.87	7.75 \pm 0.32	6.24 \pm 0.06	42.55 \pm 14.53	3.78 \pm 0.26	3.27 \pm 0.31	2.89 \pm 0.06
ReMixMatch [8]	19.10 \pm 9.64	6.27 \pm 0.34	5.73 \pm 0.16	5.14 \pm 0.04	3.34 \pm 0.20	3.10 \pm 0.50	2.83 \pm 0.30	2.42 \pm 0.09
UDA	29.05 \pm 5.93	8.76 \pm 0.90	5.87 \pm 0.13	5.29 \pm 0.25	52.63 \pm 20.51	2.76 \pm 0.17	2.55 \pm 0.09	2.47 \pm 0.15
SSL with Memory [17]	-	-	-	11.9 \pm 0.22	-	8.83	4.21	-
Deep Co-Training [99]	-	-	-	8.35 \pm 0.06	-	-	3.29 \pm 0.03	-
Weight Averaging [5]	-	-	15.58 \pm 0.12	9.05 \pm 0.21	-	-	-	-
ICT [126]	-	-	15.48 \pm 0.78	7.29 \pm 0.02	-	4.78 \pm 0.68	3.89 \pm 0.04	-
Label Propagation [57]	-	-	16.93 \pm 0.70	10.61 \pm 0.28	-	-	-	-
SNTG [87]	-	-	18.41 \pm 0.52	9.89 \pm 0.34	-	4.29 \pm 0.23	3.86 \pm 0.27	-
PLCB [4]	-	-	6.85 \pm 0.15	5.97 \pm 0.15	-	-	-	-
II-model [105]	-	53.02 \pm 2.05	31.53 \pm 0.98	17.41 \pm 0.37	-	17.65 \pm 0.27	8.60 \pm 0.18	5.57 \pm 0.14
PseudoLabel [77]	-	49.98 \pm 1.17	30.91 \pm 1.73	16.21 \pm 0.11	-	21.16 \pm 0.88	10.19 \pm 0.41	5.71 \pm 0.07
Mixup [147]	-	47.43 \pm 0.92	25.72 \pm 0.66	13.15 \pm 0.20	-	39.97 \pm 1.89	16.79 \pm 0.63	7.96 \pm 0.14
FeatMatch [73]	-	7.50 \pm 0.64	5.76 \pm 0.07	4.91 \pm 0.18	-	3.34 \pm 0.19	3.10 \pm 0.06	2.62 \pm 0.08
FixMatch [115]	13.81 \pm 3.37	5.07 \pm 0.65	-	4.26 \pm 0.05	3.96 \pm 2.17	2.48 \pm 0.38	2.28 \pm 0.11	-
SelfMatch [62]	93.19 \pm 1.08	95.13 \pm 0.26	-	95.94 \pm 0.08	96.58 \pm 1.02	97.37 \pm 0.43	97.49 \pm 0.07	-

TABLE IV
COMPARISON ON CIFAR-100 AND MINI-IMAGENET. NUMBER REPRESENTS ERROR RATES ACROSS TWO RUNS.

Method	CIFAR-100			mini-ImageNet	
	400 labels	4,000 labels	10,000 labels	4,000 labels	10,000 labels
II-model [105]	-	-	39.19 \pm 0.36	-	-
SNTG [87]	-	-	37.97 \pm 0.29	-	-
SSL with Memory [17]	-	-	34.51 \pm 0.61	-	-
Deep Co-Training [99]	-	-	34.63 \pm 0.14	-	-
Weight Averaging [5]	-	-	33.62 \pm 0.54	-	-
Mean Teacher [123]	-	45.36 \pm 0.49	36.08 \pm 0.51	72.51 \pm 0.22	57.55 \pm 1.11
Label Propagation [57]	-	43.73 \pm 0.20	35.92 \pm 0.47	70.29 \pm 0.81	57.58 \pm 1.47
PLCB [4]	-	37.55 \pm 1.09	32.15 \pm 0.50	56.49 \pm 0.51	46.08 \pm 0.11
FeatMatch	-	31.06 \pm 0.41	26.83 \pm 0.04	39.05 \pm 0.06	34.79 \pm 0.22
MixMatch	67.61 \pm 1.32	-	28.31 \pm 0.33	-	-
UDA	59.28 \pm 0.88	-	24.50 \pm 0.25	-	-
ReMixMatch	44.28 \pm 2.06	-	23.03 \pm 0.56	-	-
FixMatch	48.85 \pm 1.75	-	22.60 \pm 0.12	-	-

space or feature space? It is another interesting aspect that can be explored. For approaches, it seems it depends on the dataset, model architecture and task. Mixing augmentations in feature space is senseless. Currently, approaches are conducting experiments in data space and feature space and then selecting the best one [138]. This is not the optimal way to go. It is still an open challenge to be solved.

F. Open research questions

Despite the success of data augmentation techniques in different CV tasks, it still failed to solve challenges in SOTA data augmentation techniques. After thoroughly reviewing SOTA data augmentation approaches, we found several challenges and difficulties, which are yet to be solved, as it is listed below:

- In image mixing techniques, label smoothing has been used. It makes sense whatever portion of images is mixed, corresponding labels should be mixed accordingly. To the best of our knowledge, none has explored label smoothing for image manipulation and image erasing subcategories.

For example, if the image portion is randomly cut out in cutout data augmentation, the corresponding label should be smoothed. The same rule applies to the image erasing category and image manipulation - where the image part is lost.

- Currently, data augmentation is performed without considering the importance of an example. All examples may not be difficult for the neural network to learn, but some are. So augmentation should be applied to those difficult examples by measuring the importance of the examples.
- In image mixing data augmentations, if we mix more than two images salient parts, that are truly participating in augmentation unlike RICAP [122], what is its effect? Note, the corresponding labels of these images will be mixed accordingly.
- In random data augmentation under auto augmentations, the order of augmentations has not been explored. We believe it has significant importance. What are the possible ways to explore the order of existing augmentations such

TABLE V
COMPARISON OF TEST ERROR RATES ON CIFAR-10 & SVHN USING WIDERESNET-28 AND CNN-13.

Approach	Method	CIFAR-10 ($N_l=4000$)	SVHN($N_l=1000$)
WideResNet-28			
Pseudo Labeling	Supervised PL [77]	20.26 ± 0.38	12.83 ± 0.47
	PL-CB [4]	17.78 ± 0.57	7.62 ± 0.29
	II Model [75]	6.28 ± 0.3	-
	Mean Teacher [123]	16.37 ± 0.63	7.19 ± 0.27
	VAT [91]	15.87 ± 0.28	5.65 ± 0.47
Consistency	VAT + EntMin [91]	13.86 ± 0.27	5.63 ± 0.20
	LGA + VAT [58]	13.13 I 0.39	5.35 ± 0.19
Regularization	ICT [126]	12.06 ± 0.19	6.58 ± 0.36
	MixMatch [9]	7.66 ± 0.17	3.53 ± 0.07
	UDA	6.24 ± 0.06	3.27 ± 0.31
	ReMixMatch (Berthelot et al. 2020)	5.29 ± 0.25	2.46 ± 0.17
	FixMatch [115]	5.14 ± 0.04	2.42 ± 0.09
	CL	4.26 ± 0.05	2.28 ± 0.11
Pseudo Labeling	CL+FA [82]	8.92 ± 0.03	5.65 ± 0.11
	CL+FA [82]+Mixup [147]	5.51 0.14	2.90 ± 0.19
	CL+RA+Mixup [147]	5.09 ± 0.18	2.75 ± 0.15
		5.27 ± 0.16	2.80 ± 0.188
CNN-13			
Pseudo Labeling	TSSDL-MT	9.30 ± 0.55	3.35 ± 0.27
	LP-MT	10.61±0.28	-
	Ladder net [102]	12.36±0.31	-
	MeanTeacher [123]	12.31 ± 0.24	3.95 ± 0.19
	Temporal ensembling [75]	12.16 ± 0.24	4.42 ± 0.16
Consistency	VAT [91]	11.36 ± 0.34	5.42
Regularization	NATEntMin [91]	10.55 ± 0.05	3.86
	SNTG [87]	10.93 ± 0.14	3.86 ± 0.27
	ICT [126]	7.29 ± 0.02	2.89 ± 0.04
Pseudo Labeling	CL	9.81 ± 0.22	4.75 ± 0.28
	CL+RA	5.92 ± 0.07	3.96 ± 0.10

as first traditional data augmentations and then image mixing or weight-based?

- If we mix the masks of the objects in data augmentation for semantic segmentation, How does the model behave and what is its effect?
- Finding the optimal ordered number of data augmentation and the optimal number of samples to be augmented is another open challenge. For example, in randAug method there are N optimal number of augmentations was found but it is not known how many samples should be augmented.

V. CONCLUSION

This survey presents numerous SOTA data augmentation methods to cope with overfitting problems in computer vision tasks due to data limitations. We provided a comprehensive survey for data augmentation, in which we presented novel taxonomy of advanced data augmentation approaches, an overview of each SOTA data augmentation, and results of numerous computer vision tasks such as image classification, object detection and semantic segmentation, with data augmentation effect. We not only compiled the results for supervised learning tasks but also compiled results for semi-supervised learning. For result reproducibility, we compiled the available codes of the data augmentation by following the proposed taxonomy. We discuss a different aspects of the

data augmentation with its difficulties. Finally, we discuss the open research questions, which are very promising and open new doors, and ignite interest in the research community. We believe that the survey benefits the researchers as follows: i) Understanding of the data augmentation ii) No need to find the results for comparison purposes iii) Results can be reproduced with available codes.

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Method	Detector	BackBone	AP	AP ₅₀	AP ₇₅	AP _s	AP _m	AP _l
Hand-crafted:								
Dropblock [38]	RetinaNet	ResNet-50	38.4	56.4	41.2	—	—	—
AutoAugment+color Ops [155]	RetinaNet	ResNet-50	37.5	-	-	—	—	—
geometric Ops [155]	RetinaNet	ResNet-50	38.6	-	-	—	—	—
bbox-only Ops [155]	RetinaNet	ResNet-50	39.0	-	-	—	—	—
Mix-up [151]	Faster R-CNN	ResNet-101	41.1	-	-	-	-	-
PSIS* [128]	Faster R-CNN	ResNet-101	40.2	61.1	44.2	22.3	45.7	51.6
Stitcher [19]	Faster R-CNN	ResNet-101	42.1	-	-	26.9	45.5	54.1
GridMask [15]	Faster R-CNN	ResNeXt-101	42.6	65.0	46.5	-	-	-
InstaBoost* [32]	Mask R-CNN	ResNet-101	43.0	64.3	47.2	24.8	45.9	54.6
SNIP (MS test)* [112]	Faster R-CNN	ResNet-101-DCN-C4	44.4	66.2	49.9	27.3	47.4	56.9
SNIPER (MS test)* [113]	Faster R-CNN	ResNet-101-DCN-C4	46.1	67.0	51.6	29.6	48.9	58.1
Traditional Aug [142]	Faster R-CNN	ResNet-101	36.80	58.0	40.0	-	-	-
Traditional Aug* [29]	CenterNet	ResNet-101	41.15	58.01	45.30	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (2x)	37.4	58.7	40.5	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (2x)+GridMask (p = 0.3)	38.2	60.0	41.4	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (2x)+ GridMask (p = 0.5)	38.1	60.1	41.2	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (2x)+ GridMask (p = 0.7)	38.3	60.4	41.7	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (2x)+ GridMask (p = 0.9)	38.0	60.1	41.2	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (4x)	35.7	56.0	38.3	-	-	-
Traditional Aug+ [15]	Faster-RCNN	50-FPN (4x)+ GridMask (p = 0.7)	39.2	60.8	42.2	-	-	-
Traditional Aug+ [15]	Faster-RCNN	X101-FPN (1x))	41.2	63.3	44.8	-	-	-
Traditional Aug+ [15]	Faster-RCNN	X101-FPN (2x))	40.4	62.2	43.8	-	-	-
Traditional Aug+ [15]	Faster-RCNN	X101-FPN (2x)+ GridMask (p = 0.7))	42.6	65.0	46.5	-	-	-
Traditional Aug+ [15]	Faster-RCNN	X101-FPN (2x)+ GridMask (p = 0.7))	42.6	65.0	46.5	-	-	-
KeepAugment: [41]	Faster R-CNN	ResNet50-C4	39.5	-	-	—	—	—
KeepAugment: [41]	Faster R-CNN	ResNet50-FPN	40.7	-	-	—	—	—
KeepAugment: [41]	RetinaNet	ResNet50-FPN	39.1	-	-	—	—	—
KeepAugment: [41]	Faster R-CNN	ResNet101-C4	42.2	-	-	—	—	—
KeepAugment: [41]	Faster R-CNN	ResNet101-FPN	42.9	-	-	—	—	—
KeepAugment: [41]	RetinaNet	ResNet101-FPN	41.2	-	-	—	—	—
DADAAugment: [80]	RetinaNet	ResNet-50	35.9	55.8	38.4	19.9	38.8	45.0
DADAAugment: [80]	RetinaNet	ResNet-50(DADA)	36.6	56.8	39.2	20.2	39.7	46.0
DADAAugment: [80]	Faster R-CNN	ResNet-50	36.6	58.8	39.6	21.6	39.8	45.0
DADAAugment: [80]	Faster R-CNN	ResNet-50 (DADA)	37.2	59.1	40.2	22.2	40.2	45.7
DADAAugment: [80]	Mask R-CNN	ResNet-50	37.4	59.3	40.7	22.2	40.6	46.3
DADAAugment: [80]	Mask R-CNN	ResNet-50(DADA)	37.8	59.6	41.1	22.4	40.9	46.6
AutoAugment: [16]	EfficientDet D0	EfficientNet B0	34.4	52.8	36.7	53.1	40.2	13.9
Det-AdvProp: [16]	EfficientDet D0	EfficientNet B0	34.7	52.9	37.2	54.1	40.6	13.9
AutoAugment: [16]	EfficientDet D1	EfficientNet B1	40.1	59.2	43.2	57.9	45.7	19.9
Det-AdvProp: [16]	EfficientDet D1	EfficientNet B1	40.5	59.2	43.3	58.8	46.2	20.6
AutoAugment: [16]	EfficientDet D2	EfficientNet B2	43.5	62.8	46.6	59.8	48.7	23.9
Det-AdvProp: [16]	EfficientDet D2	EfficientNet B2	43.8	62.6	47.3	61.0	49.6	25.6
AutoAugment: [16]	EfficientDet D3	EfficientNet B3	47.0	66.0	50.8	63.0	51.7	29.8
Det-AdvProp: [16]	EfficientDet D3	EfficientNet B3	47.6	66.3	51.4	64.0	52.2	30.2
AutoAugment: [16]	EfficientDet D4	EfficientNet B4	49.5	68.7	53.7	64.9	54.0	31.9
Det-AdvProp: [16]	EfficientDet D4	EfficientNet B4	49.8	68.6	54.2	65.2	54.2	32.4
AutoAugment: [16]	EfficientDet D5	EfficientNet B5	51.5	70.4	56.0	65.2	56.1	35.4
Det-AdvProp: [16]	EfficientDet D5	EfficientNet B5	51.8	70.7	56.3	66.1	56.2	36.2
Automatic:								
AutoAug-det [155]	RetinaNet	ResNet-50	39.0	-	-	-	-	-
AutoAug-det [155]	RetinaNet	ResNet-101	40.4	-	-	-	-	-
AutoAugment [23]	RetinaNet	ResNet-200	42.1	-	-	-	-	-
AutoAug-det' [155]	RetinaNet	ResNet-50	40.3	60.0	43.0	23.6	43.9	53.8
RandAugment* [24]	RetinaNet	ResNet-200	41.9	-	-	-	-	-
AutoAug-det [155]	RetinaNet	ResNet-101	41.8	61.5	44.8	24.4	45.9	55.9
RandAug [24]	RetinaNet	ResNet-101	40.1	-	-	-	-	-
RandAug? [10]	RetinaNet	ResNet-101	41.4	61.4	44.5	25.0	45.4	54.2
Scale-aware AutoAug [18]	RetinaNet	ResNet-50	41.3	61.0	441	25.2	44.5	54.6
Scale-aware AutoAug	RetinaNet	ResNet-101	43.1	62.8	46.0	26.2	46.8	56.7
Scale-aware AutoAug	Faster R-CNN	ResNet-101	44.2	65.6	48.6	29.4	47.9	56.7
Scale-aware AutoAug (MS test)	Faster R-CNN	ResNet-101-DCN-C4	47.0	68.6	52.1	32.3	49.3	60.4
Scale-aware AutoAug	FCOS	ResNet-101	44.0	62.7	47.3	28.2	47.8	56.1
Scale-aware AutoAug	FCOS	ResNeXt-32x8d-101-DCN	48.5	67.2	52.8	31.5	51.9	63.0
Scale-aware AutoAug (1200 size)	FCOS	ResNeXt-32x8d-101-DCN	49.6	68.5	54.1	35.7	52.5	62.4
Scale-aware AutoAug (MS Test)	ResNeXt-32x8d-101-DCN	FCOS	51.4	69.6	57.0	37.4	54.2	65.1

TABLE VI

DATA AUGMENTATION EFFECT ON DIFFERENT OBJECT DETECTION METHODS USING PASCAL VOC DATASET

Method	TSet	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
FRCN[39]	7	66.9	74.5	78.3	69.2	53.2	36.6	77.3	78.2	82.0	40.7	72.7	67.9	79.6	79.2	73.0	69.0	30.1	65.4	70.2	75.8	65.9
FRCN* [132]	7	69.1	75.4	80.8	67.3	59.9	37.6	81.9	80.0	84.5	50.0	77.1	68.2	81.0	82.5	74.3	69.9	28.4	71.1	70.2	75.8	66.0
ASDN [132]	7	71.0	74.4	81.3	67.6	57.0	46.6	81.0	79.3	86.0	52.9	75.9	73.7	82.6	83.2	77.7	72.7	37.4	66.3	71.2	78.2	74.3
IRE	7	70.5	75.9	78.9	69.0	57.7	46.4	81.7	79.5	82.9	49.3	76.9	67.9	81.5	83.3	76.7	73.2	40.7	72.8	66.9	75.4	74.3
ORE	7	71.0	75.1	79.8	69.7	60.8	46.0	80.4	79.0	83.8	51.6	76.2	67.8	81.2	83.7	76.8	73.8	43.1	70.8	67.4	78.3	75.0
I+ORE	7	71.5	76.1	81.6	69.5	60.1	45.6	82.2	79.2	84.5	52.5	78.7	71.6	80.4	83.3	76.7	73.9	39.4	68.9	69.8	79.2	77.4
FRCN [39]	7+12	70.0	77.0	78.1	69.3	59.4	38.3	81.6	78.6	86.7	42.8	78.8	68.9	84.7	82.0	76.6	69.9	31.8	70.1	74.8	80.4	70.4
FRCN* [132]	7+12	74.8	78.5	81.0	74.7	67.9	53.4	85.6	84.4	86.2	57.4	80.1	72.2	85.2	84.2	77.6	76.1	45.3	75.7	72.3	81.8	77.3
IRE	7+12	75.6	79.0	84.1	76.3	66.9	52.7	84.5	84.4	88.7	58.0	82.9	71.1	84.8	84.4	78.6	76.7	45.5	77.1	76.3	82.5	76.8
ORE	7+12	75.8	79.4	81.6	75.6	66.5	52.7	85.5	84.7	88.3	58.7	82.9	72.8	85.0	84.3	79.3	76.3	46.3	76.3	74.9	86.0	78.2
I+ORE	7+12	76.2	79.6	82.5	75.7	70.5	55.1	85.2	84.4	88.4	58.6	82.6	73.9	84.2	84.7	78.8	76.3	46.7	77.9	75.9	83.3	79.2
SSD	7+12	77.4	81.7	85.4	75.7	69.6	49.9	84.9	85.8	87.4	61.5	82.3	79.2	86.6	87.1	84.7	78.9	50.0	77.4	79.1	86.2	76.3
SSD+ SD (1x) [129]	7+12	78.1	83.2	84.5	76.1	72.1	50.2	85.2	86.3	87.8	63.7	82.8	80.1	85.2	87.2	84.8	80.0	51.5	77.0	82.0	86.1	76.9
SSD + SD(2x) [129]	7+12	78.3	83.6	85.0	76.2	72.0	51.3	85.1	87.2	87.6	64.2	82.5	81.9	85.5	86.5	85.9	81.2	51.2	72.3	82.8	86.9	78.4
SSD + SD(3x) [129]	7+12	77.8	80.4	85.0	76.3	70.1	50.4	84.8	86.3	88.2	61.0	83.5	79.5	87.2	86.9	85.9	78.8	51.2	76.9	79.4	86.5	77.9
FRCN [39]	7+12	73.2	76.5	79.0	70.9	65.5	52.1	83.1	84.7	86.4	52.0	81.9	65.7	84.8	84.6	77.5	76.7	38.8	73.6	73.9	83.0	72.0
FRCN+SD(1x) [140]	7	79.9	85.1	86.6	78.6	75.7	65.2	83.5	88.4	88.9	65.8	83.6	74.3	86.4	84.7	85.5	88.0	62.0	75.5	75.3	87.7	76.3

TABLE VII

VOC 2007 TEST DETECTION AVERAGE PRECISION (%). FRCN* REFERS TO FRCN WITH TRAINING SCHEDULE IN [132] AND SD REFERS TO SYNTHETIC DATA

Model	mAP	AP50	AP75
EfficientDet-D0	55.6	77.6	61.4
+ AutoAugment	55.7 (+0.1)	77.7 (+0.1)	61.8 (+0.4)
+ Det-AdvProp	55.9 (+0.3)	77.9 (+0.3)	62.0 (+0.6)
EfficientDet-D1	60.8	82.0	66.7
+ AutoAugment	61.0 (+0.2)	82.2 (+0.2)	67.2 (+0.5)
+ Det-AdvProp	61.2 (+0.4)	82.3 (+0.3)	67.4 (+0.7)
EfficientDet-D2	63.3	83.6	69.3
+ AutoAugment	62.7 (-0.6)	83.3 (-0.3)	69.2 (-0.1)
+ Det-AdvProp	63.5 (+0.2)	83.8 (+0.2)	69.7 (+0.4)
EfficientDet-D3	65.7	85.3	71.8
+ AutoAugment	65.2 (-0.5)	85.1 (-0.2)	71.3 (-0.5)
+ Det-AdvProp	66.2 (+0.5)	85.9 (+0.6)	72.5 (+0.7)
EfficientDet-D4	67.0	86.0	73.0
+ AutoAugment	67.0 (+0.0)	86.3 (+0.3)	73.5 (+0.5)
+ Det-AdvProp	67.5 (+0.5)	86.6 (+0.6)	74.0 (+1.0)
EfficientDet-D5	67.4	86.9	73.8
+ AutoAugment	67.6 (+0.2)	87.2 (+0.3)	74.2 (+0.4)
+ Det-AdvProp	68.2 (+0.8)	87.6 (+0.7)	74.7 (+0.9)

TABLE VIII

RESULTS ON PASCAL VOC 2012. THE PROPOSED DETADVPROP GIVES THE HIGHEST SCORE ON EVERY MODEL AND METRIC. IT LARGELY OUTPERFORMS AUTOAUGMENT [23] WHEN FACING DOMAIN SHIFT.

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Method	Model	1/8	1/4	1/2	7/8	Full
SDA [144]	DeepLabV3Plus	74.1	-	-	-	-
SDA + DSBN [144]	DeepLabV3Plus	69.5	-	-	-	-
SDA [144]	DeepLabV3Plus	-	-	-	-	78.7
SDA + DSBN [144]	DeepLabV3Plus	-	-	-	-	79.2
SDA [144]	DeepLabV3Plus	-	-	-	71.4	-
SDA + DSBN [144]	DeepLabV3Plus	-	-	-	72.5	-
AdvSemi [55]	DeepLabV2	58.8	62.3	65.7	-	66.0
S4GAN + MT [90]	DeepLabV2	59.3	61.9	-	-	65.8
CutMix [35]	DeepLabV2	60.3	63.87	-	-	67.7
DST-CBC [34]	DeepLabV2	60.5	64.4	-	-	66.9
ClassMix [93]	DeepLabV2	61.4	63.6	66.3	-	66.2
ECS [89]	DeepLabV3Plus	67.4	70.7	72.9	-	74.8
DSBN [144]	DeepLabV2	67.6	69.3	70.7	-	70.1
SSBN [144]	DeepLabV3Plus	74.1	77.8	78.7	-	78.7
Adversarial [55]	DeepLab-v2	-	58.8	62.3	65.7	-
s4GAN [90]	DeepLab-v2	-	59.3	61.9	-	65.8
French et al [35]	DeepLab-v2	51.20	60.34	63.87	-	-
DST-CBC [34]	DeepLab-v2	48.7	60.5	64.4	-	-
ClassMix-Seg [93]	DeepLab-v2	54.07	61.35	63.63	66.29	-
DeepLab V3plus [148]	MobileNet	-	-	-	-	73.5
DeepLab V3plus [148]	ResNet-50	-	-	-	-	76.9
DeepLab V3plus [148]	ResNet-101	-	-	-	-	78.5
Baseline+ CutOut (16x16, p = 1) [148]	MobileNet	-	-	-	-	72.8
Baseline+ CutMix (p = 1) [148]	MobileNet	-	-	-	-	72.6
Baseline+ ObjectAug [148]	MobileNet	-	-	-	-	73.5

TABLE IX
RESULTS OF PERFORMANCE (MIOU) ON CITYSCAPES VALIDATION SET

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Method	Model	1/100	1/50	1/20	1/8	1/4	Full
GANSeg [116]	VGG16	-	-	-	-	64.1	
AdvSemSeg [55]	ResNet-101	-	-	-	-	68.4	
CCT [94]	ResNet-50	-	-	-	-	69.4	
PseudoSeg [157]	ResNet-101	-	-	-	-	73.2	
DSBN [144]	ResNet-101	-	-	-	-	75.0	
DSBN [144]	Xception-65	-	-	-	-	79.3	
Fully supervised [144]	ResNet-101	-	-	-	-	78.3	
Fully supervised [144]	Xception-65	-	-	-	-	79.2	
Adversarial [55]	DeepLab-v2	-	57.2	64.7	69.5	72.1	-
s4GAN [90]	DeepLab-v2	-	63.3	67.2	71.4	-	75.6
French et.al [35]	DeepLab-v2	53.79	64.81	66.48	67.60	-	-
DST-CBC [34]	DeepLab-v2	61.6	65.5	69.3	70.7	71.8	-
ClassMix:Seg* [93]	DeepLab-v2	54.18	66.15	67.77	71.00	72.45	-
Mixup [147]	IRNet	-	-	-	-	-	49
CutOut [27]	IRNet	-	-	-	-	-	48.9
CutMix [146]	IRNet	-	-	-	-	-	49.2
Random pasting [119]	IRNet	-	-	-	-	-	49.8
CCNN [96]	VGG16	-	-	-	-	-	35.6
SEC [66]	VGG16	-	-	-	-	-	51.1
STC [135]	VGG16	-	-	-	-	-	51.2
AdvEra [134]	VGG16	-	-	-	-	-	55.7
DCSP [13]	ResNet101	-	-	-	-	-	61.9
MDC [136]	VGG16	-	-	-	-	-	60.8
MCOF [131]	ResNet101	-	-	-	-	-	61.2
DSRG [54]	ResNet101	-	-	-	-	-	63.2
AffinityNet [2]	ResNet-38	-	-	-	-	-	63.7
IRNet [1]	ResNet50	-	-	-	-	-	64.8
FickleNet [78]	ResNet101	-	-	-	-	-	65.3
SEAM [133]	ResNet38	-	-	-	-	-	65.7
ICD [31]	ResNet101	-	-	-	-	-	64.3
IRNet + CDA [119]	ResNet50	-	-	-	-	-	66.4
SEAM + CDA [119]	ResNet38	-	-	-	-	-	66.8
DeepLab V3 [148]	MobileNet	-	-	-	-	-	71.9
DeepLab V3 [148]	ResNet-50	-	-	-	-	-	77.8
DeepLab V3 [148]	ResNet-101	-	-	-	-	-	78.4
DeepLab V3plus [148]	MobileNet	-	-	-	-	-	73.8
DeepLab V3plus [148]	ResNet-50	-	-	-	-	-	78.8
DeepLab V3plus [148]	ResNet-101	-	-	-	-	-	79.6
Baseline+R.Rotation [148]	ObjectAug	-	-	-	-	-	69.5
Baseline +R.Scaling [148]	ObjectAug	-	-	-	-	-	70.3
Baseline + R.Flipping [148]	ObjectAug	-	-	-	-	-	69.6
Baseline + R.Shifting [148]	ObjectAug	-	-	-	-	-	70.7
Baseline + All [148]	ObjectAug	-	-	-	-	-	73.8
Baseline + CutOut (16x16, p = 0.5) [148]	MobileNet	-	-	-	-	-	71.9
Baseline + CutOut (16x16, p = 1) [148]	MobileNet	-	-	-	-	-	72.3
Baseline + CutMix (p = 0.5) [148]	MobileNet	-	-	-	-	-	72.7
Baseline + CutMix (p = 1) [148]	MobileNet	-	-	-	-	-	72.4
Baseline + ObjectAug [148]	MobileNet	-	-	-	-	-	73.8
Baseline + CutOut (16x16, p=0.5) + ObjectAug [148]	MobileNet	-	-	-	-	-	73.9
Baseline + CutMix (p=0.5) + ObjectAug [148]	MobileNet	-	-	-	-	-	74.1
DeepLabv3+ [14]	EfficientNet-B7	-	-	-	-	-	84.6
ExFuse [150]	EfficientNet-B7	-	-	-	-	-	85.8
Eff-B7 [156]	EfficientNet-B7	-	-	-	-	-	85.2
Eff-L2 [156]	EfficientNet-B7	-	-	-	-	-	88.7
Eff-B7 NAS-FPN [37]	EfficientNet-B7	-	-	-	-	-	83.9
Eff-B7 NAS-FPN w/ Copy-Paste pre-training [37]	EfficientNet-B7	-	-	-	-	-	86.6

TABLE X
RESULTS OF PERFORMANCE (MIOU) ON THE PASCAL VOC 2012 VALIDATION SET

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