

A Study on the Impact of Data Augmentation for Training Convolutional Neural Networks in the Presence of Noisy Labels

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Abstract—Label noise is common in large real-world datasets, and its presence harms the training process of deep neural networks. Although several works have focused on the training strategies to address this problem, there are few studies that evaluate the impact of data augmentation as a design choice for training deep neural networks. In this work, we analyse the model robustness when using different data augmentations and their improvement on the training with the presence of noisy labels. We evaluate state-of-the-art and classical data augmentation strategies with different levels of synthetic noise for the datasets MNist, CIFAR-10, CIFAR-100, and the real-world dataset Clothing1M. We evaluate the methods using the accuracy metric. Results show that the appropriate selection of data augmentation can drastically improve the model robustness to label noise, increasing up to 177.84% of relative best test accuracy compared to the baseline with no augmentation, and an increase of up to 6% in absolute value with the state-of-the-art DivideMix training strategy.

Index Terms—label noise, deep learning, classification

I. INTRODUCTION

Convolutional Neural Networks (CNNs) have been the state-of-the-art for computer vision tasks in the last decade [1]. The training of these models requires large amounts of data with precise annotations in order to provide good generalization capabilities [2]. However, human or automatic annotations are susceptible to mislabeling due to human failure, challenging tasks, quality of data, etc [3]. Therefore, the presence of label noise is common and often not considered for most of the proposed CNNs and training strategies in literature [4]. Moreover, most real-world large datasets available for training CNNs for computer vision tasks, such as ImageNet [5], have the presence of noisy labels. Zhang et al. [6] show that when the dataset is contaminated with label noise, the performance of the model is decreased. For this purpose, different strategies for dealing with labels have been proposed in the last years [7].

Recent works have shown the importance of using data augmentation along with training strategies to deal with noisy labels. Zhang et al. [6] show that the use of regularisation, such as data augmentation, dropout and weight decay helps to

improve the generalization performance. They show that the use of simple data augmentation, such as random cropping and random perturbation of brightness helps to improve the results. Nishi et al. [8] show that the use of weak and strong data augmentation can improve training, showing that not only the choice of the data augmentation matters, but also the intensity of the augmentation. Zhang et al. propose the Mixup [9] augmentation, originally proposed for general model training, but which has shown to improve the robustness of the model in the presence of label noise [10].

Most of the recent methods to deal with noisy labels use classical data augmentation methods, such as random cropping, perturbation of brightness, saturation, hue, and contrast, as present in AutoAugment (AutoAug) [11]. Although the recent advances in training strategies and data augmentation methods, there is no consensus on which is the best state-of-the-art data augmentation for dealing with label noise. Moreover, to the best of our knowledge, there is no work analysing the impact of data augmentation design choice in the training of CNNs with noisy labels in the training set.

This work proposes the analysis of 13 classical and six state-of-the-art (SOTA) data augmentation methods in order to (1) identify the impact on model training when using different data augmentation strategies, and (2) evaluate the best data augmentation method or combination for different levels of noise rate. We perform the analysis for the symmetric, asymmetric and semantic noise over different noise rates. The results are evaluated using a vanilla ResNet-18 [12] with standard training and also with the SOTA training strategy DivideMix [10].

II. RELATED WORK

It is a common practice in modern image classification models to use data augmentation to improve the diversity of the training set and increase model generalization capabilities. Several training strategies have been proposed in the last decade to address the noisy label problem [3]. The main strategies can be classified as robust loss function [13], sample selection [14], label cleansing [15], meta-learning [16] and

semi-supervised learning [10], [17]. Although the different proposals to train the model, only a few existing data augmentation methods have been explored to address this problem. Figure 1 shows a comparison of the most used data augmentation methods present in literature for training with noisy labels. We evaluated 61 papers related to noisy labels from the last four years and the corresponding data augmentations used. Each paper can use more than one data augmentation method, and we listed the main approaches found in the literature for papers proposed to tackle the label noise problem.

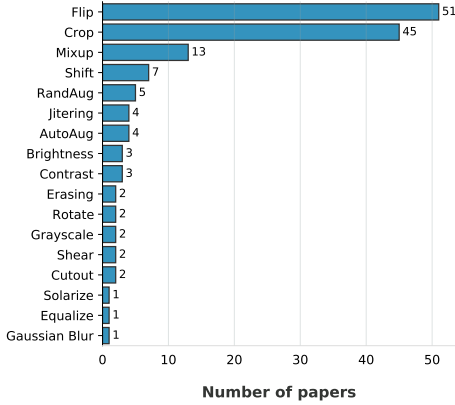


Fig. 1. Number of papers related to training with noisy labels that use each type of data augmentation. Sixty-one papers from the last years were evaluated for this analysis.

For the recent strategies to deal with noisy labels, the standard approach is to use classical image processing, such as random cropping and flip, as shown in Figure 1. A few recent approaches [10], [17], [18] have started to use SOTA data augmentation methods such as Mixup [9], CutMix [19] and RandAugment (RandAug) [20].

The Mixup [9] data augmentation proposes a linear combination between samples in order to reduce the empirical vicinal risk. Their approach showed to improve the robustness of the model to label noise and it has been used in training approaches such as DivideMix [10] and PropMix [17]. The DivideMix approach uses random crop and flipping along with Mixup, whereas PropMix also includes RandAug approach.

Chen et al. [21] evaluate the training when using no augmentation, standard augmentations (cropping and flip) and strong augmentation (using AutoAug). Their results show an improvement when using strong data augmentation, however their analysis is restricted to one strategy of SOTA data augmentation and one combination of standard augmentation.

Although several recent data augmentation methods have been proposed in the literature, they have not been evaluated in the context of noisy labels. Furthermore, there is no study addressing the analysis of the impact of different data augmentations strategies and the corresponding results for training the model with noisy labels. This work performs this analysis, comparing classical, SOTA and combinations of the data augmentations approaches, evaluating their impact on different datasets and noise rates. In a similar work, Cordeiro et al. [7]

show the main strategies to deal with noisy labels in the last years. Although they show the different techniques, there is no experiments related to data augmentation or analysis of data augmentation performance in the label noise context. Our work aims to show how the choice of data augmentation impacts the training with noisy labels and which strategies can make the model more robust under different noise scenarios.

III. METHODS

A. Problem Definition

Lets consider $D = \{(x_1, y_1), \dots, (x_n, y_n)\}$ as the training set of a classification problem, where $x_i \in \mathcal{X}$ is the i^{th} image and $y_i \in Y$ is a one-hot vector representing the label over c classes. We denote $y \in Y$ as the observed labels (which may or not contain noise). We denote y_i^* as the true label of x_i . The distribution of different labels for sample x is denoted by $p(c|x)$, and $\sum_{c=1}^C p(c|x) = 1$.

The overall noise rate is defined by $\eta \in [0, 1]$ and η_{jc} represents the probability of a class j be flipped to class c , as $p(y_i = c|y_i^* = j)$. The main types of noise evaluated in this work are described as follows: symmetric, asymmetric and semantic.

The symmetric noise represents a noise process when a label has equal probability to flip to another class. In the symmetric noise, the true label is also included in the label flipping options, which means that in $\eta_{jc} = \frac{\eta}{C-1}, \forall j \in Y$. Although the symmetric noise is unlikely to represent a realistic scenario for noisy labels, it is the main baseline for noisy label experiments.

The asymmetric noise, as described in [22], is closer to a real-world label noise based on flipping labels between similar classes. For asymmetric noise, η_{jc} is class conditional. The semantic noise depends on both the classes $j, c \in \mathcal{Y}$ and the image \mathbf{x}_i .

B. Data Augmentations

The data augmentation methods evaluated in this work are divided into two categories: basic and SOTA methods. For the basic augmentations, we evaluated *random crop*, *horizontal flip*, *rotation*, *translation*, *shear*, *autocontrast*, *invert*, *equalize*, *posterize*, *contrast*, *brightness*, *sharpness*, *solarize* and the combination of them. For the SOTA methods we evaluated AutoAug [11], RandAug [20], Cutout [23], Mixup [9], CutMix [19], AugMix [24] and their combination with the previous approaches.

For the basic augmentations, we used spatial-level and pixel-level transformations on the image, which usually are defined as weak augmentations. We added Table I describing the effects of each basic augmentation method. Figure 2 shows the different basic data augmentations and their effects on the original image.

The Mixup [9] data augmentation is one of the SOTA augmentations that has been increasingly applied to noisy label

TABLE I
DESCRIPTION OF THE BASIC AUGMENTATIONS EVALUATED IN THIS WORK,
SEPARATED AS SPATIAL-LEVEL AND PIXEL-LEVEL.

Augmentation	Type	Description
random crop	spatial-level	Crop a random part of the input
horizontal flip	spatial-level	Flip the input horizontally around the y-axis
rotation	spatial-level	Rotate the input by an angle selected randomly from the uniform distribution
translation	spatial-level	Translate the input by swapping rows and columns
shear	spatial-level	Distort an input along an axis
invert	pixel-level	Invert the input image by subtracting pixel values from 255
equalize	pixel-level	Equalize the image histogram
posterize	pixel-level	Reduce the number of bits for each color channel
contrast	pixel-level	Randomly change contrast of the input image
autocontrast	pixel-level	Remap pixels per channel maximizing contrast of an image
brightness	pixel-level	Randomly change brightness of the input image
sharpness	pixel-level	Sharpen the input image and overlays the result with the original image
solarize	pixel-level	Invert all pixel values above a threshold

scenarios. It linearly combines images and labels using the following equation:

$$\begin{aligned}\tilde{x} &= \lambda x_i + (1 - \lambda)x_j, \\ \tilde{y} &= \lambda y_i + (1 - \lambda)y_j\end{aligned}\quad (1)$$

where x_i and x_j are input images and y_i and y_j are the corresponding observed labels.

Cutout [23] is an image augmentation and regularization technique that randomly masks out square regions of input during training. The CutMix [19] augmentation, instead of removing pixels and filling them with black pixels, replaces the removed regions with a patch from another image.

AugMix [24] method consists of mixing the results from augmentation chains or compositions of augmentation operations. For the input image are applied different sequences of augmentations, such as rotation, translation and posterize, and the images are mixed using different weights. This method has not been explored in the context of noisy labels.

AutoAug [11] and RandAug [20] incorporate augmentation policies during the training, using stronger augmentations optimized for each dataset. A stronger augmentation means a higher intensity in the augmentation, causing a higher perturbation on the image. These augmentations policies include basic transformations such as rotation, shear, invert and contrast. AutoAug uses reinforcement learning to determine the selection and ordering of a set of augmentation functions in order to optimize validation loss. To remove the search phase of AutoAug and therefore reduce training complexity, RandAug drastically reduces the search space for optimal augmentations and uses grid search to determine the optimal set. Figure 3 shows Cutout, Mixup, CutMix, AugMix, AutoAug and RandAug augmentations effects on the original image.

IV. EXPERIMENTS

A. Datasets

The experiments were conducted using the datasets MNIST [25], CIFAR-10 [26], CIFAR-100 [26] and Clothing1M [27].

MNIST consists of handwritten digit images of size 28×28 pixels with a training set of 60,000 samples and a test set of 10,000 samples. For this dataset, we applied synthetic symmetric noise, where each sample has its labels j flipped randomly to another class c , with probability η_{jc} . We evaluated $\eta_{jc} \in \{0.2, 0.4, 0.9\}$, which represents low, medium and high noise scenarios.

CIFAR-10 and CIFAR-100 datasets have 50,000 training and 10,000 testing samples of size 32×32 pixels, where CIFAR has 10 classes and CIFAR-100 has 100 classes. Both datasets have the same amount of samples per class. For this dataset we introduced synthetic symmetric noise, with $\eta_{jc} \in \{0.2, 0.5, 0.8\}$. We also introduced asymmetric noise for CIFAR-10 and CIFAR-100. The asymmetric noise for CIFAR-10 is produced following the mapping used in [10], which maps the classes *truck* \rightarrow *automobile*, *bird* \rightarrow *plane*, *deer* \rightarrow *horse*, with $\eta_{jc} = 0.4$. The asymmetric noise for CIFAR-100 is produced following the mapping used in [22], which groups the 100 classes into 20 super-classes containing 5 original classes (e.g., super-class 'Aquatic Mammals' contains 'Beaver', 'Dolphin', 'Otter', 'Seal', and 'Whale'), and within each super-class the noise flips each class into the next one, circularly.

The Clothing1M dataset contains 1,000,000 clothing images taken from various online shopping sites with noisy labels that reproduce the real world. Clothing1M also contains 14 classes and samples with clean labels, where 50,000 are used for training, 14,000 for validation, and 10,000 for testing. The Clothing1M dataset contains real-world noise, which corresponds to asymmetric and semantic noises.

B. Implementation

For the implementation of the basic data augmentations, we used the set of parameters following image transformation magnitudes in [11]. For the SOTA data augmentations AutoAug, RandAug, Cutout, Mixup, CutMix and AugMix, we used the code provided by their official repositories with the default values. For the Clothing1M dataset, data augmentations were applied as in [10].

For MNIST, CIFAR-10 and CIFAR-100 we used a ResNet-18 as our baseline model, following [12]. The model for MNIST is trained with stochastic gradient descent (SGD) with momentum of 0.9, weight decay of 0.0005, learning rate 0.001 and batch size of 64. For CIFAR-10 and CIFAR-100, the model is trained with SGD with momentum of 0.9, weight decay of 0.0005, learning rate 0.02 and batch size of 64. We trained the models using 100 and 200 epochs for MNIST and CIFAR datasets, respectively.

In the DivideMix, for CIFAR-10 and CIFAR-100 we used a 18-layer PreAct-ResNet-18 (PRN18) [28] as backbone model,

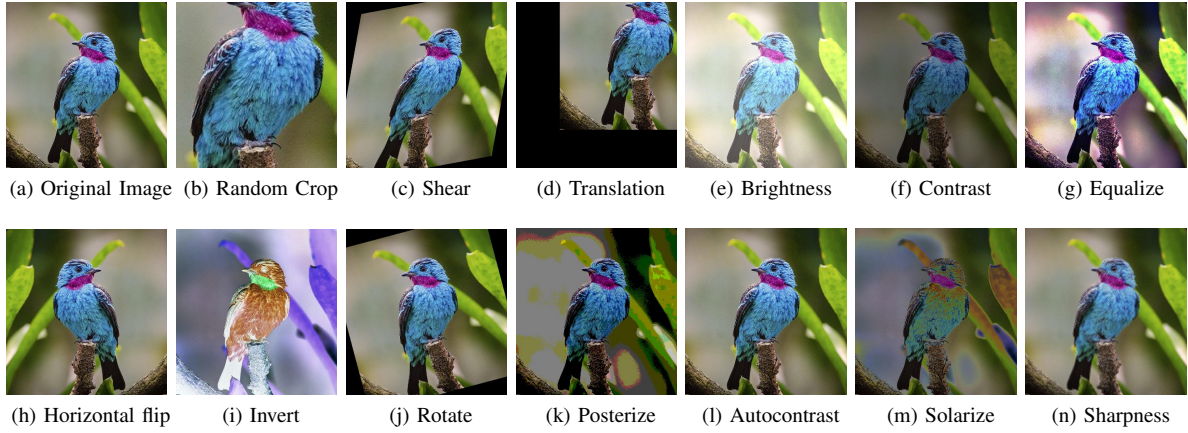


Fig. 2. Basic data augmentations based on classical image processing (b)-(n).

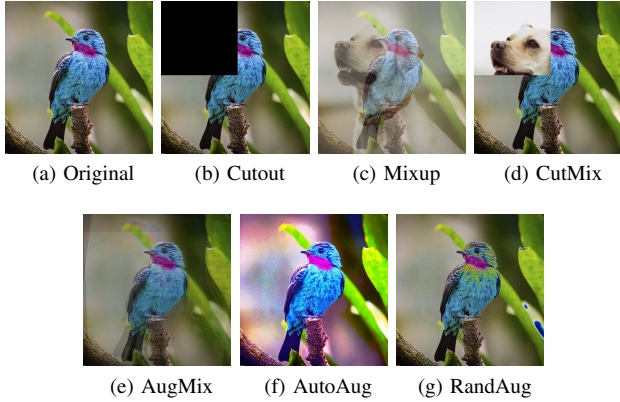


Fig. 3. Cutout, Mixup, CutMix, AugMix, AutoAug and RandAug augmentations.

as in [10]. The model is trained with SGD with momentum of 0.9, weight decay of 0.0005 and batch size of 64. The learning rate is 0.02, which is reduced to 0.002 in the middle of the training [10]. We trained the model using 300 epochs.

For Clothing1M, we use ResNet-50 as backbone, following [10]. In this protocol, a ResNet-50 with ImageNet [5] pre-trained weights is used. The ResNet-50 is trained for 80 epochs with a batch size of 32, SGD with a learning rate of 0.002 (divided by 10 at epoch 40), momentum of 0.9 and weight decay of 0.0001.

V. RESULTS

For MNIST dataset, we evaluate a ResNet-18 with synthetic symmetric noise with noise rate $\eta_{jc} \in \{0.2, 0.5, 0.9\}$ for different types of data augmentation and combinations. We used a vanilla ResNet-18, with no augmentations, as our baseline model. As the MNIST dataset is composed of binary images, we did not use the augmentations *equalize*, *posterize*, *solarize*, *contrast*, *autocontrast*, *brightness* and *solarize*. The results are shown in Table II. In Table II we report the best and last values of evaluation on the test set. We denote the random crop augmentation as *rc*.

TABLE II
RESULTS OF ACCURACY USING DIFFERENT DATA AUGMENTATIONS FOR MNIST DATASET, WITH $\eta_{jc} \in \{0.2, 0.5, 0.9\}$. THE BEST VALUES ARE REPORTED IN BOLD.

Method/Noise Ratio Accuracy	20%		50%		90%	
	Best	Last	Best	Last	Best	Last
baseline	98.31	96.70	97.16	79.21	72.96	22.04
random crop (rc)	99.45	99.08	99.09	98.41	95.19	85.44
random horizontal flip	97.62	95.51	96.06	68.76	72.80	20.68
random rotation	99.22	91.90	98.72	75.72	88.89	28.77
random translation-x	99.31	91.52	98.79	72.01	88.81	27.98
random shear-x	99.04	93.46	98.42	70.97	85.97	21.65
random invert	98.42	95.93	97.42	66.05	73.34	22.31
random sharpness	98.41	96.39	97.18	78.73	73.39	22.82
random crop + translation + shear	99.57	99.46	99.50	99.38	96.11	93.82
all basic transformations	98.59	98.14	97.70	97.62	34.42	34.42
AutoAug [11]	99.42	95.79	98.91	84.40	86.33	30.85
RandAug [20]	99.48	95.13	99.06	80.11	88.88	27.50
Cutout [23]	99.09	80.78	98.13	65.76	81.76	16.61
CutMix [19]	98.36	96.05	97.20	77.11	74.90	23.16
AugMix [24]	98.65	93.32	97.87	67.30	67.60	20.37
Mixup [9]	98.82	96.45	97.50	79.11	73.34	21.91
AutoAug + random crop	99.64	99.47	99.48	99.48	96.46	94.58
RandAug + random crop	99.66	99.52	99.38	99.25	97.10	95.64
Cutout + random crop	99.37	99.25	99.17	98.97	95.04	93.03
Mixup + random crop	99.47	99.31	99.17	99.05	95.40	90.68
CutMix + random crop	99.38	99.32	99.10	98.94	95.72	94.40
AugMix + random crop	99.55	99.28	99.20	98.74	95.80	90.92
AutoAug + rc + translation + shear	99.52	99.38	99.35	99.17	92.61	91.19
RandAug + rc + translation + shear	99.58	99.50	99.40	99.23	95.06	94.74
Cutout + rc + translation + shear	99.40	99.27	99.05	98.99	93.81	90.61
Mixup + rc + translation + shear	99.52	99.31	99.29	99.19	93.47	91.87
CutMix + rc + translation + shear	99.43	99.23	99.20	99.16	95.08	94.34
AugMix + rc + translation + shear	99.62	99.60	99.46	99.36	96.49	94.15

From Table II we can notice that all augmentations improve robustness to noisy labels over the baseline, which has no augmentation. Random crop is the main augmentation to help to deal with noisy labels. The SOTA methods only achieve high performance when combined with random crop. The main reason is because random crop helps to deal with overfitting to label noise, helping the model to learn the target class based on different features of the image. Although the data augmentations individually improve the results, the combination of them, as in *random crop + translation + shear* is more efficient. However, combining all the basic augmentations together, as in *all basic transformations* is less efficient. We also can observe that the SOTA augmentations

TABLE III

RESULTS OF ACCURACY USING DIFFERENT DATA AUGMENTATIONS FOR FOR CIFAR-10 AND CIFAR-100 DATASETS. THE BEST VALUES ARE REPORTED IN BOLD.

dataset	CIFAR-10								CIFAR-100							
Noise type	symmetric.				asym.				symmetric				asym.			
Method/Noise Ratio Accuracy	20%		50%		80%		40%		20%		50%		80%		40%	
	Best	Last	Best	Last	Best	Last	Best	Last	Best	Last	Best	Last	Best	Last	Best	Last
baseline	72.60	62.31	62.96	39.67	41.50	18.25	70.30	64.64	40.27	31.42	28.94	16.31	8.27	4.92	30.67	23.60
random crop (rc)	82.00	75.73	76.04	54.94	58.66	27.28	81.48	76.41	52.01	41.22	39.48	21.86	15.74	7.88	39.14	31.42
random horizontal flip	78.02	68.34	68.62	44.29	48.46	18.90	76.32	65.05	45.74	34.71	34.71	16.96	17.94	4.73	35.17	28.72
random rotation	76.32	67.82	67.76	44.60	48.93	20.24	73.99	67.83	44.79	35.21	33.75	18.01	17.12	5.86	34.54	26.59
random translation-x	78.71	70.90	69.03	45.17	50.43	20.25	77.21	69.22	45.08	35.59	34.26	19.25	18.43	5.39	33.84	30.91
random shear-x	75.50	66.87	63.42	41.89	43.56	20.79	73.03	65.94	41.96	31.88	32.95	16.06	15.58	4.97	31.71	24.93
random posterize	72.54	63.46	62.94	39.42	44.32	18.17	69.58	65.18	40.52	30.25	30.16	14.77	13.54	4.03	30.36	23.47
random solarize	73.48	63.18	62.80	38.15	44.87	18.54	71.76	63.86	41.05	29.33	29.91	14.22	14.55	3.98	30.45	22.97
rc + translation + shear	82.66	81.74	75.38	70.46	55.14	46.62	80.69	79.40	51.48	46.69	42.36	40.44	16.95	16.56	39.70	35.20
all basic transformations	64.71	61.67	51.08	47.42	10.52	10.00	61.46	55.49	31.64	28.67	18.53	16.65	2.47	1.67	27.14	21.52
AutoAug	77.52	67.70	67.87	42.31	46.71	19.62	75.46	65.52	44.89	34.89	34.28	16.35	16.66	4.53	34.60	28.12
RandAug	78.89	71.86	71.86	46.03	52.22	22.19	77.18	67.00	47.49	37.46	37.67	20.22	19.54	6.42	35.87	29.29
Cutout	75.86	67.13	67.34	43.76	49.56	21.38	74.64	66.39	41.87	32.83	32.29	15.88	16.38	4.63	31.44	25.83
CutMix	79.67	74.59	70.58	51.75	50.24	22.05	76.51	68.46	50.18	42.23	38.22	23.58	18.62	6.34	39.75	31.57
AugMix	75.38	66.68	65.53	43.61	46.10	20.30	72.30	66.21	41.38	34.02	31.12	17.13	15.07	4.85	31.75	24.34
Mixup	74.40	66.11	65.10	42.66	44.26	20.47	70.33	64.89	43.54	33.39	32.85	17.06	15.18	5.13	33.90	23.82
AutoAug + random crop	85.05	83.56	78.84	75.88	64.10	56.76	84.16	79.57	56.13	51.73	45.26	36.97	20.39	17.09	43.40	42.26
RandAug + random crop	84.75	82.41	77.92	72.86	62.31	49.05	82.78	79.57	55.15	45.95	43.22	25.16	19.19	11.13	41.83	33.07
Cutout + random crop	84.61	83.29	78.93	75.40	60.42	45.34	83.77	79.76	51.91	41.82	40.11	23.33	16.27	9.02	39.07	30.85
Mixup + random crop	84.53	81.88	77.15	73.93	61.64	49.08	82.53	77.79	55.64	49.30	45.10	33.45	18.56	12.23	43.46	37.61
CutMix + random crop	85.19	82.94	78.29	71.03	63.37	50.05	83.33	77.53	56.61	52.16	46.04	32.85	19.29	12.63	48.88	43.88
AugMix + random crop	83.31	80.58	77.45	63.98	59.47	34.44	81.61	75.65	52.30	43.05	41.69	24.30	17.26	9.82	40.35	31.52
AutoAug + rc + translation + shear	81.15	79.74	73.40	72.59	49.28	42.70	79.53	75.25	51.34	51.34	43.40	42.16	16.31	16.31	40.84	36.05
RandAug + rc + translation + shear	82.24	74.66	74.78	73.12	50.42	48.29	80.34	77.22	52.38	48.53	42.95	40.99	16.59	16.55	42.73	40.43
Cutout + rc + translation + shear	80.10	77.13	72.94	69.46	50.64	42.53	80.21	76.00	53.43	49.01	42.68	41.86	23.12	21.23	40.46	33.91
Mixup + rc + translation + shear	80.18	76.15	72.12	66.08	49.45	44.05	78.60	72.95	48.72	45.61	41.20	37.67	17.87	15.93	41.40	39.91
CutMix + rc + translation + shear	77.85	76.76	71.59	61.34	45.79	36.60	75.74	74.62	47.34	44.82	37.73	34.15	13.38	13.18	39.80	34.06
AugMix + rc + translation + shear	82.13	80.24	75.58	71.89	52.48	50.22	80.13	74.84	51.81	47.26	42.94	38.36	16.22	15.71	41.51	35.34
CutMix + rc + AutoAug	85.46	82.90	80.03	75.95	64.88	58.52	83.18	79.73	58.92	65.54	49.69	45.32	22.96	20.43	48.20	44.03
Mixup + rc + AutoAug	85.70	83.74	80.35	75.34	65.08	60.77	82.91	79.79	59.32	54.51	48.12	48.12	20.24	17.26	49.42	45.36
CutMix + Mixup + rc	84.29	82.15	77.59	74.10	62.27	53.20	82.04	72.53	56.07	52.37	42.78	35.16	17.65	16.14	48.14	46.88
DivideMix (w/ Mixup) [10]	96.27	96.97	94.82	94.54	93.08	92.92	93.54	91.97	77.19	76.74	74.53	74.30	54.33	54.33	60.64	53.22
DivideMix (w/ Mixup) + AutoAug	96.28	96.14	95.32	95.11	94.18	93.96	94.41	94.05	78.04	78.04	76.53	76.06	58.98	58.52	65.44	60.99
DivideMix (w/ CutMix)	96.42	95.96	95.25	94.82	92.00	91.46	93.22	86.97	79.76	78.84	75.64	74.11	54.42	54.15	61.74	53.79
DivideMix (w/ CutMix) + AutoAug	96.91	96.46	95.92	95.52	94.39	94.02	94.74	92.34	80.70	80.35	78.68	77.99	60.25	60.03	66.67	56.93

have better results when combined with random crop. Adding more augmentations, such as in the combination *AutoAug + rc + translation + shear* showed similar results. RandAug augmentation, combined with random crop, showed the best results. Compared to the baseline, the choice of a proper data augmentation improved the results up to 33% on high noise rates.

We also evaluated the augmentations for CIFAR-10 and CIFAR-100 datasets, with symmetric noise $\eta_{jc} \in \{0.2, 0.5, 0.8\}$ and asymmetric noise of 0.4. For these datasets we included all the 13 basic augmentations and SOTA methods and their combinations. We also evaluated the use of SOTA training strategy DivideMix [10], using different augmentations. DivideMix standard augmentations use Mixup, random cropping and horizontal flip. We evaluate replacing Mixup for CutMix and adding AutoAug. Results are shown in Table III. We can observe that the addition of basic augmentations to the baseline highly improve the results over different noise rates. As noticed in MNIST dataset, the combination of *rc+translation+shear* showed better results than using individual augmentations. Using all basic transformations together showed to be less efficient. We also noticed that random crop (rc) augmentation is essential to improve to results of

SOTA augmentations strategies. From the observed results, the combination of *CutMix+rc+AutoAug* and *Mixup+rc+AutoAug* showed the best combinations of augmentations when added to the baseline. The relative improvement over the baseline test accuracy is up to 61.39% on asymmetric noise and 177.84% over high symmetric noise by adding augmentations to the training process. When observing the standard DivideMix strategy, denoted in Table III as *DivideMix (w/ Mixup)*, the replacement of Mixup for CutMix and the addition of AutoAug improve the results for all the scenarios analysed. The improvement of DivideMix just by changing the augmentation strategy increases the best test accuracy by up to 6% on CIFAR-100.

We also evaluated the impact of using data augmentation on the real-world dataset Clothing1M. For this dataset, we evaluate the baseline, with no augmentation, and the use of the best strategy observed in the previous datasets (i.e. CutMix+AutoAug). We also compare standard DivideMix with the use of different augmentations. Results are shown in Table IV. From the observed results in Table IV we can notice an improvement of 1.55% over the baseline. For Clothing1M, the combination of CutMix and AutoAug showed lower results than standard DivideMix. However, the addition of AutoAug

to DivideMix increased the results.

TABLE IV
RESULTS FOR CLOTHING1M.

Method	Accuracy (%)
baseline	70.30
rc +CutMix + AutoAug	71.85
DivideMix (with Mixup)	74.32
DivideMix (with Mixup) + AutoAug	75.12
DivideMix (with CutMix)	72.63
DivideMix (with CutMix) + AutoAug	69.95

With these analyses we show that the choice of data augmentation as a design decision can drastically improve the results when using standard training in the presence of noisy labels. When using SOTA training strategies, the model’s performance also can be increased by choosing the augmentation properly. Although the best augmentation strategy seems to be dataset-dependent, we could identify the best augmentation strategies and the importance of choosing them in the training process.

VI. CONCLUSION AND FUTURE WORK

In this work, we evaluated the use of different types of data augmentation in the training of CNNs with the presence of noisy labels. The conducted experiments showed that the choice of data augmentation drastically impacts the training performance. In our analysis, we conclude that the combination of classical approaches and SOTA data augmentations is the best option, and the optimal setup of data augmentations is an important design choice. However, the choice of the best data augmentation is dataset-dependent and needs to be evaluated separately.

For future works we will explore the benefits of using weak and strong augmentations at different stages of the training. We also will investigate new data augmentation strategies and develop some strategies to automatically define the best data augmentation method.

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