Confidence-Guided Data Augmentation for Deep Semi-Supervised Training

Fadoua Khmaissia  
University of Louisville  
Louisville, KY , USA  
f0khma01@louisville.edu

Hichem Frigui  
University of Louisville  
Louisville, KY , USA  
h.frigui@louisville.edu

Abstract

We propose a new data augmentation technique for semi-supervised learning settings that emphasizes learning from the most challenging regions of the feature space. Starting with a fully supervised reference model, we first identify low confidence predictions. These samples are then used to train a Variational AutoEncoder (VAE) that can generate an infinite number of additional images with similar distribution. Finally, using the originally labeled data and the synthetically generated labeled and unlabeled data, we retrain a new model in a semi-supervised fashion.

We perform experiments on two benchmark RGB datasets: CIFAR-100 and STL-10, and show that the proposed scheme improves classification performance in terms of accuracy and robustness, while yielding comparable or superior results with respect to existing fully supervised approaches.

Keywords – Semi-supervised deep learning, data augmentation, computer vision, image classification, MixMatch, VAE

1. Introduction

Deep learning models have achieved state of the art performances, especially for computer vision applications. Much of the recent successes, however, can be attributed to the existence of large, high quality, labeled datasets. In many real-world applications, collecting similar datasets is often cumbersome and time consuming. Semi-Supervised Learning (SSL) aims to alleviate heavy labeling needs by leveraging the availability of unlabeled data to learn more robust models[4]. Data Augmentation (DA) is another solution to the problem of limited data. It aims to increase the size and variability of training datasets in order to reduce overfitting and improve the model’s generalizability [7].

Ideally, a good training set should contain enough variations within each class for the model to learn the most optimal decision boundaries. However, when there are under-represented regions in the training feature space, especially in low data regime or in presence of low-quality inputs, the model risks learning sub-optimal decision boundaries, resulting in less accurate predictions (increased misclassifications) [21, 22].

One way to address this limitation is to augment the training dataset. A common data augmentation approach is to apply different transformations to the training samples [20], or to generate new data by mixing existing samples and fusing their labels [10, 26]. Such data augmentations, however, may not fully cover the underrepresented regions because they only look at the immediate vicinity of input samples. Another approach is to use existing detailed annotations, like part landmarks, to select additional samples from external labeled resources [24] and thus, rely on similar strongly supervised tasks to obtain new data to be added. This approach may hurt the model’s performance by introducing out-of-distribution samples. Hence, generating the appropriate samples to include in the training set is a critical task.

In this paper, we use the model’s classification confidence to guide synthetic data generation in order to augment the training data with samples from the under-performing regions that include the most misclassified samples.

We investigate the effect of generating synthetic data by a trained Variational Auto-Encoder (VAE [11]), and the use of these as unsupervised information in a deep semi-supervised learning framework (MixMatch [2]).

Our contributions can be summarized as follows:

• Augment the training dataset by generating synthetic images drawn from the same distribution as those samples that are misclassified by a baseline model
• Alleviate the need to label augmented data by using an SSL framework
• Increase the diversity of the available training set, and thus, learn more accurate decision boundaries, without actually collecting new data
• Our approach can be easily integrated into existing neural networks for SSL with little efforts

We perform experiments on two benchmark datasets,
and show that, despite its simplicity, the proposed scheme yields promising improvements in terms of accuracy and robustness over fully-supervised settings.

2. Related works

To highlight the main motivations behind our proposed approach, we first review VAEs and their main applications for image data augmentation or generative modeling in general. Next, SSL state-of-the art methods are presented along with some of their main challenges.

2.1. Variational Auto-Encoder (VAE)-Based Methods for Data Augmentation

A Variational Auto-Encoder (VAE) implements a latent variable model using a composition of two neural networks. A neural network decoder maps a latent variable configuration to an observation, and a neural network encoder approximately infers the latent variable configuration given an input observation [11]. VAEs are used for learning disentangled representations, generating discrete data, and nonlinear dimensionality reduction [15]. The key difference between VAEs and typical autoencoders is that VAEs learn latent variables with continuous distributions, which has shown to be a very helpful trait for tackling generative modeling problems.

Given a set of data \( x \in \mathcal{X} \), a VAE seeks to maximize the likelihood of the associated parametric model \( \{p(\theta), \theta \in \Theta\} \). Based on the assumption that there exist latent variables \( z \) living in a lower dimensional space \( \mathcal{Z} \) (\( z \in \mathcal{Z} \)), the marginal distribution can be expressed as follows:

\[
p_{\theta}(x) = \int_{\mathcal{Z}} p_{\theta}(x \mid z)q(z)dz \tag{1}
\]

where \( q \) is a prior distribution over the latent variables acting as a regulation component and \( p_{\theta}(x \mid z) \) is often a simple distribution and is referred to as the decoder. A variational distribution \( q_{\phi} \) is most of the time taken as a simple parameterized distribution (e.g., Gaussian, Bernoulli, etc.), aiming at approximating the true posterior distribution and referred to as the encoder is then introduced. Using Importance Sampling allows to derive an unbiased estimate of \( p_{\theta}(x) \) such that \( \mathbb{E}_{z \sim q_{\phi}}[p_{\theta}(x)] = p_{\theta}(x) \). Therefore, a lower bound on the logarithm of the objective function of Equation 1 can be derived using Jensen’s inequality [3]:

\[
\log p_{\theta}(x) \geq \mathbb{E}_{z \sim q_{\phi}} [\log p_{\theta}(x, z) - \log q_{\phi}(z \mid x)] \tag{2}
\]

Equation 2 is usually referred to as the ELBO. The ELBO can be made tractable thanks to the reparameterization trick, allowing optimization with respect to both \( \theta \) and \( \phi \). Once trained, the model’s decoder functions as a generative model, allowing for the generation of new data by simply drawing a sample using the prior \( q \) and passing it to the decoder.

In recent years, generative models with improved performance, such as VAEs and Generative Adversarial Networks (GAN) [8], have become increasingly popular models for DA.

As opposed to GANS, VAEs have witnessed a limited interest to perform DA and were mostly used for audio applications [9, 14, 23]. There have also been some other attempts on medical images for both classification [27, 13] and segmentation tasks [18, 19].

The biggest barrier preventing VAEs from being used more widely is the fact that they frequently generate fuzzy and blurry samples. This drawback is further highlighted when VAEs are trained with a low number of samples which makes it hard to use them to perform DA in a low-data regime.

To address this issue, we use a VAE with a pretrained encoder which is fine-tuned on the samples of interest. These VAE training samples are selected based mainly on model’s confidence as well as additional samples from the training set.

2.2. Semi-Supervised Learning (SSL)

Semi-supervised learning [4] (SSL) is a classical learning paradigm that has gained increasing interests with the rise of deep learning models which rely heavily on labeled data. By leveraging the availability of unlabeled data, SSL methods can infer information about the inherent data structure, and thus, learn a more robust representation. In recent years, SSL algorithms based on deep neural networks (deep-SSL) have proven successful on standard benchmark tasks for various applications including computer vision [16].

Most modern deep semi-supervised learning methods consist of adding a loss term which is computed on unlabelled data to encourage the model to generalize better to unseen data. In much recent works, this loss term falls into one of three classes [16, 17]: entropy minimization, which encourages the model to output confident predictions on unlabeled data; consistency regularization, which encourages the model to produce the same output distribution when its inputs are perturbed; and generic regularization, which encourages the model to generalize well and avoid overfitting the training data.

Despite the promising performance achieved by deep SSL, there are still several theoretical challenges regarding the actual benefits of using unlabelled patterns in a supervised learning framework [1]. The inclusion of unlabeled data has proven to be very helpful when learning with limited labeled data. However, this only holds true under the appropriate assumptions or conditions.

According to recent empirical studies, there are scenar-
where the unlabeled data can degrade the model’s performance, especially when there is a distribution misalignment between labeled and unlabeled data, or when the unlabeled data contains a lot of outliers and samples from unknown classes [25].

Based on these observations, we propose a novel data augmentation approach that aims not only to alleviate the distribution mismatch between the labeled data and the unlabeled data, but also to boost the semi-supervised modeling performance by emphasizing the samples that are most likely to be misclassified.

3. Proposed method

Our approach seeks to sequentially generate new synthetic samples and integrate them within the training process in a semi-supervised fashion. The proposed data augmentation is guided by a trained, fully-supervised, baseline model’s performance. The generated samples are drawn from the same distribution as the least performing samples based on a fully supervised reference model’s outputs. This can be especially beneficial when learning from limited labeled data and/or when collecting additional data is not an option.

By training a VAE to learn the latent representation of the baseline model’s under-performing regions, we can adaptively provide the model with additional inputs that can bridge the performance gap across the different regions of the training feature space. Adopting a semi-supervised training framework increases the model’s robustness and resistance to the noise that might be introduced at the data augmentation stage.

In this section, we introduce our proposed data augmentation method for deep semi-supervised learning. Figure 1 shows a diagram of the proposed approach. The training pipeline includes four main steps: (i) Fully supervised training, (ii) Softmax filtering, (iii) VAE data augmentation, (iv) Semi-supervised training. We detail these below.

Formally, aside from a held out test set ($D_{TEST}$), we randomly split our input training dataset into three different partitions:

- $D_L = (x_i, y_i)_{i=1}^n$ denotes the labeled training subset which contains $n$ images $x_i$ with respective labels $y_i$, where $1 < i < n$.
- $D_V = (x_i, y_i)_{i=1}^{n_v}$ denotes the validation subset of size $n_v$ which is used for model selection and hyperparameters tuning.
- $D_{REF} = (x_i, y_i)_{i=1}^{n_{ref}}$, is a newly introduced subset, that is used to select the samples which will be used to train a VAE for data augmentation.

In all our experiments, $D_L$ (respectively $D_V$ and $D_{REF}$) constitutes 60% (respectively 20% and 20%) of the input data.
3.1. Fully supervised training

We first train and validate a fully supervised model \( f^{FS}_\theta \) (\( \theta \) denotes the model’s parameter) using the labeled training set \( D_L \) and the validation set \( D_V \).

As a fully supervised baseline, we train a Wide Residual Networks (WideResNet) model. WideResNets are shallower versions of ResNets where the depth is decreased and the width is increased. WideResNets have achieved state of the art performances in most standard computer vision tasks, and are usually used as backbone models for deep semi-supervised models. Moreover, WideResNet are faster to train since GPUs become more efficient on parallel computing with wider layers.

3.2. Softmax filtering

The obtained model \( f^{FS}_\theta \) is afterwards tested on the third partition of the training set: \( D_{REF} \). \( D_{REF} \) serves as a held-out reference subset that is separate from the validation and testing subsets. Based on the assumption that all three partitions are drawn from the same distribution, we expect that misclassifications from \( D_{REF} \) are likely to be similar to the potential misclassifications from \( D_{TEST} \).

This intermediate evaluation step aims to identify and select the under-performing reference samples based on the model’s prediction confidence. \( f^{FS}_\theta \) generates a logits vector \( z \) for each input sample \( x \). We approximate the model’s confidence score on a given prediction using softmax function \( S \) (Equation 3).

\[
S(z) = \frac{\exp(z)}{\sum \exp(z)} \tag{3}
\]

Softmax converts the logits vector into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the model’s logits. Hence, Softmax can reflect the prediction likelihood of each class.

We define \( D_{REF,LOW} \) as the subset of samples with the VAE reconsonce in their true classes from \( D_{REF} \) (Equation 4), i.e.,

\[
D_{REF,LOW} = \{ x \in D_{REF} \mid S(f^{FS}_\theta(x)) \leq \gamma \} \tag{4}
\]

where \( \gamma \) is a user predefined confidence threshold.

3.3. Data augmentation

\( D_{REF,LOW} \) is used to train a VAE in order to learn the latent distribution of the misclassified samples and generate similar synthetic samples. \( D_{REF,LOW} \) tends to have a relatively small size which makes training the VAE from scratch challenging. To address this issue, we (i) use a pretrained encoder network; (ii) increase the size of \( D_{REF,LOW} \) by randomly adding more samples from \( D_L \).

The trained VAE is then used to generate two synthetic datasets:

- \( D_{Rec} \) denotes the set of VAE reconstructions of all images in \( D_{REF,LOW} \) as defined in Equation 5. These images are similar to their seed images and can be assigned the same labels.

\[
D_{Rec} = \{ VAES(x) \mid x \in D_{REF,LOW} \} \tag{5}
\]

- \( D_{Synth} \) is a subset of \( K \) randomly generated images. Since these images are generated from random seeds, they cannot be assigned labels, and thus, are treated as unlabeled during semi-supervised training. This can be advantageous as we can generate as many unlabeled samples as desired by sampling from different random seeds. In our experiments we use \( K = 5000 \).

3.4. Semi-supervised training

A semi-supervised model is trained using:

- \( D_{Rec} \cup D_L \) as training labeled data.
- \( D_{Synth} \) as unlabeled training samples.
- \( D_V \) is used for model selection and hyperparameters tuning.

In this research, we adopt MixMatch [2], an SSL algorithm that proposes a holistic approach which seamlessly unifies ideas and components from the dominant paradigms in SSL, resulting in an algorithm that is greater than the sum of its parts and surpasses the performance of the traditional approaches.

4. Experimental analysis

In this section, we evaluate our proposed data augmentation technique for semi-supervised learning on two relatively challenging benchmark datasets: STL-10, and CIFAR-100.

4.1. Experimental setup

All experiments are implemented on Pytorch and ran on a computer equipped with an Intel Core i7-5930K CPU (12CPUs), an NVIDIA GeForce GTX TITAN X GPU with 12GB of VRAM and 128GB of RAM.

STL-10[5]: is a benchmark image classification dataset mainly used for developing unsupervised feature learning, deep learning, self-supervised learning algorithms. It contains 96x96 RGB images from ten different classes. Each class has few labeled training example. STL-10 consists of 5000 training samples and 8000 testing samples split over 10 predefined folds. It also comes with an additional 100000 unlabeled images for unsupervised learning. However, we focus our experiments on the provided labeled partition since we want to simulate a low data training regime.
where access to additional unlabeled data is not possible. We want to check the model’s performance can be improved by only using the available labeled data.

**CIFAR-100**[12]: CIFAR-100 is another computer vision benchmark data that is an extension of CIFAR-10. It contains 100 classes containing 600 32x32 images each. There are 500 training images and 100 testing images per class. The 100 classes in the CIFAR-100 are grouped into 20 superclasses. Each image comes with a fine label (the class to which it belongs) and a coarse label (the superclass to which it belongs). Considering its small size, and the large number of classes in CIFAR-100, and their variable granularity levels, it is also a challenging benchmark dataset.

For both datasets, we use the predefined training sets as our input data, which we randomly split into three subsets ($D_L$, $D_V$ and $D_{REF}$) as shown in Figure 1. We report the average performances over five runs. Each run corresponds to a different random split.

We use the WideResNet-50 as the backbone network. For both supervised and semi-supervised training, the network is trained for $10^4$ epochs using a stochastic gradient descent optimizer with a momentum of 0.9. The learning rate starts from $3 \times 10^{-2}$, and automatically decays by a factor of $10^{-2}$ based on the validation ($D_V$) loss. For MixMatch algorithm, we use a mixup ratio $\alpha = 0.5$, a sharpening temperature $T = 0.5$, and an unsupervised loss factor $\beta = 100$.

### 4.2. Results and analysis

The core novelty of our approach is data augmentation using a VAE trained on low confidence samples based on the baseline fully supervised predictions. For each dataset, we start by training and tuning the WideResNet-50 model on the labeled partition ($D_L$). We evaluate the obtained models on $D_{REF}$ to identify and select the low confidence predictions: $D_{REF_{LOW}}$. We experiment with difference confidence thresholds $\gamma$. The value that yields the best results is the lower outlier boundary of the reference prediction scores as defined in Equation 6.

$$\gamma = Q_1 - 1.5 \times IQR$$

(6)

where $Q_1$ is the lower quartile and $IQR$ is the interquartile range. Depending on the baseline performance, and on the number of reference samples, the size of $D_{REF_{LOW}}$ can be relatively small. Hence, training a VAE from scratch on such a small set cannot be reliable to generate synthetic images that can capture the inner distribution of the inputs. Therefore, we opt to using a pretrained encoder network [6]. We use a ResNet18 model pretrained on CIFAR-10, which is a similar natural images dataset. Figure 2 and Figure 3 show some image samples generated from both $D_{Rec}$ and $D_{Synth}$ for STL-10 with and without using a pretrained VAE encoder. Even though both VAEs can generate faithful reconstructions of the input images ($D_{Rec}$) in either cases (Figure 2), we notice that the synthetic images randomly generated by the pretrained VAE have more realistic patterns (colors, edges and shapes) (Figure 3).

It is worth noting that, the images generated by VAE are blurry. They lack sharp edges and fine details. This is because training VAEs is based on the assumption that the data follow a single Gaussian distribution whereas, natural images have multi-modal distribution. Despite this limitation, our experiments show that the VAE outputs can still improve the training process.

![Figure 2. Reconstructions generated by the VAE with and without using a pre-trained encoder - STL10](image)

![Figure 3. Synthetic samples generated by the VAE with and without using a pre-trained encoder - STL10](image)

| Method                  | STL-10          | CIFAR-100      |
|-------------------------|-----------------|----------------|
| Fully supervised        | 81.87% ± 0.13%  | 76.62% ± 0.06% |
| MixMatch (iter. 1)      | 85.44% ± 0.05%  | 78.15% ± 0.11% |
| MixMatch (iter. 2)      | 86.35% ± 0.02%  | 79.03% ± 0.04% |

Table 1. Classification testing accuracy of the first two iterations of the proposed approach on STL-10 and CIFAR-100
Our experiment were designed to answer the following three main questions:

a) Does using semi-supervised training with the synthetically generated data improve upon fully supervised training using only the available data?

b) Is there a benefit of generating new data at multiple iterations?

c) What is the impact of training with the raw reference subset $D_{REF}$ versus using it to guide augmented data generation?

Table 1 summarizes the classification accuracies on STL-10 and CIFAR-100 for the first two iterations of our approach. In the first iteration, we use the fully supervised model (first row) as a reference to select the low confidence samples from $D_{Ref}$, and then we use the output to train a MixMatch model (second row). For the second iteration, we use the obtained MixMatch model as the new reference, and we follow the same approach to retrain a second MixMatch model (third row). As shown in Table 1, our approach drastically improves the classification performance on both datasets compared to the fully supervised reference models. Moreover, iterating further gives a slight improvement which is promising for potential future works. This answers the first two questions as it proves that sequentially training a semi-supervised model using our proposed data augmentation technique improves upon fully supervised training using only the available data.

| SSL data | STL-10 | CIFAR-100 |
|----------|--------|-----------|
| $D_{Rec} = D_{REF}$ | 84.15% ± 0.08% | 77.93% ± 0.05% |
| $D_{Rec} = D_{Synth}$ | 85.44% ± 0.05% | 78.15% ± 0.11% |

Table 2. MixMatch testing accuracies for training with the raw $D_{Rec}$ vs. training with the datasets generated by the VAE starting from $D_{Ref}$ (i.e., $D_{Synth}$ and $D_{Rec}$).

To answer the third question, we train two MixMatch models. In the first model, we use all the images in $D_{REF}$ as unlabeled data. In the second model, we only use the synthetic data generated by the VAE starting from $D_{REF}$. We use $D_{Rec}$ as additional unlabeled data, and $D_{Synth}$ as unlabeled data. Table 2 shows the obtained results. For both datasets, we obtain a slight improvement from using $D_{REF}$ to guide data augmentation instead of using it as is.

5. Conclusions

In this work, we introduced a new data augmentation technique for semi-supervised training. By fine-tuning a pretrained VAE based on low confidence samples from a held-out training subset, we can generate both labeled and unlabeled augmentation that we can use to train a deep semi-supervised model. Experiments on the benchmark CIFAR100 and STL10 datasets have validated the effectiveness of our approach.

Our experimental analysis has shown that: 1) confidence-guided synthetic image generation can both improve classification accuracy, and alleviate the need to collect additional data; 2) the usage of synthetic data as unsupervised knowledge in a semi-supervised setting helps to improve the model’s performance; and 3) the approach can be extended to additional iterations while yielding sequential improvements.

Future work comprises experimenting with different deep generative models such as GANs, and designing a learning framework that integrates the four proposed components: (i) Fully supervised training; (ii) Softmax filtering; (iii) Data augmentation; and (iv) Semi-supervised training within a unified pipeline.

References

[1] S. Ben-David, T. Lu, and D. Pál. Does unlabeled data provably help? worst-case analysis of the sample complexity of semi-supervised learning. In Conference on Learning Theory (COLT), pages 33–44, 2008.

[2] D. Berthelot, N. Carlini, I. Goodfellow, N. Papernot, A. Oliver, and C. A. Raffel. MixMatch: A holistic approach to semi-supervised learning. Advances in neural information processing systems, 32, 2019.

[3] C. Chadebec, E. Thibeau-Sutre, N. Burgos, and S. Allasonnière. Data augmentation in high dimensional low sample size setting using a geometry-based variational autoencoder. arXiv preprint arXiv:2105.00026, 2021.

[4] O. Chapelle, B. Scholkopf, and A. Zien. Semi-supervised learning (chapelle, o. et al., eds.; 2006). IEEE Transactions on Neural Networks, 20(3):542–542, 2009.

[5] A. Coates, A. Ng, and H. Lee. An analysis of single-layer networks in unsupervised feature learning. In Proceedings of the fourteenth international conference on artificial intelligence and statistics, pages 215–223. JMLR Workshop and Conference Proceedings, 2011.

[6] W. Falcon and K. Cho. A framework for contrastive self-supervised learning and designing a new approach. arXiv preprint arXiv:2009.00104, 2020.

[7] I. Goodfellow, Y. Bengio, and A. Courville. Deep learning. MIT press, 2016.

[8] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. Advances in neural information processing systems, 27, 2014.

[9] W.-N. Hsu, Y. Zhang, and J. Glass. Unsupervised domain adaptation for robust speech recognition via variational autoencoder-based data augmentation. In 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), pages 16–23. IEEE, 2017.
S. Huang, X. Wang, and D. Tao. Snapmix: Semantically proportional mixing for augmenting fine-grained data. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, pages 1628–1636, 2021.

D. P. Kingma and M. Welling. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114, 2013.

A. Krizhevsky and G. Hinton. Learning multiple layers of features from tiny images. Technical Report 0, University of Toronto, Toronto, Ontario, 2009.

X. Liu, Y. Zou, L. Kong, Z. Diao, J. Yan, J. Wang, S. Li, P. Jia, and J. You. Data augmentation via latent space interpolation for image classification. In 2018 24th International Conference on Pattern Recognition (ICPR), pages 728–733. IEEE, 2018.

H. Nishizaki. Data augmentation and feature extraction using variational autoencoder for acoustic modeling. In 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), pages 1222–1227. IEEE, 2017.

S. Norouzi, D. J. Fleet, and M. Norouzi. Exemplar vae: Linking generative models, nearest neighbor retrieval, and data augmentation. Advances in Neural Information Processing Systems, 33:8753–8764, 2020.

A. Oliver, A. Odena, C. A. Raffel, E. D. Cubuk, and I. Goodfellow. Realistic evaluation of deep semi-supervised learning algorithms. Advances in neural information processing systems, 31, 2018.

Y. Ouali, C. Hudelot, and M. Tami. An overview of deep semi-supervised learning. arXiv preprint arXiv:2006.05278, 2020.

N. Painchaud, Y. Skandarani, T. Judge, O. Bernard, A. Landeau, and P.-M. Jodoin. Cardiac segmentation with strong anatomical guarantees. IEEE transactions on medical imaging, 39(11):3703–3713, 2020.

R. Selvan, E. B. Dam, N. S. Detlefsen, N. Rischel, K. Sheng, M. Nielsen, and A. Pai. Lung segmentation from chest x-rays using variational data imputation. arXiv preprint arXiv:2005.10052, 2020.

C. Shorten and T. M. Khoshgoftaar. A survey on image data augmentation for deep learning. Journal of big data, 6(1):1–48, 2019.

R. Taori, A. Dave, V. Shankar, N. Carlini, B. Recht, and L. Schmidt. Measuring robustness to natural distribution shifts in image classification. Advances in Neural Information Processing Systems, 33:18583–18599, 2020.

A. Torralba and A. A. Efros. Unbiased look at dataset bias. In CVPR 2011, pages 1521–1528. IEEE, 2011.

S. Wang, Y. Yang, Z. Wu, Y. Qian, and K. Yu. Data augmentation using deep generative models for embedding based speaker recognition. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 28:2598–2609, 2020.

Z. Xu, S. Huang, Y. Zhang, and D. Tao. Webly-supervised fine-grained visual categorization via deep domain adaptation. IEEE transactions on pattern analysis and machine intelligence, 40(5):1100–1113, 2016.

X. Yang, Z. Song, I. King, and Z. Xu. A survey on deep semi-supervised learning. arXiv preprint arXiv:2103.00550, 2021.

S. Yun, D. Han, S. J. Oh, S. Chun, J. Choe, and Y. Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In Proceedings of the IEEE/CVF international conference on computer vision, pages 6023–6032, 2019.

P. Zhuang, A. G. Schwing, and O. Koyejo. Fmri data augmentation via synthesis. In 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), pages 1783–1787. IEEE, 2019.