The (de)biasing effect of GAN-based augmentation methods on skin lesion images

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Abstract. New medical datasets are now more open to the public, allowing for better and more extensive research. Although prepared with the utmost care, new datasets might still be a source of spurious correlations that affect the learning process. Moreover, data collections are usually not large enough and are often unbalanced. One approach to alleviate the data imbalance is using data augmentation with Generative Adversarial Networks (GANs) to extend the dataset with high-quality images. GANs are usually trained on the same biased datasets as the target data, resulting in more biased instances. This work explored unconditional and conditional GANs to compare their bias inheritance and how the synthetic data influenced the models. We provided extensive manual data annotation of possibly biasing artifacts on the well-known ISIC dataset with skin lesions. In addition, we examined classification models trained on both real and synthetic data with counterfactual bias explanations. Our experiments showed that GANs inherited biases and sometimes even amplified them, leading to even stronger spurious correlations. Manual data annotation and synthetic images are publicly available for reproducible scientific research.

Keywords: Generative Adversarial Networks \cdot Skin Lesion Classification \cdot Explainable AI \cdot Bias

1 Introduction

Deep learning-based approaches need a large amount of annotated data to perform well. High-quality images can be easily generated using publicly available pretrained Generative Adversarial Networks (GANs). It seems especially useful in medical applications like skin lesion classification, detection of lung cancer nodules, or even brain tumor segmentation, where balanced data is a definite must-have.

However, if GAN's training set is biased, augmentation might backfire instead of helping. Bias is often defined as a systematic error from erroneous assumptions in the learning algorithm [17]. In this work, we focused primarily on bias in data and models. With the term 'bias in data,' we referred to four common data biases in machine learning (ML): observer bias which might appear when annotators use personal opinion to label data [15]; sampling bias when not all samples have the same sampling probability [17]; data handling bias when the way of handling the data distort the classifier's output; and instrument bias meaning imperfections in the instrument or method used to collect the data [11]. By 'bias in models', we referred to the broad term of the algorithmic bias [1]. Some sources define an algorithmic bias as amplifying existing inequities in, e.g., socioeconomic status, race, or ethnic background by an algorithm [19].

The problem of bias amplification is often mentioned e.g. in recommending engines [14], word embeddings [7], or any other discriminate model [16]. This leads to the question: if these models can amplify biases, does GANs do it too? If it does, how strongly GAN-augmented data affects the models?

Hence, to answer those questions, we studied the influence of data augmentation with unconditional and conditional GANs in terms of possible bias amplification. We analyzed with counterfactual bias insertion (CBI) GAN's ability to reproduce artifacts observed in a dataset, such as frames, pen markings, and hairs. In addition, we evaluated GANs in terms of fidelity, diversity, speed of training, and performance of classifiers trained on mixed real and synthetic data.

Our contributions are the following. Firstly, we performed the extensive research on the (de)biasing effect of using GAN-based data augmentation. Secondly, we introduced the dataset with manual annotations of biasing artifacts in six thousands synthetic and real skin lesion images, which can serve as a benchmark for further studies. Finally, we showed that the most represented biases in the real data are enhanced by the generative network whereas the least represented artifacts are reduced.

2 Related works

Previous studies have showed that skin lesion datasets are not free from bias. Winkler et al. [26] proved that common artifacts like surgical pen markings are strongly correlated with the skin lesion type, influencing the model. Bissotto et al. [4] presented that certain artifacts in skin lesion datasets affect classification models so strongly that they achieve relatively good results even when the lesion is removed from the image. Using global explainability and CBI methods, Mikołajczyk et al. [18] examined how strongly artifacts can influence the training. The result showed that the model is strongly biased towards black frame artifacts, as inserting one into the image often leads to significant prediction shifts. Bevan et al. [3] presented that skin tone is also a biasing factor that can influence the models. Considering the literature review, the most commonly mentioned artifacts are hair, rulers, frames, and others like gel bubbles or surgical pen markings. In the paper we examine and annotate those artifacts in Section 3.2.

Some works on measuring bias suggested simply comparing the performance metrics on biased and unbiased dataset [20]. But in a real-world scenario, it is usually not possible to access an unbiased dataset. Such an approach would require removing all biases before training. In the case of skin lesions, removing artifacts like black frames, surgical pen markings, and even hair is very difficult, especially when these artifacts are on top of the lesions. A CBI is a contrasting approach, where one needs to insert the bias instead [18]. CBI introduced a set of metrics that can be used to evaluate prediction shift after adding the bias to the input data: mean and median prediction shift and a number of *switched* predictions. Higher rates mean a higher risk of giving biased predictions. As those numbers do not indicate the accuracy or correctness of the predicted category, it is worth measuring the F_1 score, recall, or other performance metrics to observe if the accuracy is lower on the dataset with inserted bias.

The problem of instrument bias in melanoma classification for the ISIC2020 dataset was addressed before using different debiasing techniques for artifact bias removal [2]. However, the authors mitigated only two selected biases: the surgical marking and ruler. They investigated the generalization capabilities of the bias removal approaches across different CNN architectures and human diagnosis. On average, EfficientNet-B3, ResNet-101, ResNeXt-101, DenseNet, and Inception-v3 models reached better accuracy ($AUC \approx 0.88$) than experienced dermatologists, performing similarly amongst themselves. In these studies, artificial data was not utilized to augment real data.

The generation of synthetic data not only increases the amount of data and balances the dataset but also serves as an anonymization technique that facilitates its exchange between different institutions as a proxy dataset [5]. Despite many attempts to generate artificial samples of skin images, the evaluation methods for the generated data's quality, diversity, and authenticity are still unclear. In some works [8], researchers point out the inadequacies of commonly used open datasets, such us data imbalance, bias or unwanted noise and artifacts. As GANs are learning the distributions of all provided images, they might as well learn and generate those unwanted features.

3 Experiments

The main goal of the experiments was to examine if GAN-generated data makes classification models more prone to biases. We selected a skin lesion ISIC dataset for distinguishing between malignant and benign lesions. Our procedure consists of three main steps: data generation, manual artifacts annotation and counterfactual bias insertion. The steps are presented in Fig. 2. For the data generation, we explored unconditional and conditional settings and evaluated their performance in terms of fidelity, diversity and training speed. The generated data was examined in terms of bias inheritance, and further annotated with selected artifacts. We present the statistics and our remarks in the Section 3.2. Then, we train our



Fig. 1. The procedure behind (de)biasing effect of using GAN-based data augmentation

classification models with different data configurations for both unconditional and conditional GANs: classic approach (training on the real data), augmentation approach (both real and synthetic data), and GANs-only (synthetic data). Each mode is tested how they respond to counterfactual bias insertion. The details behind CBI are presented in the Section 3.3.

3.1 Data and training details

All our experiments were performed using ISIC Archive challenges 2019 [24,9,10] and 2020 [22] data as our main datasets⁴. We splited that dataset randomly into a training set (30 118 samples) and a test set (7 530 samples) both for classification and generation tasks. In some experiments the training subset was augmented with artificial samples, while the test subset remained the same for all conducted studies⁵. Detailed statistics are presented in Supplementary Table 1.

Image generation was performed using the StyleGAN2-ADA modified implementation from NVIDIA Research group⁶. The ADA mechanism stabilized training in limited data regimes that we faced in malignant samples. To select the best model, we considered both the Fréchet Inception Distance (FID) [12] and Kernel Inception Distance (KID) [6] metrics, along with training speed, similarly as proposed in [5]. Achieved results are presented in Supplementary Table 2.

As for the classification model, we used pre-trained EfficientNet-B2 [23] and trained it for 20 epochs with an early stopping with three epochs patience. We

⁴ https://www.kaggle.com/nroman/melanoma-external-malignant-256

⁵ Data, annotations and additional results are publicly available on GitHub repository:

https://github.com/AgaMiko/debiasing-effect-of-gans

⁶ https://github.com/aidotse/stylegan2-ada-pytorch

used Adam optimizer with an adaptive learning rate initialized to 5e-4 and batch size 32.

3.2 Descriptive statistics

To better understand a skin lesion dataset, or more precisely, the distribution of the artifacts, we have manually annotated 6000 real and synthetic images of skin lesions. We distinguish three main groups with two thousand annotations each: authentic images (real), synthetic images generated with unconditional GANs trained only on images from one class (GAN), and conditional GANs (cGAN). The exact numbers of annotated images are presented in Table 1.

Based on the literature, we selected four types of artifacts for annotations: hair, frames, rulers and other (see Fig. 2). Hair is defined as thick and thin hair of various colors, from light blond to black. Additionally, we annotated hair types: normal, dense (covering a significant part of an image) and short (shaved hair). Frames are black and white round markings around the skin lesion, black rectangle edges, and vignettes. Rulers can come in different shapes and colors, either fully or partially visible. Other are any other artifacts visible that are not as common as ruler marks, frames, and hair. It includes dermatoscopic gel or air bubbles, ink or surgical pen markings, patches and papers, dates and numbers, background parts, light reflection, and dust.

The annotation process was carried out by a trained professional working with the ISIC collection and identification of its biases for over 4 years. Additionally, we measured Inter-Annotator Agreement on a small subsample of data. The mean Cohen's kappa coefficient was over 70%, with the highest values on *ruler* annotations and lowest on the *other*.



Fig. 2. Example artifacts in real and GAN generated data.

Interestingly, it seems that both, unconditional and conditional GANs, generate fewer artifacts than in the original images. Most rare or minor artifacts (like dust, paper, number, and dates) are never generated, leading to a significant decrease in the number of images with at least a single artifact. For instance, in unconditional GANs, almost half benign images were rendered without any artifacts. Moreover, in GANs, the artifacts are rarely correlated with each other, which means that there is usually one single artifact in the image at a time. The correlation calculated between each artifact and skin lesion type is presented in the Supplementary Table 4.

There is also a significant reduction in a number of hair and rulers generated in unconditional GANs and a slight one for conditional GANs. Short hair is pretty rare in the original dataset, but they almost entirely vanish in GANgenerated examples. Interestingly, manual annotations showed that conditional GANs seem to generate two rulers in one image of the benign class, which did not happen in the case of malignant skin lesions. This might be connected to the type of rulers annotated, as the GANs almost never generate small, partially visible rulers that are more common in real data.

Similarly, the surgical pen markings were generated only for the benign class in conditional and unconditional GANs, with no single example in the dataset with generated pen marking for the malignant class. The selectivity in artifacts generation can also be observed in the frame artifact. Frames are a common artifact strongly correlated with the skin lesion category: there are five times more examples of malignant skin lesions with frames than benign. This also affected the GANs training, as in the generated dataset, we observe much more images with frames for both GANs. Even more concerning is the fact that GANs generated only slightly visible vignettes or tiny, few pixel rectangular frames for benign moles. There was no single case of benign skin lesion generated with a large black frame, round frame, or strong vignette. All frames in benign class were almost invisible. On the contrary, the malignant class was always present with large round black frames or strong vignettes. This alone shows a huge amplifying effect on already pre-existing solid bias in the dataset.

This concludes that GANs might amplify strong biases but mitigate the small ones making it a double-edged sword. GANs might increase already strong biases (or essential features), leading to even more spurious correlations and, at the same time, loose information about insignificant tendencies and rare patterns. This property might be connected to the GANs architectures (such as kernel filter sizes) or the number of artifacts in the training dataset. Additionally, we provide the Predictive Power Scores (PPS) that, in contrast, to feature importance, are calculated using only a single feature (here: an artifact) trying to predict the target column (malignant/benign class) [25]. The result supports our conclusion about (de)biasing effect of GAN-based augmentation. The scores are presented in Supplementary Table 3.

Table 1. Statistics for manually labeled real and artificial images of malignant (mal) and benign (ben) class. cGAN refers to conditional GAN, while GAN – unconditional trained only on images from one class.

	class	hair (normal)	hair (dense)	hair (short)	ruler	frame	other	none	total
Real	ben	467	110	45	211	57	201	269	1000
	mal	444	50	51	287	251	402	141	1000
cGAN	\mathbf{ben}	319	57	8	186	84	106	352	1000
	mal	223	29	8	110	365	128	328	1000
GAN	\mathbf{ben}	190	43	4	94	78	257	412	1000
	mal	234	40	16	41	381	197	289	1000

3.3 Counterfactual bias insertion

The previous section identified three possible sources of bias in skin lesion classification: hair (regular, short, and dense), black frames, and ruler marks. We have tested several different ways and proportions of real to synthetic data to find the best performance metrics, as we wanted to mimic the realistic approach to data augmentation. We achieved the best scores when augmenting only the malignant class with 15k synthetic images. Achieved results are described in Table 2.

We use the CBI metrics [18] to measure bias influence. Frame bias insertion was done by adding a frame to an image. Hair and ruler insertion required more care to achieve a realistic look. We copied artifacts from the source image to the target image using provided segmentation masks [21]. We selected samples for each bias for a broader analysis, resulting in five frames, five types per hair type (regular, short, and dense), and five rulers. The segmentation masks used for the analysis are provided in Supplementary Fig. 1. The CBI was calculated for each image in the dataset, by inserting each of 25 biases. The mean CBI scores for each bias group are presented in Table 2. As the results strongly depended on the segmentation mask used, we also calculated standard deviation per bias.

Experiments allow understanding of how each artifact type affects the training, e.g., thin frames usually make predictions switch from malignant to benign, and large frames from benign to malignant. Rulers usually make predictions shift from malignant to benign, but in the GAN-augmented case, a thin ruler in the bottom causes prediction switch from benign to malignant.

The best performance and CBI scores were for real and augmented (aug. GAN) data. We also analyzed different augmentation policies and found that not every approach with augmentation gives better results than real data. Only the proposed approach did not provide worse CBI results than real. In all cases, the worst scores were observed for synthetic datasets. In general higher F_1 scores seemed to be a surprisingly accurate measure in case of vulnerability to biases. However, it also appears that quite a high score (90%) is needed to trust it: models with lower F_1 were not necessarily less biased.

Additionally, it is worth noticing that unconditional GANs performed better and were less prone to learn biases. Better performance might be connected with the lower Perceptual Path Length (PPL) [13] scores in unconditional GANs

Table 2. CBI metrics and F_1 scores measuring bias influence for each selected bias and type of training data: real data (real), augmented with synthetic images (aug.) and synthetic data (synth.), generated both with conditional (cGAN) and unconditional GANs (GAN) trained only on one class: benign (ben) or malignant (mal). Higher F_1 score means better performance, while higher number of switched images mean a higher bias influence.

bias	data			s	witched		F_1 (%)			
		mean	std^1	median	mal to ben	ben to mal	F_1	aug	std^2	mean
frame	real	129	119.39	77	24 (2.39%)	104 (1.60%)	91.99	88.97	4.01	90.48
	aug. cGAN	223	55.25	199	40 (3.88%)	183 (2.81%)	89.65	84.93	2.26	87.29
	aug. GAN	59	16.07	51	22 (2.19%)	37 (0.57%)	91.52	90.49	0.61	91.01
	synth. cGAN	290	43.97	271	125 (12.24%)	165 (2.54%)	80.39	79.28	1.26	79.84
	synth. GAN	413	33.17	404	297 (29.13%)	116(1.78%)	76.04	74.99	0.82	75.51
ruler	real	81	86.76	29	76 (7.48%)	5 (0.07%)	91.99	88.59	4.30	90.29
	aug. cGAN	79	44.21	69	55(5.43%)	24~(0.37%)	89.65	89.18	1.08	89.41
	aug. GAN	81	96.08	24	78 (7.60%)	3 (0.05%)	91.52	87.05	5.81	89.29
	synth. cGAN	200	137.26	151	194 (18.96%)	6 (0.09%)	80.39	78.31	5.11	79.35
	synth. GAN	154	109.89	107	65~(6.33%)	90~(1.38%)	76.04	74.69	1.82	75.36
dense	real	109	33.63	118	90 (8.81%)	19 (0.29%)	91.99	88.42	1.62	90.20
	aug. cGAN	439	269.40	459	96~(9.38%)	344~(5.28%)	89.65	78.85	9.04	84.25
	aug. GAN	122	28.48	113	74 (7.29%)	48 (0.73%)	91.52	87.03	1.42	89.28
	synth. cGAN	325	71.38	357	272 (26.66%)	52 (0.81%)	80.39	80.00	1.43	80.20
	synth. GAN	1089	651.43	1101	61 (5.97%)	1028 (15.79%)	76.04	59.94	10.27	67.99
medium	real	27	7.37	26	17 (1.63%)	10 (0.15%)	91.99	91.60	0.14	91.79
	aug. cGAN	74	17.85	74	38 (3.74%)	36~(0.55%)	89.65	89.31	0.97	89.48
	aug. GAN	28	8.23	26	12(1.19%)	16 (0.25%)	91.52	91.11	0.25	91.32
	synth. cGAN	163	47.93	177	113 (11.05%)	50 (0.77%)	80.39	80.49	1.84	80.44
	synth. GAN	284	141.58	298	46 (4.47%)	238 (3.66%)	76.04	73.51	3.20	74.78
\mathbf{short}	real	77	99.49	38	67 (6.52%)	10 (0.16%)	91.99	88.72	5.21	90.35
	aug. cGAN	180	114.84	224	12 (1.16%)	168 (2.59%)	89.65	84.73	3.56	87.19
	aug. GAN	54	50.91	32	37 (3.64%)	17 (0.26%)	91.52	89.55	2.40	90.54
	synth. cGAN	249	135.44	282	221~(21.67%)	28~(0.43%)	80.39	78.80	1.31	79.60
	synth. GAN	380	445.91	191	57 (5.62%)	323~(4.96%)	76.04	70.36	9.30	73.20

1 – standard deviation for *switched* metric for different bias types,

² – standard deviation for F_1^{aug} . STD for F_1 is equal to 0.

(see Supplementary Table 2). PPL measures the difference between consecutive images when interpolating between two random inputs. Lower PPL scores mean that the latent space is regularized better. Here, unconditional GANs have to learn the pattern distribution of only one class: either malignant or benign. We hypothesized this is also one of the reasons why unconditional GANs are better at capturing the consistency of the images. In contrast, cGANs seemed to link some biases to a one, specific class, resulting in a more biased dataset.

4 Conclusions

Descriptive statistics indicated that GANs amplified strong biases: large black frames, common dermoscopy artifacts, were never generated in benign skin lesions but were more prevalent in the generated dataset than in the original one. At the same time, the amount of clean images was much higher in the case of synthetic images. This observation and the manual exploration of generated artifacts implied that GANs also have debiasing properties, especially in the case of small, rare biases. In addition, for better reproducibility of our studies we provided manual annotations of biasing artifacts, which can serve as a benchmark for further studies. Future directions will be focused on generating unbiased data by learning directions for each of the biases in the latent space, to create a more complex, fair and diverse dataset.

The counterfactual bias insertion analysis supported the theory of GANs (de)biasing attributes. The study demonstrated an inverted correlation between the model's accuracy and bias robustness. This suggested that a well-trained model, even on biased data, is less likely to switch predictions after inserting biases. Ultimately, the best results in terms of accuracy and robustness were achieved for models trained on real data, or augmented with synthetic images produced by unconditional GANs. This shows that GANs can be successfully used to enrich data but should be monitored, as they can amplify preexisting inequities in data.

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References

- Baeza-Yates, R.: Bias on the web. Communications of the ACM 61(6), 54–61 (2018)
- Bevan, P.D., Atapour-Abarghouei, A.: Skin deep unlearning: Artefact and instrument debiasing in the context of melanoma classification. ArXiv abs/2109.09818 (2021)
- Bevan, P.J., Atapour-Abarghouei, A.: Detecting melanoma fairly: Skin tone detection and debiasing for skin lesion classification. arXiv preprint arXiv:2202.02832 (2022)
- Bissoto, A., Fornaciali, M., Valle, E., Avila, S.: (de) constructing bias on skin lesion datasets. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. pp. 0–0 (2019)
- 5. Bissoto, A., Valle, E., Avila, S.: Gan-based data augmentation and anonymization for skin-lesion analysis: A critical review (04 2021)
- Bińkowski, M., Sutherland, D.J., Arbel, M., Gretton, A.: Demystifying mmd gans (2021)
- Bolukbasi, T., Chang, K.W., Zou, J.Y., Saligrama, V., Kalai, A.T.: Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in neural information processing systems 29, 4349–4357 (2016)
- 8. Cassidy, B., Kendrick, C., Brodzicki, A., Jaworek-Korjakowska, J., Yap, M.H.: Analysis of the isic image datasets: Usage, benchmarks

and recommendations. Medical Image Analysis **75**, 102305 (2022). https://doi.org/https://doi.org/10.1016/j.media.2021.102305, https://www.sciencedirect.com/science/article/pii/S1361841521003509

- Codella, N.C., Gutman, D., Celebi, M.E., Helba, B., Marchetti, M.A., Dusza, S.W., Kalloo, A., Liopyris, K., Mishra, N., Kittler, H., et al.: Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic). In: 2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018). pp. 168–172. IEEE (2018)
- Combalia, M., Codella, N.C., Rotemberg, V., Helba, B., Vilaplana, V., Reiter, O., Carrera, C., Barreiro, A., Halpern, A.C., Puig, S., et al.: Bcn20000: Dermoscopic lesions in the wild. arXiv preprint arXiv:1908.02288 (2019)
- 11. He, J., van de Vijver, F.: Bias and equivalence in cross-cultural research. Online readings in psychology and culture **2**(2), 2307–0919 (2012)
- Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B., Hochreiter, S.: Gans trained by a two time-scale update rule converge to a local nash equilibrium. In: Guyon, I., Luxburg, U.V., Bengio, S., Wallach, H., Fergus, R., Vishwanathan, S., Garnett, R. (eds.) Advances in Neural Information Processing Systems. vol. 30. Curran Associates, Inc. (2017), https://proceedings.neurips.cc/paper/2017/ file/8a1d694707eb0fefe65871369074926d-Paper.pdf
- Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., Aila, T.: Analyzing and improving the image quality of stylegan. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 8107–8116 (2020). https://doi.org/10.1109/CVPR42600.2020.00813
- Lloyd, K.: Bias amplification in artificial intelligence systems. arXiv preprint arXiv:1809.07842 (2018)
- Mahtani, K., Spencer, E.A., Brassey, J., Heneghan, C.: Catalogue of bias: observer bias. BMJ evidence-based medicine 23(1), 23 (2018)
- 16. Mayson, S.G.: Bias in, bias out. YAle lJ **128**, 2218 (2018)
- Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., Galstyan, A.: A survey on bias and fairness in machine learning. ACM Computing Surveys (CSUR) 54(6), 1–35 (2021)
- Mikołajczyk, A., Grochowski, M., Kwasigroch, A.: Towards explainable classifiers using the counterfactual approach-global explanations for discovering bias in data. Journal of Artificial Intelligence and Soft Computing Research 11(1), 51–67 (2021)
- Panch, T., Mattie, H., Atun, R.: Artificial intelligence and algorithmic bias: implications for health systems. Journal of global health 9(2) (2019)
- Park, J.H., Shin, J., Fung, P.: Reducing gender bias in abusive language detection. arXiv preprint arXiv:1808.07231 (2018)
- Ramella, G.: Hair removal combining saliency, shape and color. Applied Sciences 11(1), 447 (2021)
- 22. Rotemberg, V., Kurtansky, N., Betz-Stablein, B., Caffery, L., Chousakos, E., Codella, N., Combalia, M., Dusza, S., Guitera, P., Gutman, D., Halpern, A., Helba, B., Kittler, H., Kose, K., Langer, S., Lioprys, K., Malvehy, J., Musthaq, S., Nanda, J., Reiter, O., Shih, G., Stratigos, A., Tschandl, P., Weber, J., Soyer, H.P.: A patient-centric dataset of images and metadata for identifying melanomas using clinical context. Scientific Data 8(34) (2021). https://doi.org/https://doi.org/10.1038/s41597-021-00815-z
- Tan, M., Le, Q.V.: Efficientnet: Rethinking model scaling for convolutional neural networks (2019), http://arxiv.org/abs/1905.11946, cite arxiv:1905.11946Comment: Published in ICML 2019

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- Tschandl, P., Rosendahl, C., Kittler, H.: The ham10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific data 5(1), 1–9 (2018)
- Wetschoreck, F., Krabel, T., Krishnamurthy, S.: 8080labs/ppscore: zenodo release (Oct 2020). https://doi.org/10.5281/zenodo.4091345, https://doi.org/10.5281/ zenodo.4091345
- 26. Winkler, J.K., Fink, C., Toberer, F., Enk, A., Deinlein, T., Hofmann-Wellenhof, R., Thomas, L., Lallas, A., Blum, A., Stolz, W., et al.: Association between surgical skin markings in dermoscopic images and diagnostic performance of a deep learning convolutional neural network for melanoma recognition. JAMA dermatology 155(10), 1135–1141 (2019)

Supplementary materials

Table 1. Exact number of real and synthetic images for each proposed experiment. In case of GANs training we used images only from training subset.

	real		synthetic		total		mode
	ben	mal	ben	mal	ben	mal	
train	26033	4085	-	-	26033	4085	real
	26033	4085	-	15000	26033	19085	augmented
	-	-	27500	27500	27500	27500	synthetic
\mathbf{test}	6509	1021	-	-	6509	1021	real, augmented, synthetic

Table 2. Calculated metrics for each of the tested generative models. The best KID and FID scores were achieved for conditional StylGAN2-ADA without color augmentations. Unconditional GAN for non-melanoma is slightly better in terms of precision and recall. The unconditional models have lower PPL scores, showing a better regularization of the latent space due to the fact that here we modeled only the distribution of one class.

class	KID (%)	FID	Precision	Recall	PPL
GAN mal	0.42	7.99	0.77	0.45	60
GAN ben	0.47	15.46	0.62	0.40	51
cGAN ben and mal	0.24	7.02	0.75	0.44	101

Table 3. PPS score calculated for every feature with metric weighted F1 and a Decision Tree Classifier. PPS score was calculated for every combination of artifacts with type, and only the ones above 0 are presented.

feature	value	PPS real	GANc	GANu	$baseline_F1$	$model_F1$
hair	type	0.55%		9.40%	51.86%	52.13%
frame	type	6.76%	23.87%	22.18%	51.86%	55.12%
other	type	13.40%			51.86%	58.31%



Fig. 1. Segmentation masks used to insert artifacts with Counterfactual Bias Insertion method.

Table 4. Correlation matrix. Artifacts and class correlation is calculated for uncondi-tional GAN, conditional GAN (cGAN), and real images.

	hair	frame	ruler	other	type
GAN hair		-0.26%	-3.43%	-15.61%	6.02%
cGAN		-3.48%	-13.65%	-3.45%	-13.27%
Real		-4.46%	-8.79%	-12.11%	-4.49%
GAN frame	-0.26%		-13.26%	-9.99%	36.03%
cGAN	-3.48%		-19.73%	-3.18%	33.67%
Real	-4.46%		8.65%	-4.21%	28.72%
GAN ruler	-3.43%	-13.26%		-7.44%	-10.56%
m cGAN	-13.65%	-19.73%		0.16%	-10.70%
Real	-8.79%	8.65%		0.94%	9.46%
GAN other	-15.61%	-9.99%	-7.44%		-7.16%
cGAN	-3.45%	-3.18%	0.16%		3.42%
Real	-12.11%	-4.21%	0.94%		21.18%
GAN class (mal)	6.02%	36.03%	-10.56%	-7.16%	
m cGAN	-13.27%	33.67%	-10.70%	3.42%	
Real	-4.49%	28.72%	9.46%	21.18%	