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***Abstract*— These days deep learning is the fastest-growing field in the field of Machine Learning (ML) and Deep Neural Networks (DNN). Among many of DNN structures, the Convolutional Neural Networks (CNN) are currently the main tool used for the image analysis and classification purposes. Although great achievements and perspectives, deep neural networks and accompanying learning algorithms have some relevant challenges to tackle. In this paper, we have focused on the most frequently mentioned problem in the field of machine learning, that is the lack of sufficient amount of the training data or uneven class balance within the datasets. One of the ways of dealing with this problem is so called data augmentation. In the paper we have compared and analyzed multiple methods of data augmentation in the task of image classification, starting from classical image transformations like rotating, cropping, zooming, histogram based methods and finishing at Style Transfer and Generative Adversarial Networks, along with the representative examples. Next, we presented our own method of data augmentation based on image style transfer. The method allows to generate the new images of high perceptual quality that combine the content of a base image with the appearance of another ones. The newly created images can be used to pre-train the given neural network in order to improve the training process efficiency. Proposed method is validated on the three medical case studies: skin melanomas diagnosis, histopathological images and breast magnetic resonance imaging (MRI) scans analysis, utilizing the image classification in order to provide a diagnose. In such kind of problems the data deficiency is one of the most relevant issues. Finally, we discuss the advantages and disadvantages of the methods being analyzed.**

Keywords—Machine learning, style transfer, data augmentation, deep learning, medical imaging.

I. Introduction

Growing interest of deep learning made convolutional neural networks (CNN) the most common tool used for the image analysis and image classification. CNNs achieved state-of-the-art results in a variety of classification tasks, but despite wide perspectives, they still have some challenges to deal with. They are mainly driven by the large size of the networks reaching millions of parameters as well as the lack of reliable training data sets, have problem with overfitting as well as with generalization abilities. Last but not least, a growing concern for researchers is the avoidance of the adversarial attacks [1] that can mislead the DNNs. The researchers are fighting to overcome these problems and achieve better results by modifying the networks architecture, developing new learning algorithms and acquiring the data. The most common problem is the lack of good-quality data or uneven class balance within the datasets. These days, the most effective DNNs are very large, hence require huge amount of data which in many cases may be hard to provide. For instance, very popular CNN architecture VGG16 is made of 16 layers of neurons and consist 138 millions of parameters in total [2]. Moreover, the efficiency of new architectures are usually tested on ImageNet, the dataset which contain more than one million images from 1000 non-overlapping categories [3]. One of the ways of dealing with this problem is data augmentation and data synthesis. The interest in data augmentation rapidly increased along with the growing popularity of CNNs. Most popular and proven as effective current practice for data augmentation is to perform traditional affine and elastic transformations: creating new images by performing rotation or reflection of the original image, zooming in and out, shifting, applying distortion, changing the color palette. Although their many advantages in some cases simple classical operations are not enough to significantly improve the neural network accuracy or to overcome the problem of overfitting [4]. Moreover, the current research about so called adversarial attacks on CNNs showed that deep neural networks can be easily fooled into misclassification of images just by partial rotations and image translation [1], adding the noise to images [5] and even changing one, skillfully selected pixel in the image [6]. Increasing the dataset size via data augmentation and image synthesis make it generally more robust and less vulnerable for the adversarial attacks [1].

In the paper, we do not aim to give a broad survey of all existing methods, but to briefly describe the current state-of-the-art of methods used for a data augmentation. We bring readers closer to the texture transfer and style transfer methods that allow to produce the new images of high perceptual quality that combine the content of a base image with the appearance of another ones [7]. We present a fresh look at the style-transfer method along with the new application idea and relevant examples. Finally, we discuss the advantages and disadvantages of the methods being analyzed and present our conclusions.

II. Data augmentation methods

Existing image augmentation methods can be put into one of two very general categories: traditional, white-box methods or black-box methods based on deep neural networks. In this section we briefly introduce groups of methods that made the biggest impact in the field of image synthesis and augmentation

A. *Traditional transformations*

The most popular current practice for data augmentation is to perform combination of the affine image transformations and color modification. As the affine transformations we define: rotation, refection, scaling (zoom in/out) and shearing (Fig. 1).

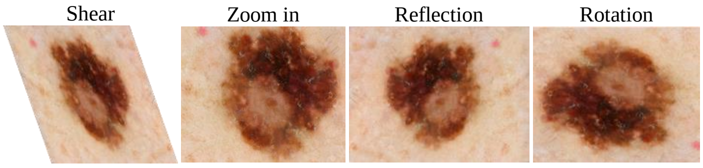

Fig. 1 Same image after different types of affine transformations

Geometric distortions or deformations are commonly used to increase the number of samples for training the deep neural models [8], to balance the size of datasets [9] as well for their efficiency improvement [10] widely used as affine transformations for data augmentation but it is still the subject of research. The most popular methods are: histogram equalization, enhancing contrast or brightness, white-balancing, sharpening and blurring [11] (Fig. 2).

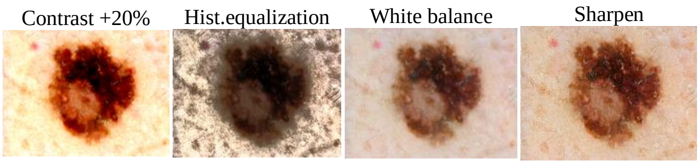

Fig. 2 Same image after different types of color transformations

Those easy to understand methods have been proven as a fast, reproducible and reliable and its implementation code is relatively easy and also available to download for the most known deep learning frameworks, which makes it even more popular [4].

B. *Generative Adversarial Networks*

Generative Adversarial Network is a relatively new and powerful tool to perform unsupervised generation of new images using min-max strategy [1]. GANs are found to be extremely useful in many different image generation and manipulation problems like text-to-image synthesis [12], super-resolution (generating high-resolution image out of low-resolution one) [13], image-to-image translation (e.g. convert sketches to images) [14], image blending (mixing selected parts of two images to get a new one) [15], image inpainting (restoring missing pieces of an image) [16].

The overall idea of GANs is to use two adversarial networks (G(z) and D(x)), where one generates a photorealistic image in order to fool the other net (generator G(z)) trained to better distinguish fake images from the real ones (discriminator D(z)). In other words, the generator task is to minimize a cost (value) function V(D,G) (for example maximum likelihood), while discriminator needs to maximize it [17] (Fig. 3).

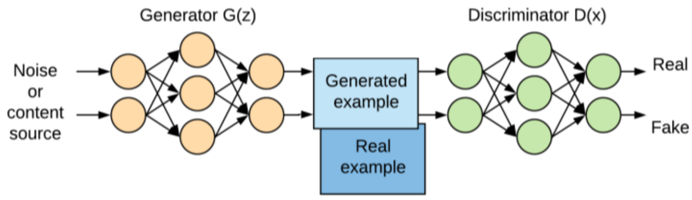

Fig. 3 Simplified idea of Generative Adversarial Network

Although this technique can give very satisfactory outcomes, it is still unclear how to quantitatively evaluate the generative models. Models that generate good samples can have poor maximum likelihood (the probability that the model is similar to the training data) and models that obtain good likelihood can generate bad samples. Mentioned limitations also include: problems with compliance with reality (e.g. generating the animals with the wrong number of body parts), lack of idea of three-dimensional perspective (e.g. generating the images of objects that are too flat or highly axis-aligned), have troubles with coordinating a global structure (e.g. a structure seen both from the front and from the side) [18].

C. *Texture transfer*

The goal of the texture transfer [19] is to synthetize a texture from a texture-source image while constraining the semantic content of a content-source image. The difficulty of this task is to apply a given texture to a new image in such a way that, the visual attributes of the original image, like contour, shading, lines, strokes and regions, remain visible. Most of the classical texture transfer methods rely on the idea of resampling the texture to a given content image [7]. For example, the famous technique called image quilting is a method of synthesizing a new image by stitching together small patches of existing images [19]. Also Hertzman introduced a technique called an image analogies which is able to transfer the texture from one image to another one with a pixel resampling [20].

D. *Other approaches*

Currently developed image augmentation methods are not limited to the traditional and CNN-based methods. One of interesting approaches is a random erasing technique proposed in [21], fast and relatively easy to implement yet giving good results in generalization ability of CNNs. In the method one randomly paints a noise-filled rectangle in an image resulting in changing original pixels values. As authors explained, expanding the dataset with images of various levels of occlusion reduces the risk of overfitting and makes the model more robust.

Another approach was inducted by the need of creating a robust CNN which can defense itself against adversarial attacks. Dataset of images is augmented by adding a stochastic additive noise to the images which made them more robust against the noise adversarial attacks [5].

III. STYLE TRANSFER

A. *Fundamentals*

Recently the style transfer method, which is closely related to texture and color transfer, began to gain more attention of researchers and even its previously vanishing interest in traditional techniques is slowly raising. The goal of the style transfer is to synthetize a new image which mimics the style of a style-source image while constraining the semantic content of a content-source image.

A classical approach, similarly to the traditional texture transfer methods is to carefully resample the pixels from one image to another. In 2016 Frigo et al. [22] presented a novel example-based adaptive patch sampling method for unsupervised style transfer which enabled achieving very good results. Frigo suggested that a correct style transfer can be thought as a local transfer of texture (which must capture the style while preserving the image structure) and a global transfer of color. Later in 2017 Elad et al. [23] introduced the style transfer via texture synthesis which achieved results competitive with the recent CNN style transfer algorithms, along with a brief review of existing methods and rational self-critic.

The growing interest of artificially mimicking the style began after the presentation of a neural algorithm of artistic style based on a deep neural network that creates artistic images of high perceptual quality [24]. An algorithm allows to separate and recombine the image content and style giving the potential for high level image synthesis and manipulation. Authors have noticed that the convolutional neural networks used for image classification develop a representation of the image that makes object information increasingly explicit along the processing hierarchy. Higher layers in the network capture the high-level features and their arrangement in the input image but do not constrain the exact pixel values of the reconstruction, while the lower layers simply reproduce the exact pixel values of the original image (low-level features).

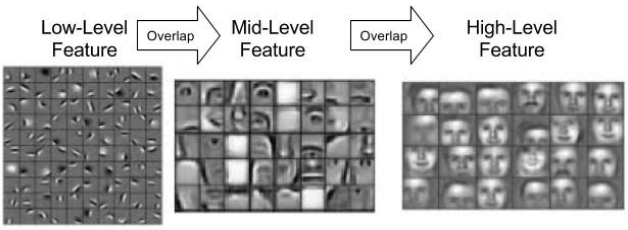

Fig. 4 Feature map in CNN [44]

As authors mentioned, the key idea of the paper is that the representations of content and style in the CNN are separable which means we can manipulate both representations independently to produce new, perceptually meaningful images.

The idea was improved and widely described in [7]. In order to generate new image, first one need to choose which layers will generate the content and which the style. Authors suggest to select one of the last layer as the content source and first and middle layers as the style source. Then, to extract and store content and style features: pass through the network both style, content and white-noise image and save the responses on the selected layers. Next, compute a total loss function which is the sum of the element-wise mean squared difference between the responses in white-noise and the style layers and between the responses in white-noise and the content layer. Derivative of total loss function with respect to the pixel values is used to update the white-noise image using backpropagation, until it matches the style features of the style image and the content features of the content image.

B. Style transfer for data augmentation

High potential of style transfer idea still remains underestimated in the field of image augmentation. In this paper we would like to propose a fresh look at the style-transfer technique and to prove that with expert knowledge it can be applied in a variety of fields.

Currently this method is widely used mostly to synthetize artistic style to create new visually pleasing artworks. In some recent works authors proposed the use of this method to change pictures from day to night [7], clear day to rain [25], or other landscape changes [26], however currently it is still applied in very limited fields in contrary to the wide existing possibilities.

Problems with highly unbalanced datasets are often encountered in a wide range of diagnostic systems, because of the shortage of data describing potential abnormal conditions. Atypical cases such as data collected during detection of variety of industrial plant and other faults [27], [28] detection and localization of leakages in drinking water distribution networks [29], [30], [31] diagnostics of the induction motor [32], [33] or other machines [34], and all kind of medical diseases and problems [35]. We would like to present our results on the three different medical case studies, concerned with data-balance problem: skin lesion analysis, breast histopathology and breast mammography.

In the case of malignant melanoma the datasets are highly unbalanced: there is around ten times more pictures of healthy skin lesions compared to the number of malignant ones. The most popular datasets are the Dermofit Image Library consisting of 1300 images of skin [36], the MoleMap dataset (over 32 000 images) [37], the ISIC Archive (over 13 000) [38], and the database from ISBI melanoma recognition challenge (around 1300 images) [39]. One of the key-points of dermoscopic differentiation between melanoma malignant lesions and benign moles is observing the structure and color of the mole. Malignant lesions usually have more complicated structure with pigmented network, branched streaks, structureless or homogeneous areas, dots, and globules and at the same times more colors. On the other hand, typical benign lesions usually are brown and dark brown, and do not contain any atypical structures. Merging both the content of the picture of the benign mole with the style of malignant lesion will effect in the image of completely new lesion with characteristic of both images. As we can see in the Fig. 5 size and shape of the content image remained the same while the colors of structure drastically changed, mimicking the malignant-style picture.

Fig. 5 Synthetic image created on the base of content and style images – Skin lesion example

Depending of the number of performed iterations we can control how much the synthetic image will resemble the style and the content. Approximately in the first 5 iterations there were still visible unwanted artifacts, which usually completely disappeared after around 10 iterations (Fig. 6).

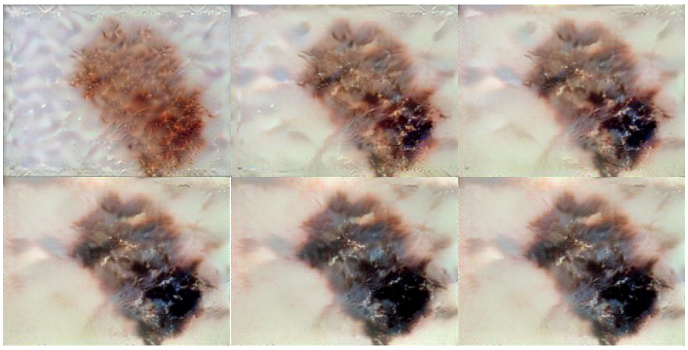

Fig. 6 Synthetic images created on the base of the same image with improved contrast by 10% – Skin lesion example (Iterations number: 1,5,10,25,50,100)

One content picture can be augmented many times with using different style images. Even though, the base of the image is the same, the final image varies in appearance because of differences in the applied style. This allows to create millions of new pictures, with a huge variety in appearance, using just available public databases. In Fig. 7 we present a skin lesion image and its augmented images by using 32 random moles.

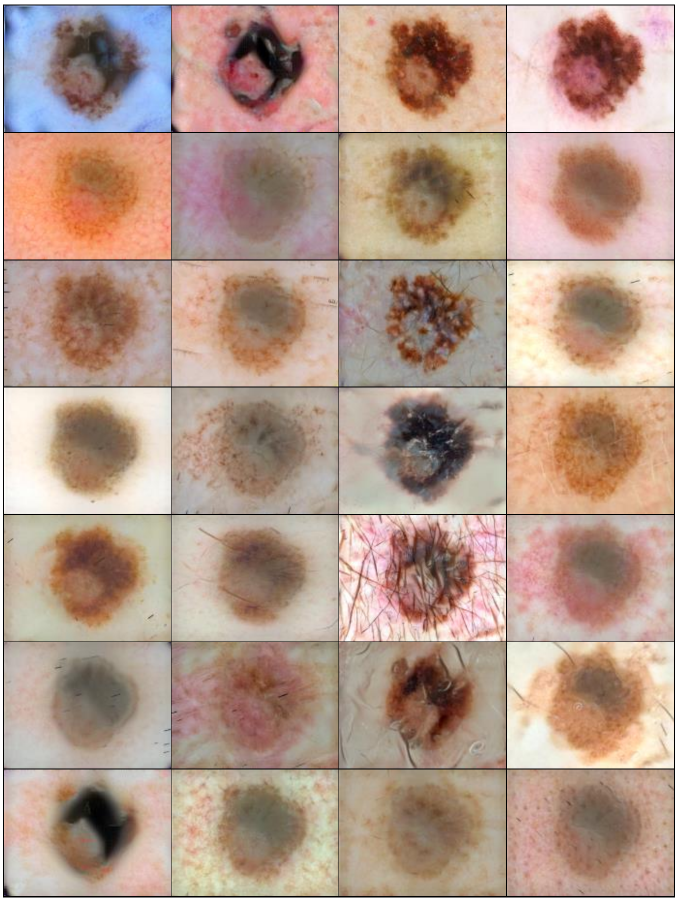

Fig. 7 Artificial images created on the base of the same image – Skin lesion example (huge color variation with small variations of the shape, visible hair, different skin texture, different white balance, change of border, visible new structures)

We want to emphasize that the potential of this technique does not end at the skin lesion example but it can find application also in many different fields. For example in a breast histopathology: mixing two images ended in creating a new one with more dense structure and different color palette (Fig. 8), or in breast mammography where augmentation changed the inner structure of the breast (Fig. 9).

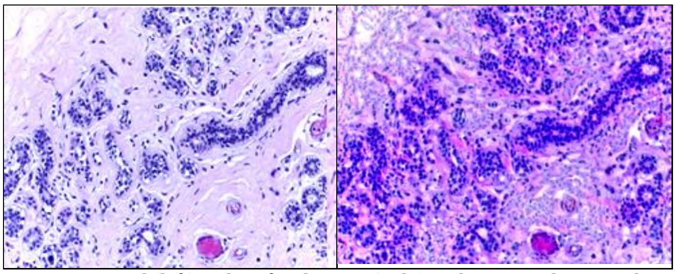

Fig. 8 Original (left) and artificial image (right) with improved contrast by 20% – Breast histopathology example

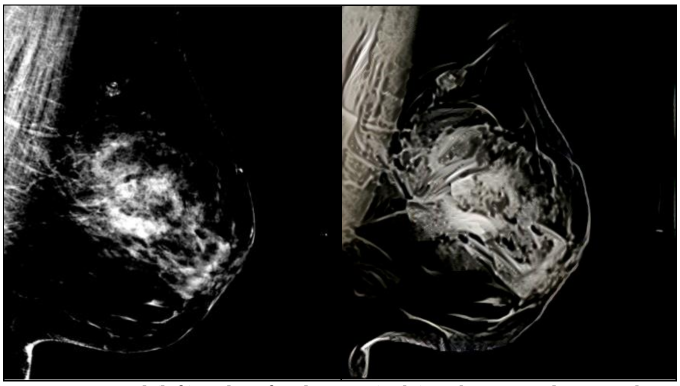

Fig. 9 Original (left) and artificial image (right) with improved contrast by 20% - Breast mammography example

With an expert knowledge the style transfer method can be applied in a variety of fields, especially in images from the same category but with slightly different type (like category of skin moles and malignant/benign type). It is worth noticing that even with the data of lower quality, algorithms can perform better as long as useful information can be extracted [40]. Artificially augmented datasets can be used to pre-train the CNN (transfer learning technique [41]) in order to obtain the suitable initial conditions of the network weights and biases and then trained once again on the real dataset, to fine tune the searched parameters.

C. *Implementation details*

In our work we used the neural style transfer based on [24] with improvements detailed in [42], implemented in Keras 2.0 [43]. We would like to thank Somshubra Majumdar for making it available to our use. In details, we used VGG16

Convolutional Neural Network, with the input image size of 224x224 px, Conv5_2 as the content layer. Each image was initialized by the content picture, the content weight equal 0.025, style weight equal 1.0, and pooling layer with pool by maximum operator.

IV. Discussion

Traditional methods of data augmentation based on combination of affine image transformations and color modification are fast and easy to implement and are proven to be a good methods for increasing the training dataset. Those methods, even though successfully applied in many fields are vulnerable for adversarial attacks. Moreover, they do not bring any new, visual features of the images that could significantly improve the learning abilities of the algorithm used as well as further generalization abilities of the networks. The other approaches like adding a random white-noise to a picture or random-erasing parts of an image were proven as a way of increasing the robustness of network. However, the changes of the appearance of an image are relatively small and they are obvious for a human eye. It changes in the case of classical texture transfer methods which usually rely on the idea of resampling the texture from the source image to a given content image. The process is transparent which is an advantage but the texture is only copied and not created from a scratch. For CNN which scans the image with a small steps it may not provide any new information.

On the other hand, methods based on deep learning models often give results which are new also to the human eye. GANs can synthetize images from any given category from the scratch and the combination of GANs with other methods can give satisfying results (like combination of random erasing with image inpaiting via GAN). Obviously, GANs are not free from limitations: computation time is very high, also noticeable problems with counting, lack of idea of the perspective, trouble coordinating global structure [18].

The style transfer problem is closely related to the texture and the color transfer. Traditional style transfer methods are similar to traditional texture transfer methods with an additional color transfer. Recently, more popularity gains transfer learning which like GANs uses deep learning models. An algorithm created for generating an artistic-style images, allows to separate and to recombine the image content and its style. Merging both, the content of one picture with the style of another one, effects in the completely new picture with characteristic of both images. As we presented it gives the potential for high level image synthesis and manipulation, especially for augmenting data in diagnostic. With an expert knowledge it can be applied in many different fields, but because it’s based on texture and color transfer it might be limited to the images where structure plays important role. For example images from the same category but of slightly different type (like category of skin moles and malignant/benign type).

Not all of the mentioned methods are equally popular and not all of them are currently treated as the methods of increasing training dataset size. Nowadays, usually only the traditional affine transformations are widely used, even though wide range of other interesting methods were developed in the past. Merging and using all of the methods can bring huge potential for improving data-hungry deep learning algorithms.

V. Conclusion and future work

In the paper we presented variety of different commonly used algorithms for data augmentation and data synthesis.

Wide range of promising methods were developed in the past but usually only the traditional affine transformations are widely used. Mentioned methods are not equally popular and not all of them are currently treated as the methods of increasing training dataset size. Merging and using all of the methods can bring huge potential for improving data-hungry deep learning algorithms. Our future work related to this paper will contain but will not be limited to testing the neural network efficiency after pre-training it with the usage of synthetic images generated with the style transfer methods.

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