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THE EFFECT OF ADDING ARTIFICIAL NOISE ON THE SUCCESS OF A DEEP LEARNING NETWORK

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ABSTRACT

Image pre-processing methods have a significant impact on increasing the success of the deep learning network. For deep learning networks to be successful, a large amount of data is needed. Obtaining these datasets is a challenging task that requires effort and observation. Therefore, the researchers aim to increase the success of the deep learning network by modifying the existing images and making it more prepared for new test images. In this way, they artificially increase the number of images in the data sets by using methods such as modifications to the colour bands, adding noise, and histogram equalization. In this study, the change in success rates of the network will be investigated in detail by adding different noise types to the data set used to train the deep learning network.

Keywords: Image Pre-processing, Deep Learning, Skin Segmentation

1.INTRODUCTION

One of the most constraining things in the field of deep learning is the scarcity of data sets. Today, hardware and software are sufficient for deep learning analysis. But collecting, organizing, and labelling data sets is a very difficult task. In addition, group imbalances between datasets also affect the success of the network. For example, when it is desired to classify a rare disease; The data of unhealthy people are very few compared to the data of healthy people. Therefore, the deep learning network will tend to detect even unhealthy people as healthy people. Researchers are conducting various studies to solve this class imbalance problem. [1-5] Rahman, Shaza M., and Ajith Abraham have a review article that summarizes these studies. [6] In these types of studies, data sets are generally increased artificially by applying various image pre-processing methods. These methods are called SMOTE. Images in datasets can be reproduced by applying multiple image pre-processing methods. For example, taking a mirror image is one of them. Mirroring usually aims to augment the dataset without distorting the original image. If the mirror image of each image in the dataset is saved, it is possible to get 2 times more data. In addition, rotating the images at a certain rate will enable the network to be robust against images taken at new different shooting angles. Such image pre-processing methods do not have much negative impact on the original training set. Artificial data augmentation removes data set imbalances and increases the amount of data. It should be noted that data augmentation does not always improve the network. (Like adding noise) Incorporating artificial versions of the original data into the network causes the network to drift away from the original images and fail. This is called the overfitting problem. There is a limit to this artificial image augmentation. In this study, noise, one of the image pre-processing methods called “noise addition”, will be discussed.

One of the factors that reduce the success of the deep learning network is noise. There is noise in each image in the dataset used in the network. Noise is generally the undesirable effect in the image depending on the magnetic effects in the external environment, the shaking of the shooting camera, and the amount of light. Noise is not a fixed attribute that is easily detected like colour. There is random noise in each image. Training the deep learning network without interfering with noisy images will cause difficulties and errors in detecting images with different noise structures and ratios.
One of the aims of this study is to increase the amount of data by adding random noise and to observe the effect of different noise models on the success of the network. In this way, it is to guide the researchers working on this subject by showing the effect of artificial image augmentation methods on network success

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2. METHODS

In this paper, the skin segmentation problem was chosen as a case study. Distinguishing human skin from images is a very difficult and interesting process. This research area attracts the attention of researchers. [7-8] The deep learning network and datasets that are used for skin segmentation should be well designed. The challenges in skin segmentations are people's gender, race, hair colour, skin colour, shifts in the photograph taken, ambient light, and most importantly, noise. Because of these difficulties, it is possible to see high success changes in the smallest changes.

There are many datasets in the literature to be used for skin segmentation. In this study, the Pratheepan dataset will be used, which contains a few amounts of data.[9] The success of a dataset containing such little data is extremely low. This dataset has been deliberately chosen to demonstrate the success of image augmentation.
The dataset contains a total of 156 images and labelled images. By adding different types of noise to these images, the amount of data set would be increased, and the success changes would be observed by inserting them into a simple deep learning semantic network. Figure 1. shows the original image and an image with random noise.

Figure 1. A sample image from the dataset (Left=original, Right=with random noise)

Finding the optimal data augmentation rate is one of the goals. The main reason for calling it "optimum data augmentation" is that adding random noise to the data set and increasing its amount does not always increase the network's success. On the one hand, the amount of data sets increases, and the network is more prepared for new test images, on the other hand, the network moves away from the original images. This causes a problem called overfitting and reduces the success of the network. This situation can be seen in Tables 1 and 2. Such effects will be discussed next.

Table 1. Description of groups

	Type of data	Tested with
Group 1	Original images	Original images
Group 2	Original images+ İmage with random noise	Original images
Group 3	İmage with random noise	İmage with random noise

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Table 2. Success rates of different groups

		Accuracy	IoU	MeanBFScore
Group 1	Skin	0.87995	0.32534	0.49909
	Nonskin	0.72796	0.71428	0.67123
Group 2	Skin	0.44926	0.23996	0.26468
	Nonskin	0.86296	0.79423	0.7486
Group 3	Skin	0.0017216	0.0017093	0.030271
	Nonskin	0.99889	0.86531	0.82596

In the study, 156 original images in the Pratheepan dataset were used to train the deep learning network. The same network has been tested with the original images and is named "Group 1". Image pre-processing methods were not applied to Group 1 images. The definition of each group is given in Table 1. For Group 1, The success metrics are very low as expected because the data set is very small for deep learning applications. In Table 2, skin and nonskin achievements for group 1 may seem high, but the IoU score is very low for the skin. The IoU score is a metric that shows how much the ground truth predicted result overlaps with each other. That is why IoU is a useful parameter that shows success very clearly. In Group 1, IoU success is sufficient for Nonskin, but it is not seen that it is very successful for the skin.

In Group 2, 156 original images and their noise-added versions were included. The deep learning network is trained with 312 images. After the training network, images were tested with the original images. The skin IoU score decreases slightly compared with Group 1, but an increase in the nonskin's IoU is visible. Although adding noise to images and moving the data set far from its original state, there does not appear to be a serious decrease in success rate. On the contrary, even if the success rate drops, the network will be better prepared for new noise-containing test images. The decrease in skin detection success is something that can be sacrificed for this cause.

In Group 3, there are only images with random noise added. The network trained with this dataset will be tested again with noisy images. In other words, the deep learning network is completely deprived of the original images. This will result in the network having a very difficult time recognizing the new incoming images. The already unsuccessful results are not surprising. The network fails

CONCLUSION

In this study, noise addition, which is one of the methods of increasing datasets artificially, has been investigated. Adding noise to images makes the network more prepared for new images. The deep learning network is trained with three different datasets and each one is discussed. It has been examined how much the success rates decrease as the dataset moves away from its original state. Although the network is prepared for the upcoming noisy images, the success of detecting existing original images has decreased. This is something that can be sacrificed. In the next study, different datasets will be tested with images from different sources. The optimum rate of adding noise to these datasets to avoid overfitting and increase success will be investigated.

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CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

REFERENCES

[1] M. Gaoa , X. Honga, S. Chenb and C. J. Harrisb,” A combined SMOTE and PSO based RBF classifier for two-class imbalanced problems,” Neurocomputing, vol. 74, pp. 3456–3466, 2011

[2] F. Fernandez-Navarro, C. Hervas-Martinez and P. A. Gutierrez,” A dynamic over-sampling procedure based on sensitivity for multi-class problems,” Pattern Recognition, vol. 44, pp. 1821–1833, 2011

[3] M. A. Mazurowski, P. A. Habas , J. M. Zurada , J. Y. Lob , J. A. Baker and G. D. Tourassi, Training neural network classifiers for medical decision making: The effects of imbalanced datasets on classification performance, Neural Networks, (21) pp.427-436, 2008.

[4] Cohena, M. Hilariob , H. Saxc , S. Hugonnetc and A. Geissbuhlera, “Learning from imbalanced data in surveillance of nosocomial infection,” Artificial Intelligence in Medicine, vol. 37, pp. 7—18, 2006

[5] H. Yua, J. Nib and J. Zhaoc, “ACOSampling: An ant colony optimization-based undersampling method for classifying imbalanced DNA microarray data,” Neurocomputing, vol. 101, pp. 309–318, 2013

[6] Rahman, Shaza M., and Ajith Abraham. "A review of class imbalance problem." Journal of Network and Innovative Computing 1.2013 (2013): 332-340.

[7] Phung, Son Lam, Abdesselam Bouzerdoum, and Douglas Chai. "Skin segmentation using color pixel classification: analysis and comparison." IEEE transactions on pattern analysis and machine intelligence 27.1 (2005): 148-154.

[8] Phung, Son Lam, Douglas Chai, and Abdesselam Bouzerdoum. "Adaptive skin segmentation in color images." 2003 IEEE International Conference on Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03).. Vol. 3. IEEE, 2003.

[9] Al-Tairi, Zaher Hamid, et al. "Skin segmentation using YUV and RGB color spaces." Journal of information processing systems 10.2 (2014): 283-299.

[10] Phung, Son Lam, Abdesselam Bouzerdoum, and Douglas Chai. "Skin segmentation using color and edge information." Seventh International Symposium on Signal Processing and Its Applications, 2003. Proceedings.. Vol. 1. IEEE, 2003.

[11] Gasparini, Francesca, and Raimondo Schettini. "Skin segmentation using multiple thresholding." Internet Imaging VII. Vol. 6061. SPIE, 2006.

[12] http://cs-chan.com/downloads_skin_datase