Double pre-training for detecting fetal heart diseases with Deep Learning: A Chilean case



NACIONAL DE INTELIGENCIA ARTIFICIAI

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1. Abstract

Fetal heart disease represents the second cause of death during the first year of life in Chile. The detection of this group of pathologies can be performed during the pregnancy stage; however, the fetal heart disease detection rate is not sufficient. On the other hand, when the number of samples is small, as our case, typical models pre-trained with ImageNet may not fit sufficiently. The present work proposes the use of a double pre-training of deep learning models to detect cardiopathies in fetuses from a Chilean database using a database with semantically close images. We apply this scheme to classical CNNs, and show that the double pre-training surpass in terms of average accuracy by 8% the network based on the classic pre-training of EfficientNet.

2. Introduction

A congenital disorder corresponds to a structural or functional anomalies that occur during intrauterine life, being one of the most common and severe, the congenital heart disease, which affects about 0.8% to 1.2% of live births worldwide. In Chile, according to the Ministry of Health (MINSAL), congenital heart defects are the most frequent malformations, with an incidence between 4 and 13 per 1000 live newborns and account for 20% of neonatal deaths and nearly 50% of infant mortality due to malformations. In this country, the fetal heart screening is applied in the second trimester of the pregnancy. The screening requires the use of an ultrasound scanner (US), which provides images for the evaluation of the physician.

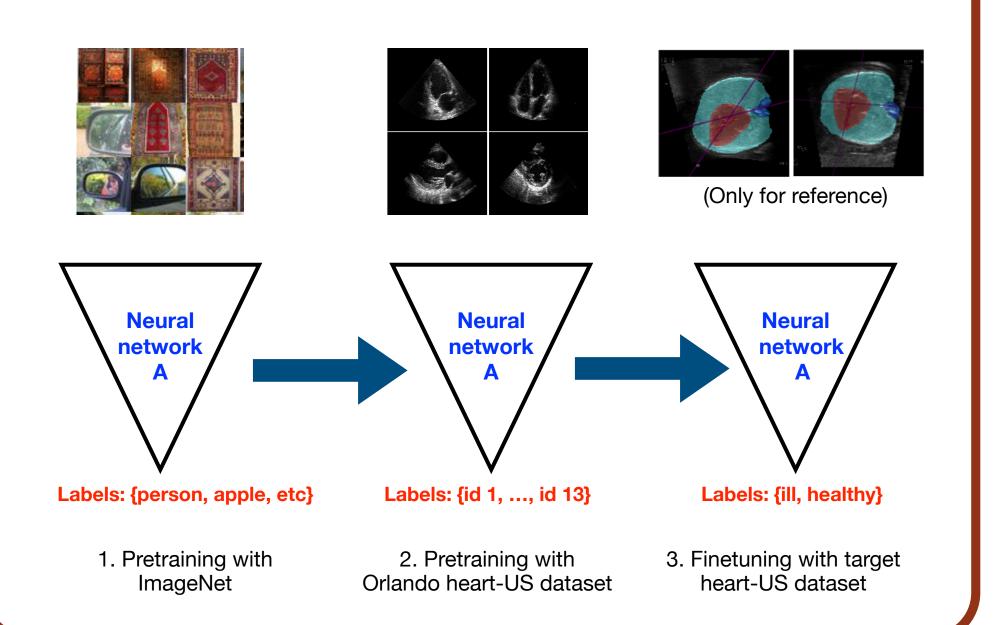
4. Experiments

Our target dataset consists of 209 anonimized fetal heart images. We perform (i) single pre-training: We use pre-trained networks in ImageNet, and then apply fine-tuning to the target dataset. Then we made (ii) double pre-training: a second experiment where we first make a fine adjustment in the Orlando-heart dataset [3]. This dataset considers the identity of US adult heart images. Then, we apply fine-tuning in the target dataset. In this case, it should be noted that the first fine adjustment in Orlando-heart dataset is carried out only once. The experimental scheme considers 100 random hold-out. Approximately, each training subset includes 174 images, and the testing subset includes 35 images. The intention of using this scheme is to repeat the experiment many times, unlike the typical cross-validation, since the neural networks in small data can fall into local minima. On the other hand, when separating the training data from the test data, we have carefully ensured that there are never images with the same patients in both sets, to avoid data leakage. Validation is based on a random percentage of the training image set (20%). We test MobileNet, EfficientNet, ResNet50, InceptionNet and VGG16 networks. Finally, we report the mean accuracy (std.deviation in parentheses) in both the training and testing sets, for each neural network tested.

3. Proposed methodology

Deep learning techniques has been applied to visually detect fetal heart diseases with US images [1, 2]. However, these techniques are usually based on a typical pre-training on ImageNet . We posit that these images are far removed from typical ultrasound images, so networks may require a large number of images to function. However in the case of a small database, this requirement may not be feasible. We propose the use of a double pre-training to combat this effect, considering a database of ultrasonic images of adult hearts, considering the task of identity identification. The proposed scheme is shown in the following Figure:

Neural Net-	Avg. Accuracy	Avg. Accuracy	Avg. Accuracy	Avg. Accuracy
work	Training (Single	Testing (Single	Training (Dou-	Testing (Double
	Pre-training)	Pre-training)	ble Pre-training)	Pre-training)
MobileNet	$79.9\%(\pm 12.6\%)$	$62.8\%(\pm 10.0\%)$	$64.0\%(\pm 11.6\%)$	$54.3\%(\pm 9.8\%)$
EfficientNet	98.8% $(\pm 1, 6\%)$	$81.5\%(\pm7.1\%)$	$98.9\%(\pm 1,51\%)$	$89.7\%(\pm 6.4\%)$
ResNet50	$62.3\%(\pm 11.0\%)$	$58.0\%(\pm 9.3\%)$	$66.1\%(\pm 11.5\%)$	$58.5\%(\pm 10.7\%)$
InceptionNet	$61.0\%(\pm 14.0\%)$	$54.2\%(\pm 10.1\%)$	$71.7\%(\pm 13.0\%)$	$58.7\%(\pm 11.0\%)$
VGG16	$85.0\%(\pm 8.1\%)$	$72.2\%(\pm 10.0\%)$	$92.6\%(\pm 4.5\%)$	$75.3\%(\pm 8.2\%)$

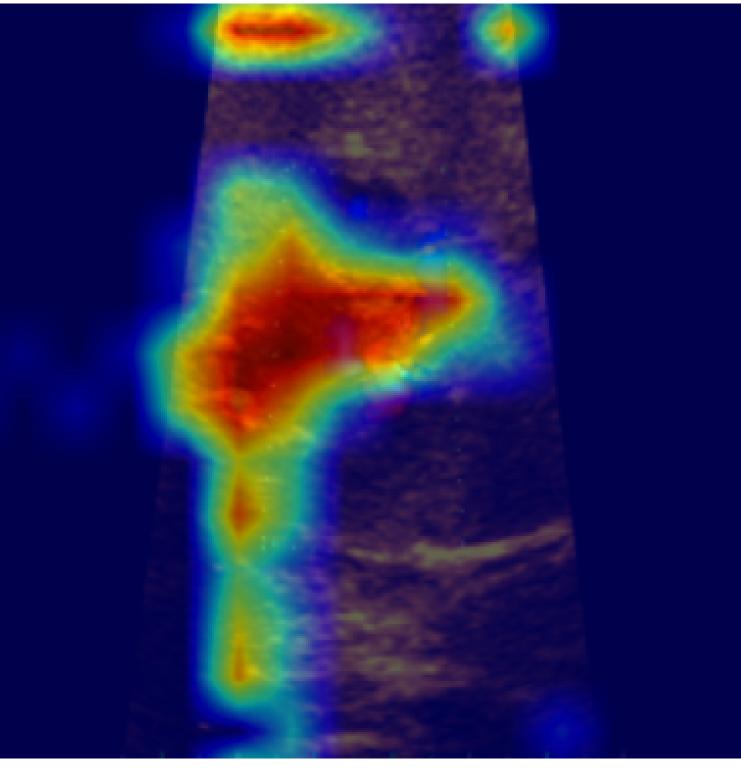


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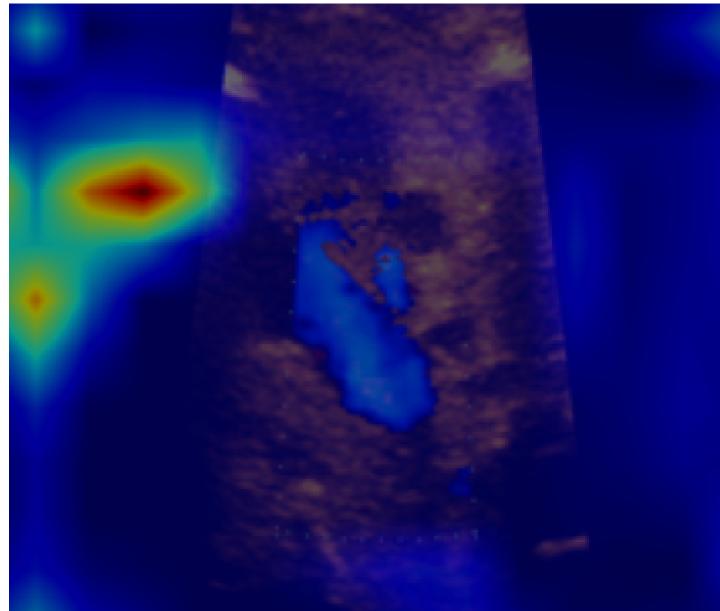
5. Qualitative results

We show the results of the heat map according to the GradCAM method when applying EfficientNet over images from a test set. The figure on the left shows a successful case, where the network classifies a disease case as positive. Looking at the heat map, we can see that the model is centered on the region of the heart. Finally, in the figure on the right, a failure case is observed, where the network classifies as negative but it is a true positive.

Grad Cam: model



Grad Cam: model



8. References

- [1] P. Garcia-Canadilla and et al. Machine learning in fetal cardiology: what to expect. *Fetal diagnosis and therapy*, 2020.
- [2] R. Arnaout and et al. Expert-level prenatal detection of complex congenital heart disease from screening ultrasound using deep learning. *medRxiv*, 2020.
- [3] S. Vitale and et al. Improving realism in patientspecific abdominal ultrasound simulation using cyclegans. International Journal of Computer Assisted Radiology and Surgery, 2019.



6. Conclusions

The experiments show that double pre-training tends to improve results compared to single pretraining. However, a large variability is also shown in the results of accuracies. This suggests that more data is required to be able to strengthen the model, which will remain a future task.

7. Acknowledgements

B.Peralta and D.Mery appreciate the support of the National Center for Artificial Intelligence CENIA FB210017, Basal ANID. D. Mery also appreciate the support of iHealth, Millennium Science Initiative Program ICN2021 004.