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Empirical Study of Quality Image Assessment for Synthesis of Fetal Head Ultrasound Imaging with DCGANs

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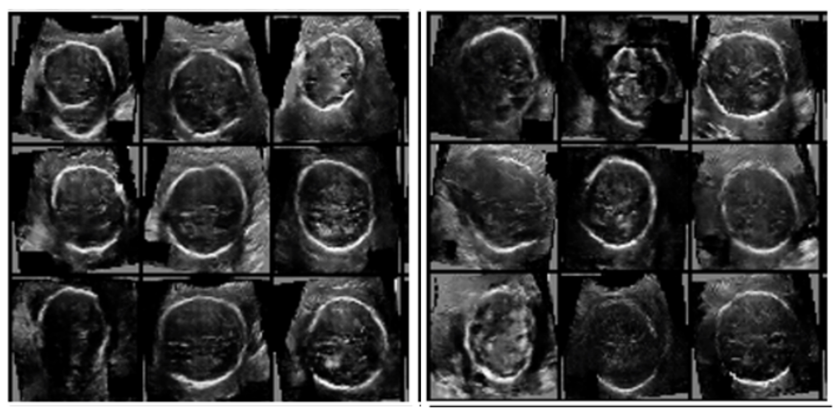
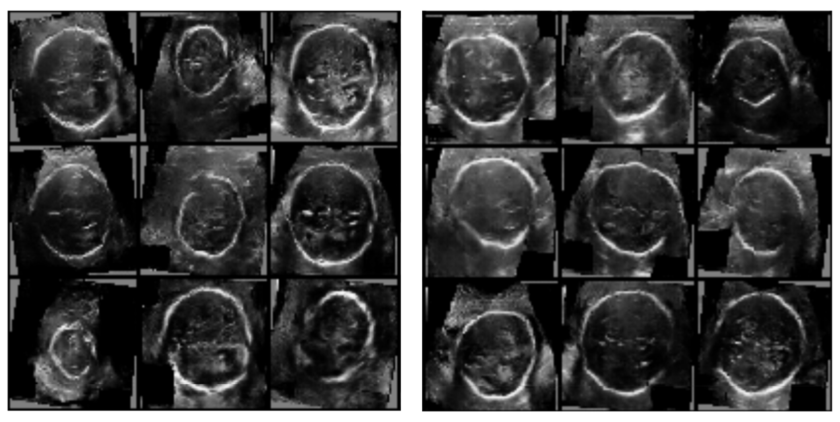
Generated images wtih DCGAN64 using 300 training images



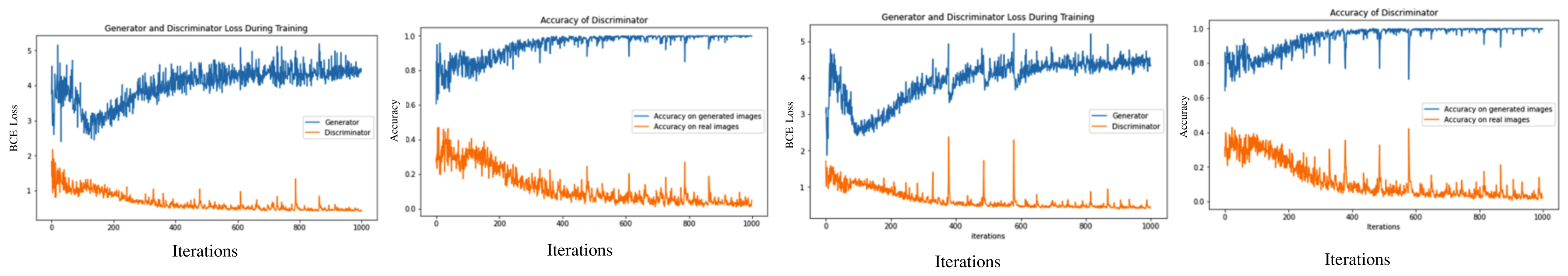
500 epochs   1000 epochs

Generated images wtih DCGAN64 using 800 training images



500 epochs   1000 epochs

Generator and discriminator training loss curves and discriminator accuracies on real and synthetic images



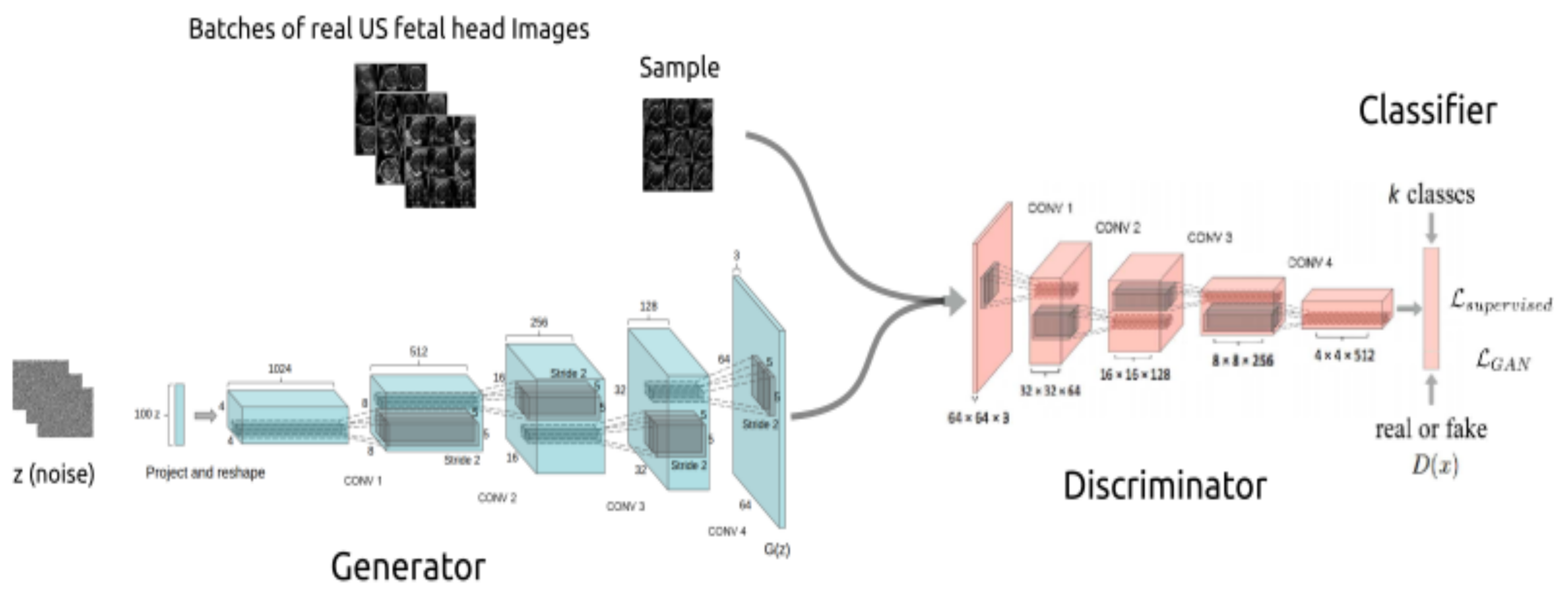
Using 300 training images   Using 800 training images

1. INTRODUCTION

Ultrasound (US) image synthesis have been used to address the scarcity of datasets due to the cost of data collection, annotation and ethical policies [1]-[3]. Skanarani *et al.* presented an empirical study for Generative Adversarial Networks (GANs) in medical imaging on the impact for sensitivity of hyperparameters, dataset, computer scale, image quality, and its clinical usability [4] but there are little to no empirical studies on the use of GANs for fetal US images. As Deep Convolutional GANs (DCGANs) improve image quality generation and training stability [5], we apply DCGAN architecture for different synthetic image pixel sizes using an open dataset of 999 fetal head US images.

2. GENERATIVE ADVERSARIAL NETWORKS

GANs are able to create synthetic images by learning data distributions. Radford et al. 2016 proposed Deep Convolutional GANs (DCGANs) to improve image quality generation and training stability of the networks with the use of stride CNNs, extensive use of batchNorm [5].

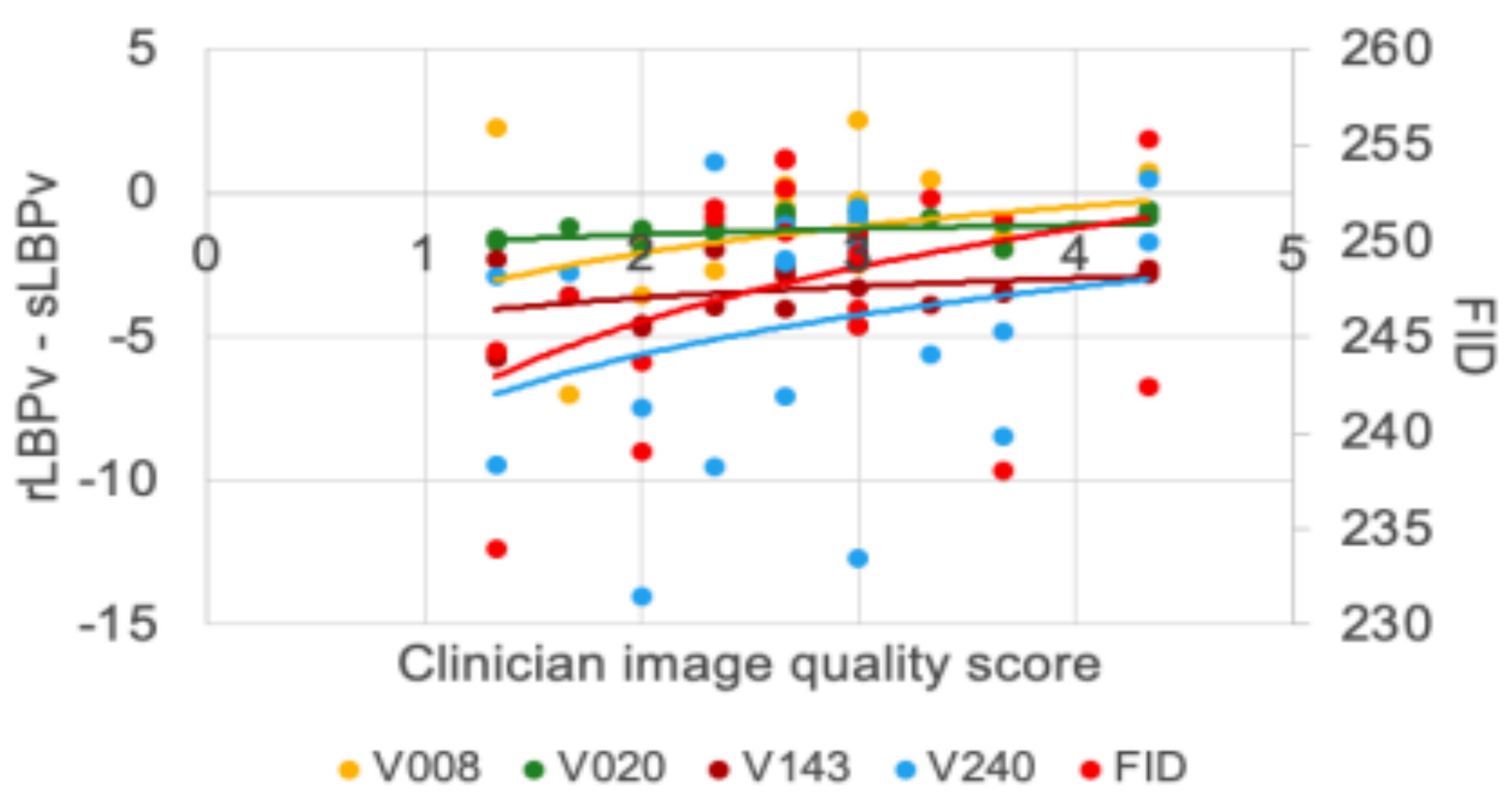


3. DATASETS

We make use of an open dataset of 999 real fetal head US images [6]. Fetal US images are from all trimesters with a pixel size of width 800 x height 540.

4. RESULTS

FID and elements of the local binary vector (LBPv) had strongest relationship to clinician scores in comparison to MI and PSNR. Regression plots for FID and elements of the LBPV: V8, V20, V143 and V240 (shown as difference from a reference LBPV (rLBPV) and synthetic LBPV (sLBPV) with clinician image quality scores is shown below.



5. CONCLUSIONS & FUTURE WORK

* DCGANs are capable of learning the data distribution of the training images so as to create synthetic fetal US images indifferentiable from the originals.

* FID and LBPv metrics show potential for image quality assessment of synthetic fetal US images in comparison to MI and PSNR.

* Future work may lead to testing other GAN models, architectural alterations, hyperparameter optimization, addresing mode collapse and artefacts and using other forms of data augmentation with other fetal US image datasets.

6. REFERENCES

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