Boosting Classification Accuracy of Fertile Sperm Cell Images leveraging cDCGAN



Introduction

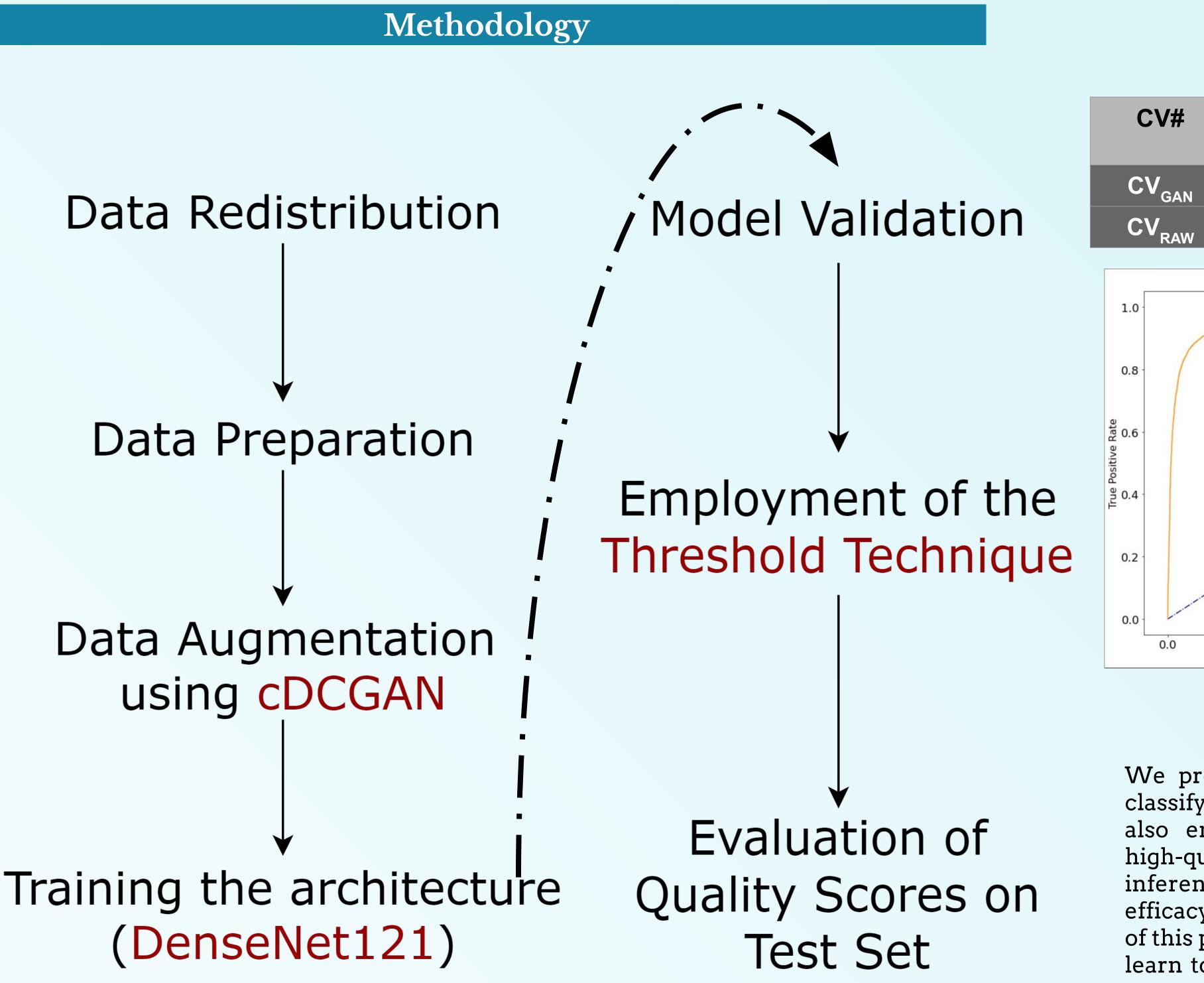
Drawing inferences from a spermatozoon (Sperm Cell) image based on its morphology is ubiquitous, challenging, and of substantial practical interest. In the present study, we endeavour to deconstruct and demonstrate a framework to distinguish between the binary classes, which constitutes 'Good' (Fertile) and 'Bad' (Infertile) Sperm Cell images. We have selected the DenseNet121 architecture to train our model for this task. Furthermore, Conditional Deep Convolutional Generative Adversarial Networks (cDCGAN) was used to tackle the minority Class imbalance problem, which was heavily prominent in the dataset chosen for this task. We have hand-picked numerous statistical inferential tests and metrics to validate our model to accentuate the reliability of the obtained results, thus finally formulating and delineating a table based on the respective 'Quality' Scores' of the test samples provided. With the cDCGAN training data augmentation, the test-set accuracy was recorded to be 86.2%, while the model without cDCGAN scored only 24.3%.

Background of the study

It is estimated that infertility affects 48.5 million couples globally. Males are found to be solely responsible for 20-30% of infertility cases and contribute to 50% of cases overall. Visually analyzing the sperm is a very sophisticated evaluation tool of human fertility and is a strong indicator of a man's physical and, thus, reproductive health.



Dipam Paul^{1,2}, Alankrita Tewari¹, Jiwoong Jeong², Imon Banerjee^{2,3} ¹Department of Electronics Engineering, KIIT University, Bhubaneswar, India ²Department of Biomedical Informatics, Emory School of Medicine, Atlanta, GA, USA ³Department of Radiology, Emory School of Medicine, Atlanta, GA, USA



Conclusion We present a method by virtue of which we could exhibit the task of classifying Sperm Cell images based on morphology. However, this method also encompasses a real-world approach to train an architecture on high-quality annotated images and using the same architecture to draw inferences on low-quality annotated unlabelled images. We explored the efficacy of our method through the means of various statistical tests. In light of this proposition, we have also made meticulous efforts to make our model learn to classify and validate the results using a different distribution (with greater variance) than the former.



Results

F1-Scor	e ro	oc_auc Sco	ore be	e best_thr 0.715±0.02 0.185±0.04		r Test Accurac	
0.602±0.0)2	0.922±0.03	0.71			0.8	362±0.02
0.452±0.0)5	0.512±0.03	0.18			0.243±0.06	
CVgan - ROC Curve					Test Samples Quality Scores		
			and the second se		D	926	0
		and the second se			E	383	35
		and the second se			E	902	0
					E	914	27
_	and the second se				E	919	17
and the second sec					E	950	34
					E	952	10
					E	979	46
).2 0.	4	0.6 0.8	ROC curve (area = 0.92)		E	986	38
	.4 False Positive F		3 1.0				