

cases	doc_1		doc_2			decision	id	
			authors	<ul style="list-style-type: none"><li>Anisie Uwimana1</li><li>Ransalu Senanayake</li></ul>			DUPLICATES	114
	authors	<ul style="list-style-type: none"><li>Anisie Uwimana</li><li>Ransalu Senanayake</li></ul>	title	Out of Distribution Detection and Adversarial Attacks on Deep Neural Networks for Robust Medical Image Analysis				
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	doi	None	urls	<ul style="list-style-type: none"><li>http://arxiv.org/pdf/2107.04882v1</li><li>http://arxiv.org/abs/2107.04882v1</li><li>http://arxiv.org/pdf/2107.04882v1</li></ul>				
	urls	<ul style="list-style-type: none"><li>https://openalex.org/W3214961495</li></ul>	id	id1381411009384522840				
	id	id5819437435903861242	abstract	Deep learning models have become a popular choice for medical image analysis. However, the poor generalization performance of deep learning models limits them from being deployed in the real world as robustness is critical for medical applications. For instance, the state-of-the-art Convolutional Neural Networks (CNNs) fail to detect adversarial samples or samples drawn statistically far away from the training distribution. In this work, we experimentally evaluate the robustness of a Mahalanobis distance-based confidence score, a simple yet effective method for detecting abnormal input samples, in classifying malaria parasitized cells and uninfected cells. Results indicated that the Mahalanobis confidence score detector exhibits improved performance and robustness of deep learning models, and achieves stateof-the-art performance on both out-of-distribution (OOD) and adversarial samples.				
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