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cases		Murat Sensoy     Lance M. Kaplan		Murat Sensoy     Lance Kaplan     Federico Cerutti     Maryam Saleki		
	authors	Federico Cerutti     Maryam Saleki	title	Uncertainty-Aware Deep Classifiers using Generative Models		
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	title	Uncertainty-Aware Deep Classifiers Using Generative Models	source	SupportedSources.INTERNET_ARCHIVE		
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	journal	Proceedings of the AAAI Conference on Artificial Intelligence	doi	httms://www.onshive.ons/www./20200610070244/httms://onsive.ons/mdf/2006.04192v1.mdf	DUPLICATES 1:	S 134
	volume	34	urls	<ul> <li>https://web.archive.org/web/20200610070344/https://arxiv.org/pdf/2006.04183v1.pdf</li> </ul>		
	doi	10.1609/aaai.v34i04.6015	id	id-3208312883179761422		
	urls	<ul> <li>https://openalex.org/W2997563872</li> <li>https://doi.org/10.1609/aaai.v34i04.6015</li> <li>https://ojs.aaai.org/index.php/AAAI/article/download/6015/5871</li> </ul>		Deep neural networks are often ignorant about what they do not know and overconfident when they make uninformed predictions. Some recent approaches quantify classification uncertainty directly by training the model to output high uncertainty for the data samples close to class boundaries or from the outside of the training distribution. These approaches use an auxiliary data set during training to represent out-of-distribution samples. However, selection or creation of such an auxiliary data set is non-trivial, especially for high dimensional data such as images. In this work we develop a novel neural network model that is able to express both aleatoric and epistemic uncertainty to distinguish decision boundary and out-of-distribution regions of the feature space. To this end, variational autoencoders and generative adversarial networks are incorporated to automatically generate out-of-distribution exemplars for training. Through extensive analysis, we demonstrate that the proposed approach provides better estimates of uncertainty for in- and out-of-distribution samples, and adversarial examples on well-known data sets against state-of-the-art approaches including recent Bayesian approaches for neural networks and anomaly detection methods.		
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