Abstract: It is widely accepted that optimization of medical imaging systems should be guided by task-based measures of image quality (IQ). Task-based measures of IQ quantify the ability of an observer to perform a specific task such as detection or estimation of a signal. When optimizing imaging systems for signal detection tasks (e.g., detection of a tumor), the Bayesian Ideal Observer (IO) sets an upper limit of observer performance and has been advocated for use as a figure-of-merit (FOM). Except in special cases, the IO test statistic depends non-linearly on typical medical imaging measurements and is analytically intractable to determine. Sampling-based methods employing Markov-Chain Monte Carlo (MCMC) techniques have been developed to address this problem. However, current applications of MCMC methods have been limited to relatively simple object models. When the IO test statistic is difficult to compute, the optimal linear observer, i.e., the Hotelling Observer (HO), can be employed. However, to compute the HO test statistic, potentially large covariance matrices must be accurately estimated and subsequently inverted, which can present computational challenges. In this work, we propose a supervised learning-based method to approximate the HO test statistic without estimating and inverting covariance matrices. Additionally, we propose and investigate deep learning approaches to approximate non-linear IO test statistics by using convolutional neural networks (CNNs). We also investigate an augmented generative adversarial network (GAN) named AmbientGAN for learning stochastic object models from raw imaging measurements, which further enables the assessment and optimization of imaging systems for specific tasks.