

Hiding in Plain Sight: Adversarial Neural Net Facial Recognition

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Background

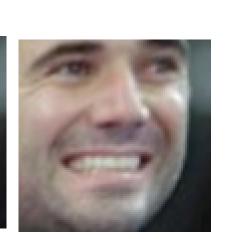
Deep neural networks (DNNs) excel at pattern-recognition tasks, particularly in visual classification. Implementations of DNN-based facial recognition systems approach and even exceed human-level performance on certain datasets. However, recent studies have revealed that imperceptible image perturbations can result in object misclassification in neural network-based systems. We explore the effects of image-agnostic perturbation methods at various stages of the facial recognition pipeline on network prediction errors, specifically training perturbations of the widely-used Labeled Faces in the Wild (LFW) dataset on FaceNet.

Approach

We chose FaceNet as our recognition system because of its strong performance on the LFW dataset (99.63% accuracy). Our LFW dataset is condensed to 6,715 images of 610 people instead of 13,233 images of 5,759 people, filtered so that all people in our dataset have at least 4 images for cross-validation.

We target the alignment, representation, and classification stages of the recognition pipeline. Faces are aligned by the outer eyes and nose (left) and inner eyes and bottom lip (right).





Images are perturbed with Poisson noise and Gaussian noise. Poisson noise is calculated as follows, with k=1 and lambda sampled from the image. The image on the left is unaltered; the image on the right has applied Poisson noise.



$$f(k,\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

Poisson noise is used in comparison with a similar Gaussian perturbation to compare the results of applied and additive noise. The additive Gaussian distribution is calculated as follows, with mu as the mean pixel value and sigma as the standard deviation.

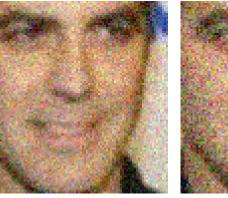
$$f(z) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

Left to right: unaltered, sigma * sigma = 16, 100, 500, 1000.







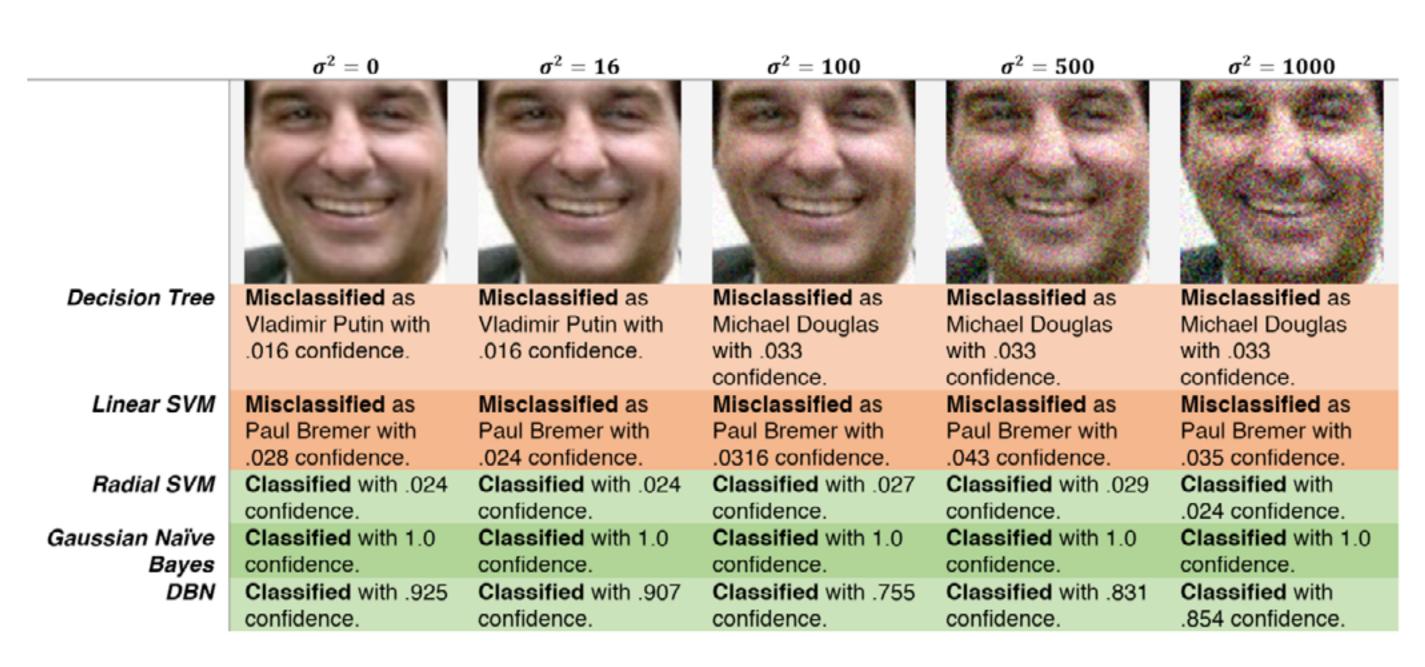


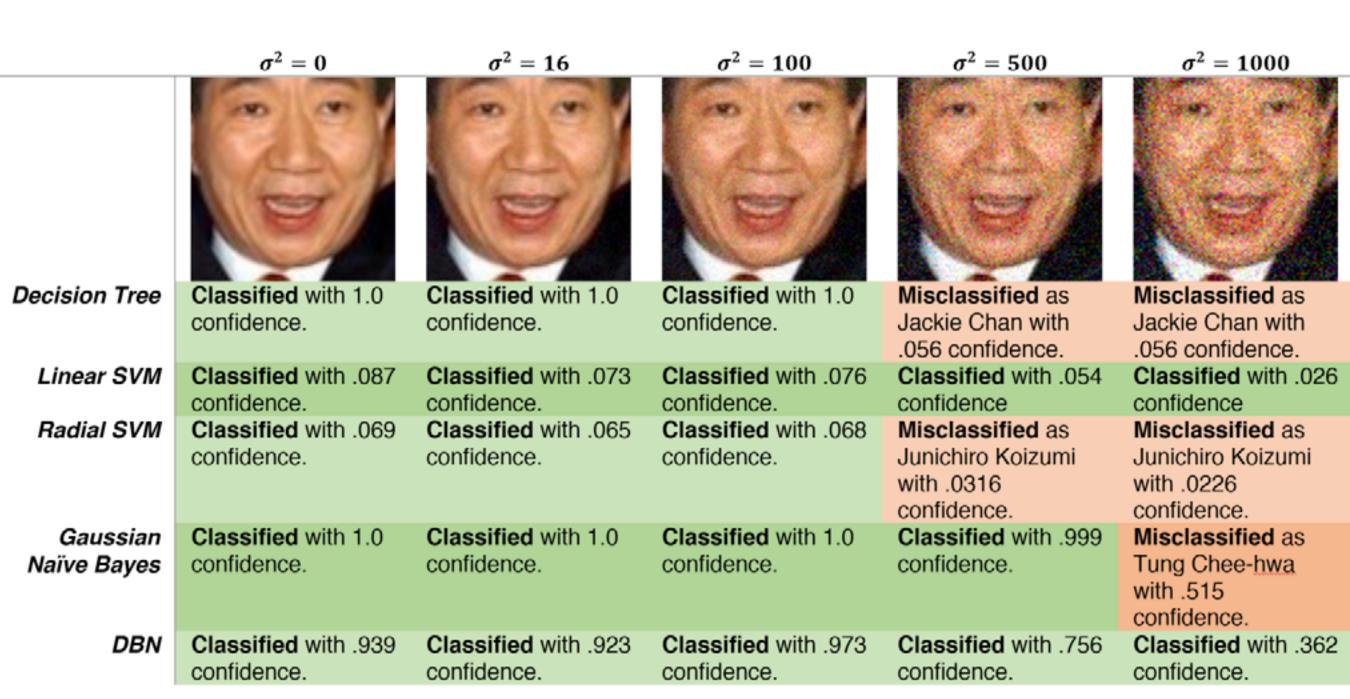


Experiments

Can random noise significantly decrease the accuracy rate of various neural networks with minimal perturbation? Do networks trained on different classifiers respond similarly to perturbation? Do all types of noise: additive, multiplicative, applicative, etc. applied in the same amount result in the same degree of accuracy? Below is a summary of the parameters we tested on, as well as case studies at various levels of Gaussian noise on inner alignment. Notice the inconsistencies in classification confidence scores.

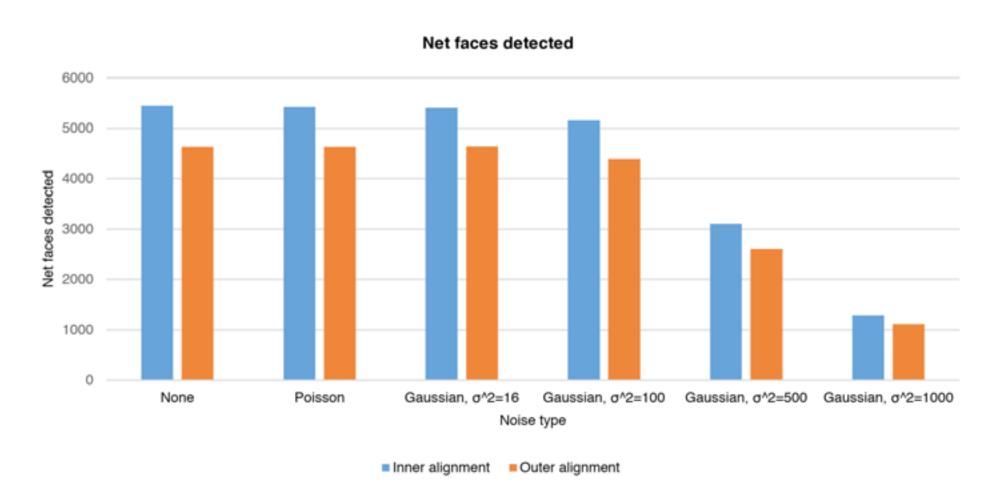
Alignment Methods	Noise Generators	Classification Systems				
Outer eyes and nose	Poisson	Linear SVM				
Inner eyes and bottom lip	Gaussian, $\sigma^2 = 16$	Radial SVM, $\gamma = 2$				
	Gaussian, $\sigma^2 = 100$	Decision Tree, max depth 20				
	Gaussian, $\sigma^2 = 500$	Gaussian Naive Bayes				
	Gaussian, $\sigma^2 = 1000$	Deep Belief Network, 300				
		epochs (learning decay .3,				
		learning rate .3)				



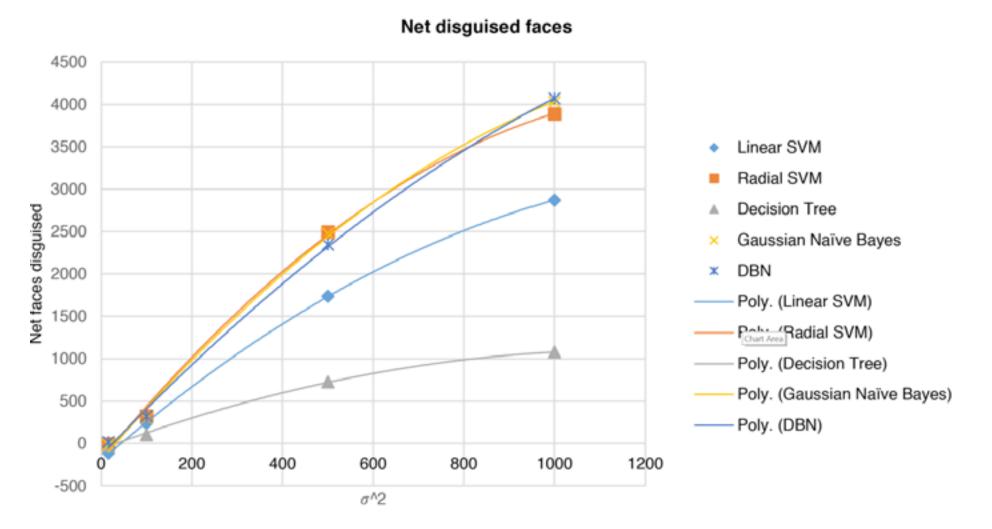


Results

Alignment: Faces aligned by the inner eyes and upper lip were more readily detected than those aligned by the outer eyes and nose; however, alignment had no effect on relative classification accuracies.



Classification: The different classifiers showed varying success in correctly labelling faces. When the recognition scores were normalized by success of detection, the classifier had no effect on relative classification accuracies.



Perturbation: The most interesting results showed that adding small amounts of random noise to faces at times revealed (R) more images than disguised (D). Faces that were originally not detected or correctly classified tended to become correctly classified with minor perturbation.

The more perceptible noise is added to our dataset, the more faces are misclassified. However, the relationship between these changes is inconsistent on an individual basis; adding noise can increase classification confidence or expose faces in many cases.

	$\sigma^2 = 16$			$\sigma^2 = 100$			$\sigma^2 = 500$			$\sigma^2 = 1000$		
	D	R	Т	D	R	Т	D	R	Т	D	R	Т
Decision Tree	287	304	1664	340	234	1513	863	135	739	1134	56	250
Linear SVM	325	440	4612	454	217	4281	1862	94	2112	2896	25	722
Radial SVM	285	288	3618	628	300	3266	2604	107	1735	3916	29	632
Gaussian Naïve Bayes	261	272	4830	585	284	4518	2597	119	2341	4057	29	791
DBN	278	260	4911	585	268	4612	2648	118	2399	4100	30	859