Hiding in Plain Sight: Adversarial Neural Net Facial Recognition

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Abstract

Deep neural networks (DNNs) excel at pattern-recognition tasks, particularly in visual classification. Implementations of DNN-based facial recognition systems [1, 5, 8] approach and even exceed human-level performance on certain datasets [2]. However, recent studies [4, 6, 8] 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.

1. Introduction

Deep neural networks are widely implemented in facial recognition systems due to their excellent performance in visual classification. However, these networks do exhibit certain counterintuitive defects; for example, applying imperceptible non-random perturbations to images can arbitrarily change the network's prediction [8]. That is, because neurons in the network are activated on a linear combination of inputs, slight changes to the input accumulate in large changes to the output. These perturbations cause misclassifications across varied neural network-based systems, so we know that the intrinsic "blind spots" exist within the neural networks themselves [8].

In this paper, we present results on neural network object misclassification specifically focused on facial recognition systems and the Labeled Faces in the Wild (LFW) dataset. To that end, we experiment with perturbations along the alignment, representation, and classification steps of the generally accepted facial recognition pipeline.

Additionally, our results focus on the effects of random perturbations rather than non-random perturbations; in other words, noise. We convolute images at varying levels of noise with Gaussian and Poisson noise distributions. The visual results are not imperceptible, but recognizable to varying degrees.

Research in this space has demonstrated the effects of non-random perturbations through the generation of adversarial examples. While these examples yield higher misclassification rates relative to the degree of convolution, it is important to study the effects of image-agnostic convolution to, at the least, present a more robust baseline than is currently available.

2. Previous work

Labeled Faces in the Wild (LFW) is a database of 5,749 labelled people spanning 13,233 images. Most facial recognition systems test accuracy on this database as a benchmark; supervised recognition systems far exceed the performance of traditional recognition systems.

System	Accuracy	Supervised
Eigenfaces	0.6000	No
Fisherfaces	0.8747	No
DeepFace	0.9725	Yes
Human vision	0.9750	-
FaceNet	0.9963	Yes

Table 1: Accuracy of recognition systems on the LFW dataset [2, 5, 9].

Additionally, certain flaws have been exposed in neural network recognition systems, leading to misclassification of objects. Generally, imperceptible changes in an image should not alter the classification. However, smoothness assumptions that underlie certain kernel methods do not necessarily hold for neural networks.

Szegedy et. produced the following objective of applying a perturbation r to an input *x* (classified as *f(x)* by a deep neural network):

$$\mathrm{argmin}_r\ (|f(x+r) - h_t| + \kappa|r|$$

$x+r \in [0,1]$, f produces a probability distribution over possible classes, κ is a constant and h_t is a one-hot vector of an arbitrary class (the class is encoded as a vector of booleans, with 1 or 0 indicating the presence of a characteristic). Minimizing $|f(x+r) - h_t|$ results in misclassification, and minimizing $\kappa|r|$ increases imperceptibility [7]. To generate imperceptible perturbations that serve as adversarial examples for recognition systems, we optimize this function.

The ability to generate these adversarial examples is a "blind spot" in neural network-based recognition systems because these examples are improbable to encounter in training when learning from finite training sets; the non-flexibility of classification models further encourages this result [8].

Thus far, the effects of these non-random perturbations have been studied on object classification datasets like MNIST and ImageNet, but not so much on facial recognition datasets. Sharif et. al generated adversarial examples for a small sample of faces (DNN_B trained on 10 subjects and DNN_C trained on 143), but largely focused on physically realizable disguises to counter facial recognition systems.

Most studies have generated adversarial examples through non-random perturbation. Szedezy et. al does observe the effects of Gaussian noise (with stddev = 1) as a baseline on the MNIST dataset as a baseline; the results are vaguely recognizable and resulted in 51% accuracy of classification.

Though the results on MNIST were visually perceptible, we should study the effects of noise on recognition systems as well; at the least, to provide a baseline for future studies in generating adversarial examples for neural network-based facial recognition. 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?

3. Methodology

We chose FaceNet (and the OpenFace/ OpenCV implementation) 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. Our experiments target most stages of the recognition pipeline [9].

1. Detection
2. **Alignment**
3. **Classification**
4. **Representation**

Detection isn't altered because all images in LFW are guaranteed to be of labelled faces.

3.1 Alignment

We align faces by the outer eyes and nose, and by the inner eyes and bottom lip. Does alignment affect classification accuracy?

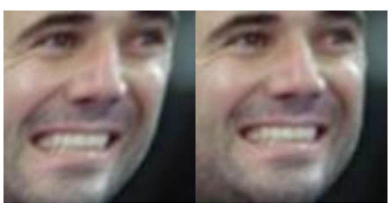


Figure 1: Andre_Agassi_007.jpg. *Left:* outer eyes and nose alignment. *Right:* inner eyes and bottom lip alignment.

3.2 Classification

We classify faces using the following models and parameters.

- A support vector machine with linear kernel (**linear SVM**).
- A support vector machine with radial basis function kernel (**radial SVM**) and $\gamma = 2$.
- A **decision tree** classifier with maximum depth = 20.
- **Gaussian Naïve Bayes**, taking in LFW as a training set.
- A deep belief network (**DBN)** with a learning rate decay of .9, learning rate of .3, and 300 epochs.

Does the classifier used in training the neural network affect response to perturbation? Are different types of classifiers sensitive to certain types or degrees of noise?

3.3 Representation

We mainly apply noise in an additive Gaussian distribution, with $\sigma^2 = 16$, $\sigma^2 = 100$, $\sigma^2 = 500$, and $\sigma^2 = 1000$. We also test the effects of Poisson noise (applied noise). Do different types of noise, applied in the same degree, affect classification accuracy to the same extent?

Parameters for Gaussian noise's σ were determined at intervals where the differences in perceptibility could easily be identified.

Figure 2: George_Clooney_0005.jpg. *Top left:* original image. *Top middle:* $\sigma^2 = 16$. *Top right:* $\sigma^2 = 100$. *Bottom left:* $\sigma^2 = 500$. *Bottom right:* $\sigma^2 = 1000$.

Figure 3: Adam_Sandler_0001.jpg. *Top left:* original image. *Top middle:* $\sigma^2 = 16$. *Top right:* $\sigma^2 = 100$. *Bottom left:* $\sigma^2 = 500$. *Bottom right*: $\sigma^2 = 1000$.

With μ is as mean pixel value and σ as the standard deviation, the additive Gaussian distribution is calculated as follows:

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

Noise for the Poisson distribution is calculated with the following:

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

Where $k = 1$ and λ is sampled from the image, taking in factors such as the number of unique pixels.

We test this Poisson noise against Gaussian noise $\sigma^2 = 16$, which has the same amount of perturbation (summed absolute value of all changes made to each pixel).

Figure 4: Britney_Spears_0001.jpg. *Left:* original image. *Middle:* image with Poisson noise. *Right:* image with Gaussian noise, $\sigma^2 = 16$.

3.4 Implementation

The code used is written in a mix of Python, Lua, and Bash scripts, and is largely reliant on OpenFace and scikit. This is available at github.com/cjqian/facetraining.

4. Experimentation and results

Here are the parameters we alter at different stages of the recognition pipeline: alignment, representation, classification.

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
	Gaussian, $\sigma^2 = 500$	Gaussian Naive Bayes
	Gaussian, $\sigma^2 = 1000$	Deep Belief Network

Table 2: Summary of experiment parameters.

4.1 Metrics

We use individual and comparative metrics on each *experiment* (tests run on one alignment method, one noise generator and one classification system) for evaluation.

Individual: We use the following individual metrics. A **detected** ratio is the number of faces detected out of the total number of faces in the dataset (in our case, 6715). A **recognized** ratio is the number of recognized faces (correctly identified labels) out of detected faces.

Metric	Value	Value Probability
Detected	5425/6715	.807
Recognized	3503/5425	.645

Table 3: Individual metrics for inner aligned dataset, no noise generated and linear SVM.

Metric	Value	Value Probability
Detected	5152/6715	.767
Recognized	3266/5152	.633

Table 4: Individual metrics for inner aligned dataset, Gaussian noise with $\sigma^2 = 100$ and linear SVM.

With no noise, here are some examples of misclassification using inner alignment.

Figure 5: *Left:* Pamela_Anderson_0003 misclassified as Angelina Jolie with .029 confidence. *Right:* Angelina_Jolie_0006.

Figure 6: *Left:* Queen_Latifah_0004 misclassified as Condoleezza Rice with .013 confidence. *Right:* Condoleezza_Rice_0001.

Comparative: We test experiments with generated noise (altered) against the same experiments with no generated noise (baseline) using the following comparative metrics:

- The **lost** count: faces detected in the baseline but not detected in the altered experiment.
- The **found** count: faces not detected in the baseline but detected in the altered experiment.
- The **disguised** count: faces were correctly classified in the baseline but misclassified or not detected in the altered experiment.
- The **exposed** count: faces not correctly identified or not detected in the baseline but correctly classified in the altered experiment.

Metric	Value
Lost	409
Found	136
Disguised	454
Exposed	217
Improved	1266/3049 (.412)
Improved score	12.96

Table 5: Comparative metrics for inner aligned dataset, Gaussian noise with $\sigma^2 = 100$ and linear SVM.

Metric	Value
Lost	4151
Found	17
Disguised	2896
Exposed	25
Improved	108/607 (.1779)
Improved score	50.69

Table 6: Comparative metrics for inner aligned dataset, Gaussian noise with $\sigma^2 = 1000$ and linear SVM.

Here are examples of disguised or exposed faces after applying Gaussian noise at $\sigma^2 = 100$.

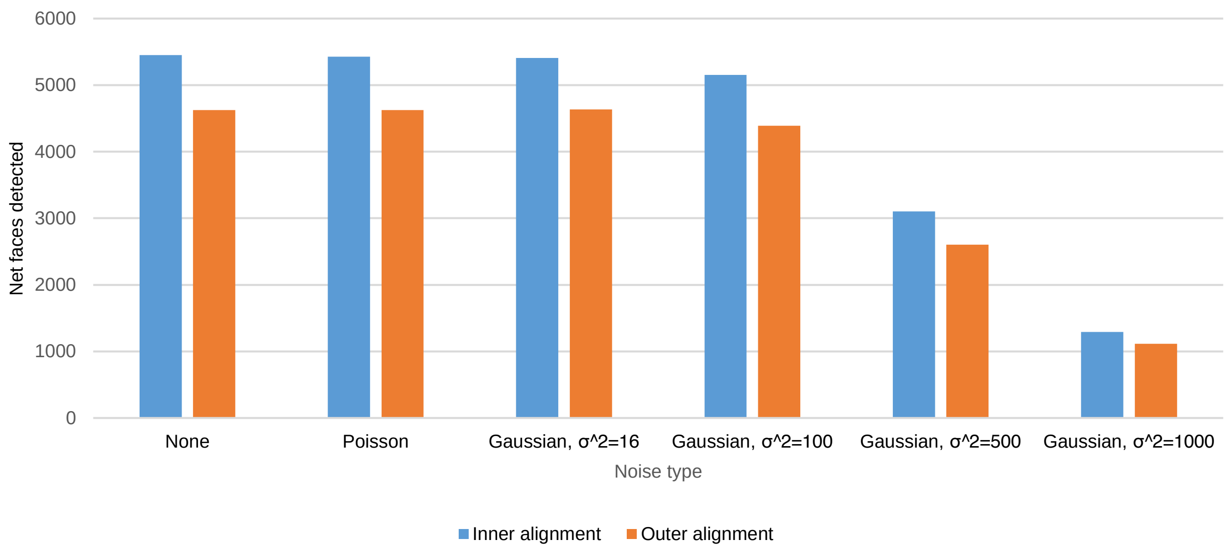
Figure 7: *Left:* Vladimir_Putin_0032 with .097 confidence (no noise). *Right:* Silvio Berlusconi with .071 confidence. **Disguised.**

Figure 8: *Left:* Christina_Aguilera_0003 identified as Anna Kournikova with .014 confidence (no noise). *Right:* Correctly identified Christina Aguilera with .012 confidence. **Exposed.**

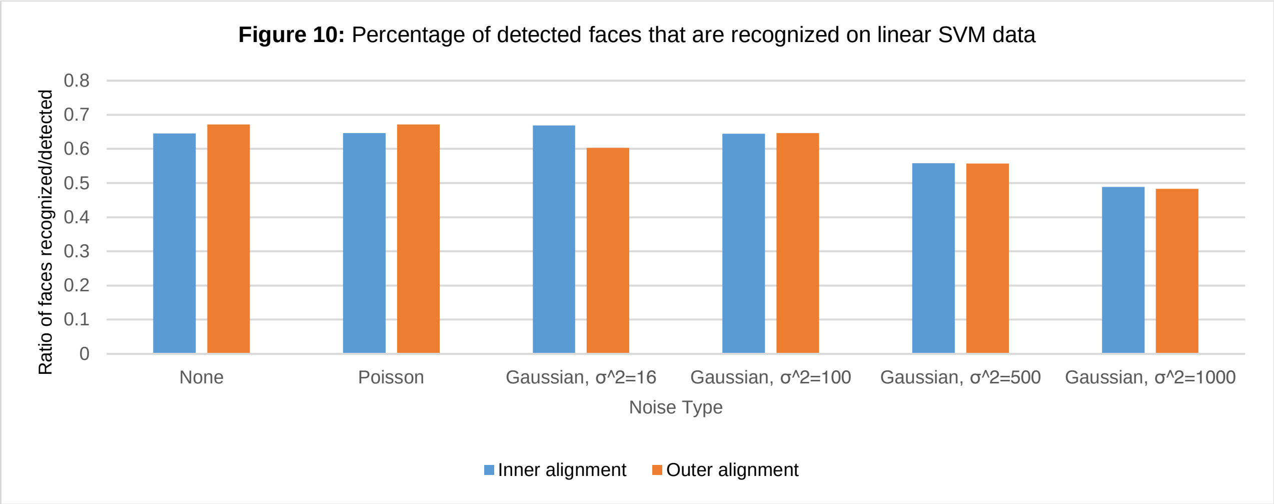
4.2 Alignment Results

Detection: All classification systems detected the same number of faces per noise type within their alignment. Images aligned by the inner eyes and bottom lip consistently detected more faces than in images aligned by the outer eyes and nose. The graph below shows these results; we computed the net faces detected by subtracting the number of faces exposed from the number of faces disguised.

Figure 9: Net detected faces



Recognition: Although the type of classification system in use did affect the number of faces recognized, inner aligned faces were more correctly classified in most cases. The ratio of faces detected to recognized stays approximately the same for the two alignment methods across classification systems, indicating that although alignment by the inner eyes and bottom lip cause more faces to be detected (and subsequently correctly classified), differing alignment methods do not affect the classification accuracy.



Here are some results with the two alignments and no noise. We use the linear SVM classifier.

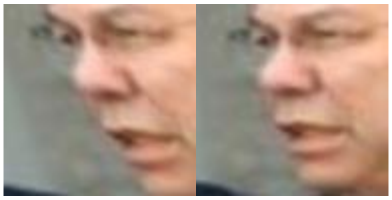


Figure 11: Colin_Powell_0071. *Left:* outer alignment, no face detected. *Right*: inner alignment, no face detected.

Figure 12: Colin_Powell_0207. *Left:* outer alignment, face detected and correctly classified with .621 confidence. *Right:* inner alignment, face detected and correctly classified with .806 confidence.

Figure 13: Anna_Kournikova_0004. *Left:* outer alignment, face detected but misclassified as Arnold Schwarzenegger with .016 confidence. *Right:* inner alignment, face detected and correctly classified with confidence .015.

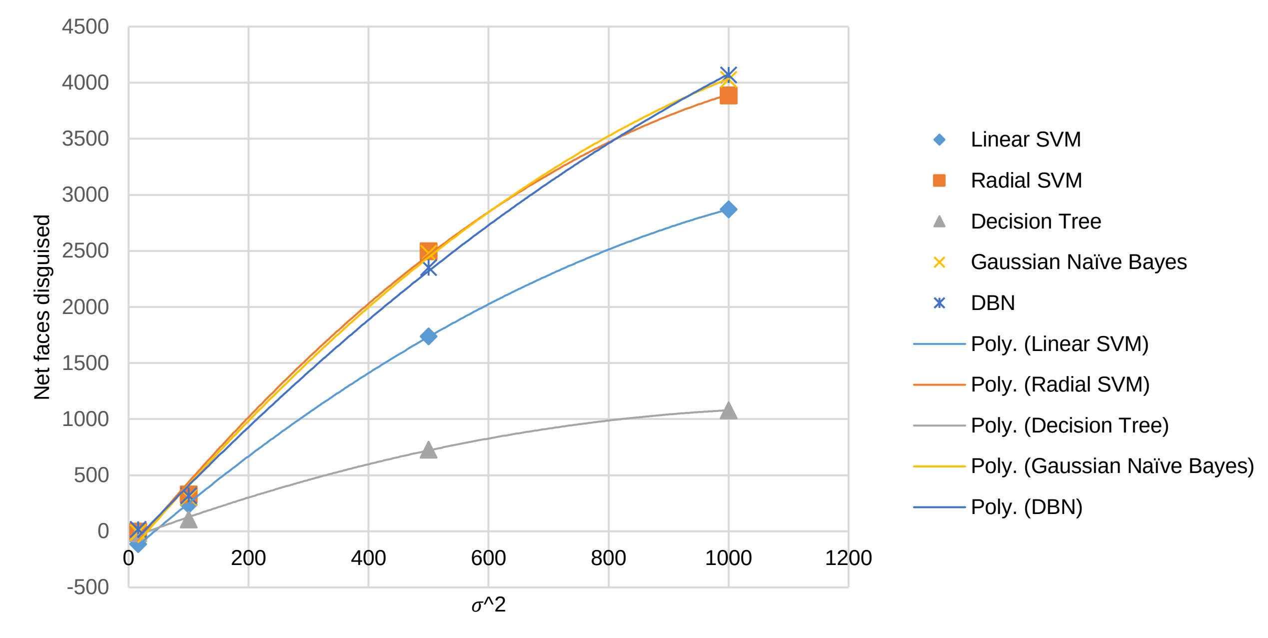
Figure 14: Michelle_Yeoh_0003. *Left:* outer alignment, no face detected. *Right:* face detected but misclassified as Anna Kournikova with .0139 confidence.

Moving forward, we'll mainly use results of inner alignment, since we've show that classification accuracy of varying perturbations is consistent across alignments.

4.3 Classifier Results

We decided to test primarily the effects of Gaussian (additive) noise. To calculate net faces disguised across different classifiers along different values for σ^2, we subtract the number of faces exposed from the number of faces disguised. For each classifier, the results fit a quadratic trendline nicely with minimal $r^2 = .998$.

Figure 15: Net disguised values



This indicates that the number of faces disguised scales linearly with the amount of perturbation added to the image.

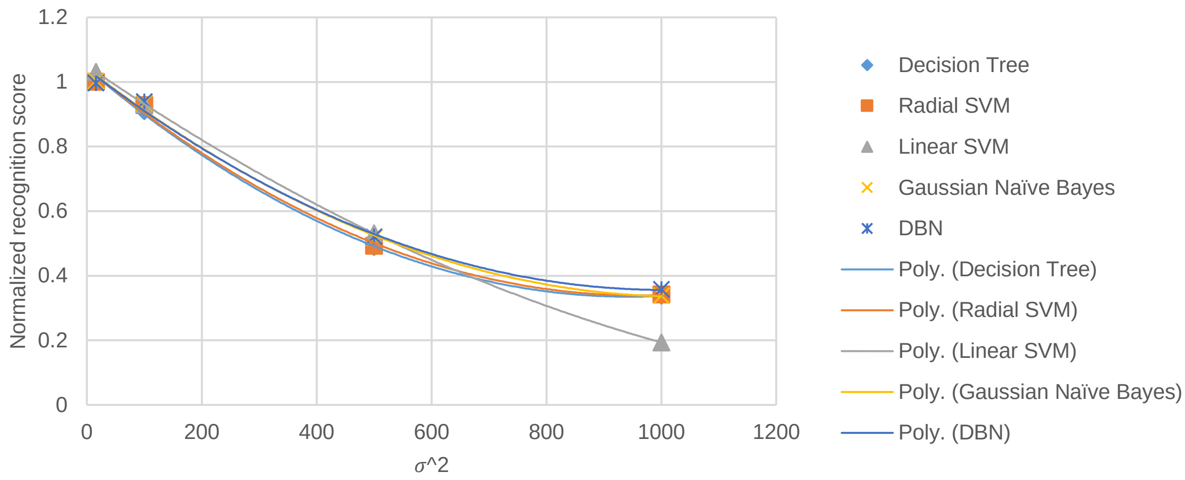
Here are the classifiers in ascending order by number of faces disguised. The numbers are in dark green if more faces were disguised than revealed, and red if the opposite is true. Notice that for $\sigma^2 = 16$, perturbing the faces improve the detection rate slightly. (Discussed more in 4.3). “D” is short for “Disguised,” “R” is short for “Revealed,” and “T” is the total number of faces recognized.

	$\sigma^2 = 16$			$\sigma^2 = 100$			$\sigma^2 = 500$			$\sigma^2 = 1000$		
	D	**R**	**T**	**D**	**R**	**T**	**D**	**R**	**T**	**D**	**R**	**T**
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

Table 7: Number of faces disguised v. revealed for inner aligned data.

To check if certain types of classifiers are more susceptible to misclassification, we normalize the net disguise value found in table X and divide by the “quality of recognition,” calculated by dividing T over the total number of faces recognized at $\sigma^2 = 0$, or at no perturbed noise.

Figure 16: Normalized disguised values



All the trendlines fit along a quadratic curve with minimum correlation = .995, and the lines are mostly similar (with the exception of linear SVM). The similarities in the trendlines indicate that the classification systems are equally susceptible to perturbations.

Here are some case studies showing the results of classification on single faces. Notice the unexpected variance of confidence values along classifiers.

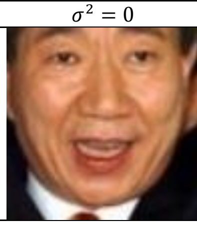
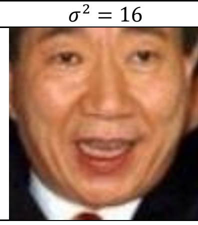
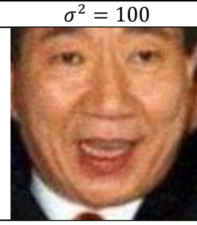
	$\sigma^2 = 0$	$\sigma^2 = 16$	$\sigma^2 = 100$	$\sigma^2 = 500$	$\sigma^2 = 1000$
					
Decision Tree	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Misclassified** as Jackie Chan with .056 confidence.	**Misclassified** as Jackie Chan with .056 confidence.
Linear SVM	**Classified** with .087 confidence.	**Classified** with .073 confidence.	**Classified** with .076 confidence.	**Classified** with .054 confidence	**Classified** with .026 confidence
Radial SVM	**Classified** with .069 confidence.	**Classified** with .065 confidence.	**Classified** with .068 confidence.	**Misclassified** as Junichiro Koizumi with .0316 confidence.	**Misclassified** as Junichiro Koizumi with .0226 confidence.
Gaussian Naïve Bayes	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Classified** with .999 confidence.	**Misclassified** as Tung Chee-hwa with .515 confidence.
DBN	**Classified** with .939 confidence.	**Classified** with .923 confidence.	**Classified** with .973 confidence.	**Classified** with .756 confidence.	**Classified** with .362 confidence.

Table 8: Case study of Roh_Moo-hyun_0004.

	$\sigma^2 = 0$	$\sigma^2 = 16$	$\sigma^2 = 100$	$\sigma^2 = 500$	$\sigma^2 = 1000$
					
Decision Tree	**Misclassified** as Vladimir Putin with .016 confidence.	**Misclassified** as Vladimir Putin with .016 confidence.	**Misclassified** as Michael Douglas with .033 confidence.	**Misclassified** as Michael Douglas with .033 confidence.	**Misclassified** as Michael Douglas with .033 confidence.
Linear SVM	**Misclassified** as Paul Bremer with .028 confidence.	**Misclassified** as Paul Bremer with .024 confidence.	**Misclassified** as Paul Bremer with .0316 confidence.	**Misclassified** as Paul Bremer with .043 confidence.	**Misclassified** as Paul Bremer with .035 confidence.
Radial SVM	**Classified** with .024 confidence.	**Classified** with .024 confidence.	**Classified** with .027 confidence.	**Classified** with .029 confidence.	**Classified** with .024 confidence.
Gaussian Naïve Bayes	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.	**Classified** with 1.0 confidence.
DBN	**Classified** with .925 confidence.	**Classified** with .907 confidence.	**Classified** with .755 confidence.	**Classified** with .831 confidence.	**Classified** with .854 confidence.

Table 9: Case study of Joan_Laporta_0008.

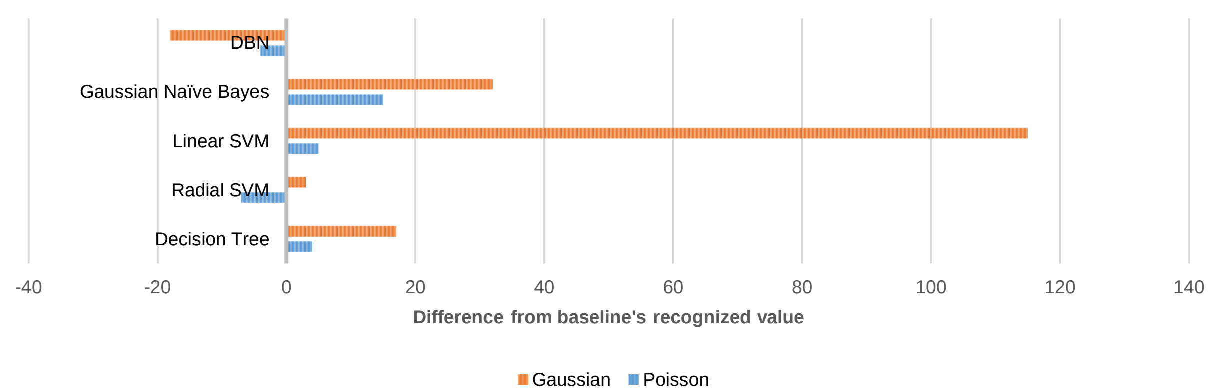
Each classifier's relationship with the perturbations is not intuitive. Glaring inconsistencies, like how confidences can increase with added perturbation or how faces can be revealed with added perturbation, reaffirm that deep neural networks learned by back propagation "have nonintuitive characteristics and intrinsic blind spots, whose structure is connected to the data distribution in a non-obvious way" [8].

4.4 Noise Generation Results (Poisson v. Gaussian)

Intuitively, adding random noise to a face should lower the number of recognized faces across our dataset for all classification systems. This assumption is consistent with the results that we've seen for perceptible amounts of random Gaussian noise.

However, for nearly imperceptible amounts of noise (Poisson noise, Gaussian with $\sigma^2 = 16$), there is a net increase in exposed faces in evaluating the classifications from each individual experiment.

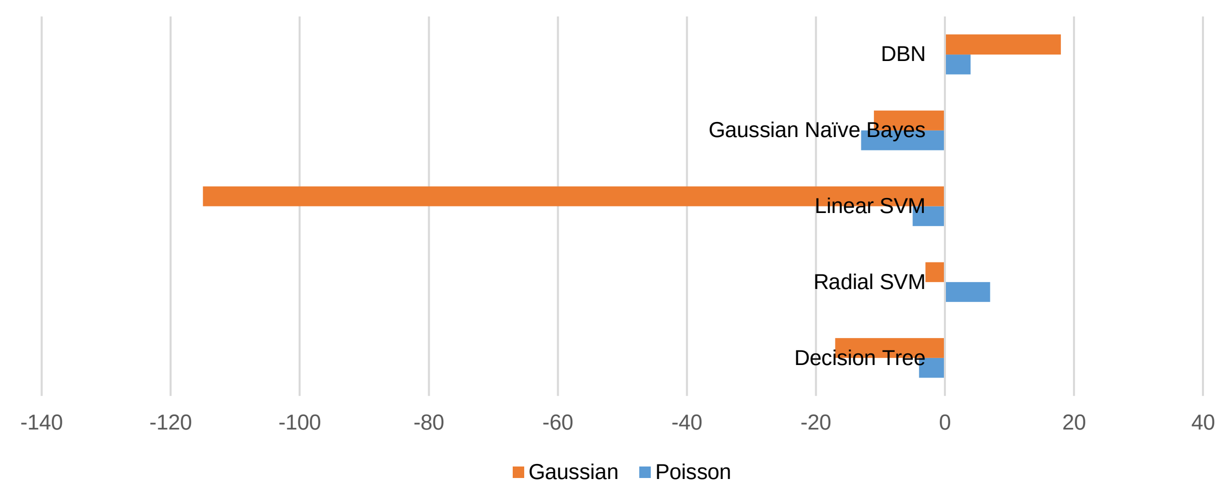
Figure 17: Difference in recognition values from baseline



This irregularity is further indicated when comparing the net disguised value (number of disguised faces – number of exposed faces) across classifiers. For perceptible Gaussian noise perturbations, this value is consistently positive. For small perturbations, more faces are exposed by perturbation than are disguised, leading to a negative net disguised value.

Additionally, the small Gaussian and Poisson perturbations contribute roughly the same amount of noise in the face. However, the Gaussian noise does a statistically significant worse job at disguising faces than the Poisson noise.

Figure 18: Net disguised values



4.5 Other Results

Raw data used for analysis can be found in the appendix. Also, files, code, and log files can be found here: github.com/cjqian/facetraining. This includes specific lists for each experiment indicating which images where disguised, exposed, lost, etc.

For individual metrics, we also computed a **confidence** score. If a face was correctly classified with *n* confidence, we add *n* to the score. If a face was misclassified with *m* confidence, we subtract *m* from the score. At a glance, this confidence score seems loosely related to the recognized/detected ratio.

For comparative metrics, we compute an additional **improve** value and corresponding score. If a face is correctly classified in both the baseline and additional experiment, it is considered improved if the confidence value is higher in the additional experiment. The score sums the degree to which this improvement is made. A disguise is considered more successful if the improve ratio is small.

5. Conclusions

We altered parameters at various stages of the recognition pipeline (see ***Table 2***) to test how the perturbation of faces affects classification.

Alignment: Aligning faces by the inner eyes and bottom lip result in higher detection and recognition accuracy than aligning faces by the outer eyes and nose. This result is consistent across the five classifiers tested. However, the ratio of faces disguised across varying perturbations over the total amount of faces classified is approximately the same for either alignment method, indicating that alignment plays no apparent role in disguising faces.

Representation: The more perceptible (significant) noise is added to our dataset, the more faces are misclassified. However, the relationship between these changes is relatively inconsistent on an individual basis; adding noise can increase confidence or expose faces in many cases. Furthermore, adding small amounts of noise exposes more faces overall, even to a statistically significant amount in the case of certain classifiers.

Classification: Neural networks trained with different classifiers result in different detection and recognition accuracies. In order from highest accuracy to lowest on our dataset:

1. DBN
2. Gaussian Naïve Bayes
3. Radial SVM
4. Linear SVM
5. Decision Trees

Refer to ***Table 7*** for more detail. Although the disguised accuracies varied across classifiers, these accuracy scores normalized (by dividing against each classifier's recognition accuracies) showed that these classifiers responded similarly to perturbations.

In summary, alignment and classification method do not noticeably alter the effects of perturbation on the LFW dataset, showing that the classification abilities of neural networks are consistent across classification methods and the skewing of images in our dataset. However, these perturbations are proven to alter the classifications in unintuitive ways.

6. Future Work

The unintuitive classifications should be explored in much greater detail.

Why does adding small amounts of noise increase the exposure of faces across classifiers? To verify that this is a consistent result, we should test on other datasets and recognition systems aside from FaceNet.

Why does the Gaussian noise distribution do a worse job at disguising faces than the Poisson noise distribution in most cases, despite contributing overall the same amount of change? Expanding the study to include more types of additive, multiplicative, and applied noise to similar degrees can indicate if the type of noise plays a more significant role in disguising faces.

Can we gain an intuition for how misclassification occurs in neural networks-based recognition systems? The results of our experiments reveal inconsistencies; faces that are not detected or recognized should not become exposed by adding random noise as they are currently. Which layers of DNNs or features of these classifiers cause the unpredictable confidence score changes and classifications?

6. Honor Statement

I pledge my honor that this paper represents my own work in accordance with University regulations.

7. References

[1] Amos, Brandon, Bartosz Ludwiczuk, and Mahadev Satyanarayanan. *OpenFace: A general-purpose face recognition library with mobile applications*. Technical report, CMU-CS-16-118, CMU School of Computer Science, 2016.

[2] Huang, Gary B., et al. *Labeled faces in the wild: A database for studying face recognition in unconstrained environments*. Vol. 1. No. 2. Technical Report 07-49, University of Massachusetts, Amherst. 2007.

[3] Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples." *arXiv preprint arXiv:1412.6572*. 2014.

[4] Nguyen, Anh, Jason Yosinski, and Jeff Clune. "Deep neural networks are easily fooled: High confidence predictions for unrecognizable images." *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2015.

[5] Schroff, Florian, Dmitry Kalenichenko, and James Philbin. "Facenet: A unified embedding for face recognition and clustering." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2015.

[6] Seyed-Mohsen, Moosavi-Dezfooli, Alhussein Fawzi, Omar Fawzi, and Pascal Frossard. “Universal adversarial perturbations.” *CoRR abs/1610.08401*. 2016.

[7] Sharif, Mahmood, et al. "Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition." *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*. ACM, 2016.

[8] Szegedy, Christian, et al. "Intriguing properties of neural networks." *arXiv preprint arXiv:1312.6199* (2013). Sharif, Mahmood, et al. "Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition." *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*. ACM, 2016.

[9] Taigman, Yaniv, et al. "Deepface: Closing the gap to human-level performance in face verification." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2014.

8. Appendix

The following data is for inner alignment experiments, since we use these for the majority of results in this paper. Refer to 4.5 for additional information or data.

8.1. Output files

Linear SVM:

	None	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Detected Value	5425	5428	5409	5152	3104	1291
Detected Ratio*	.807	.808	.805	.767	.462	.192
Recognized Value	3503	3508	3618	3266	1735	632
Recognized Ratio**	.645	.646	.668	.633	.558	.489
Confidence	698.2	697.4	677.6	657.0	335.6	113.6

Table 10: Individual metrics.

	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Lost	123	140	409	2372	4151
Found	126	124	136	51	17
Disguised	190	325	454	1862	2896
Exposed	195	440	217	94	25
Improved	1617/3313	1535/3178	1266/3049	399/1641	108/607
Improved ratio	.488	.483	.415	.243	.175
Improved score	-1.41	29.20	12.96	82.34	.369

Table 11: Comparative metrics.

Radial SVM:

	None	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Detected Value	5425	5428	5409	5152	3104	1291
Detected Ratio	.807	.808	.805	.767	.462	.192
Recognized Value	4609	4602	4612	4281	2112	722
Recognized Ratio	.849	.847	.852	.830	.558	.559
Confidence	684.3	687.2	689.9	647.1	328.5	105.6

Table 12: Individual metrics.

	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Lost	123	140	409	2372	4151
Found	126	124	136	51	17
Disguised	290	285	628	2604	3916
Exposed	283	288	300	107	29
Improved	2181/4319	2171/4324	1780/3981	553/2005	132/693
Improved ratio	.505	.502	.447	.275	.190
Improved score	-4.01	-4.92	6.05	73.26	51.76

Table 13: Comparative metrics.

Decision Tree:

	None	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Detected Value	5425	5428	5409	5152	3104	1291
Detected Ratio	.807	.808	.805	.767	.462	.192
Recognized Value	1647	1651	1664	1513	739	250
Recognized Ratio	.303	.304	.307	.293	.238	.193
Confidence	513.1	483.4	523.3	385.0	-59.3	483.4

Table 14: Individual metrics.

	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Lost	123	140	409	2372	4151
Found	126	124	136	51	17
Disguised	289	287	466	1096	1441
Exposed	293	304	332	188	50
Improved	4/1358	4/1360	9/1181	4/551	0/200
Improved ratio	.003	.003	.008	.007	0
Improved score	1.463	2.847	.417	6.01	1.141

Table 15: Comparative metrics.

Gaussian Naïve Bayes:

	None	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Detected Value	5425	5428	5409	5152	3104	1291
Detected Ratio	.807	.808	.805	.767	.462	.192
Recognized Value	4819	4832	4830	4518	2341	791
Recognized Ratio	.888	.890	.892	.876	.754	.612
Confidence	4229	4244	4261	3899	1600	306.4

Table 16: Individual metrics.

	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Lost	123	140	409	2372	4151
Found	126	124	136	51	17
Disguised	237	261	585	2597	4057
Exposed	250	272	284	119	29
Improved	538/4582	508/4558	461/4234	203/2222	57/762
Improved ratio	.117	.11	.109	.09	.074
Improved score	.565	.354	.872	8.6	4.109

Table 17: Comparative metrics.

DBN:

	None	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Detected Value	5425	5428	5409	5152	3104	1291
Detected Ratio	.807	.808	.805	.767	.462	.192
Recognized Value	4929	4925	4911	4612	2399	859
Recognized Ratio	.908	.907	.907	.895	.772	.665
Confidence	3916	3912	3903	3578	1564	465.8

Table 18: Individual metrics.

	Poisson	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Lost	123	140	409	2372	4151
Found	126	124	136	51	17
Disguised	268	278	585	2648	4100
Exposed	264	260	268	118	30
Improved	2260/4661	2272.4651	1840/4344	624/2281	183/829
Improved ratio	.485	.488	.424	.274	.223
Improved score	6.322	-1.75	73.28	198.4	112

Table 19: Comparative metrics.

* Detected ratio is of detected value over all faces (6715)

** Recognized ratio is of recognized value over detected value.

8.2 Tables accompanying figures

	Inner alignment	**Outer alignment**
None	5452	4625
Poisson	5428	4625
Gaussian, σ^2=16	5409	4634
Gaussian, σ^2=100	5152	4392
Gaussian, σ^2=500	3104	2605
Gaussian, σ^2=1000	1291	1116

Table 20: Table accompanying ***Figure 9***: Net detected faces.

	Inner alignment	**Outer alignment**
None	0.645	0.672
Poisson	0.646	0.672
Gaussian, σ^2=16	0.668885	0.603582218
Gaussian, σ^2=100	0.644	0.646
Gaussian, σ^2=500	0.558	0.557
Gaussian, σ^2=1000	0.489	0.483

Table 21: Table accompanying ***Figure 10***: Percentage of detected faces that are recognized on linear SVM data.

	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Linear SVM	-115	237	1738	2871
Radial SVM	-3	328	2497	3887
Decision Tree	-17	106	728	1078
Gaussian Naïve Bayes	-11	301	2478	4028
DBN	18	317	2350	4070

Table 22: Table accompanying ***Figure 15***: Net disguised values.

	Gaussian $\sigma^2 = 16$	Gaussian $\sigma^2 = 100$	Gaussian $\sigma^2 = 500$	Gaussian $\sigma^2 = 1000$
Decision Tree	1.010472	0.909255	0.488434	0.338295
Radial SVM	1.000651	0.928231	0.493343	0.341856
Linear SVM	1.031357	0.931015	0.531231	0.193509
Gaussian Naïve Bayes	1.002283	0.935404	0.51815	0.33789
DBN	0.996348	0.939116	0.520165	0.358066

Table 23: Table accompanying ***Figure 16***: Normalized disguised values.

	No Noise	Poisson	Gaussian	Poisson Difference	Gaussian Difference
Decision Tree	1647	1651	1664	-4	-17
Radial SVM	4609	4602	4612	7	-3
Linear SVM	3503	3508	3618	-5	-115
Gaussian Naïve Bayes	4229	4244	4261	-13	-11
DBN	4929	4925	4911	4	18

Table 24: Table accompanying ***Figure 18***: Net disguised values (for Poisson distribution and Gaussian $\sigma^2 = 16.$)