

# Deep learning and face recognition: the state of the art.

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## ABSTRACT

Deep Neural Networks (DNNs) have established themselves as a dominant technique in machine learning. DNNs have been top performers on a wide variety of tasks including image classification, speech recognition, and face recognition.<sup>1-3</sup> Convolutional neural networks (CNNs) have been used in nearly all of the top performing methods on the Labeled Faces in the Wild (LFW) dataset.<sup>3-6</sup> In this talk and accompanying paper, I attempt to provide a review and summary of the deep learning techniques used in the state-of-the-art. In addition, I highlight the need for both larger and more challenging public datasets to benchmark these systems.

Despite the ability of DNNs and autoencoders to perform unsupervised feature learning, modern facial recognition pipelines still require domain specific engineering in the form of re-alignment. For example, in Facebook's recent DeepFace paper, a 3D "frontalization" step lies at the beginning of the pipeline. This step creates a 3D face model for the incoming image and then uses a series of affine transformations of the fiducial points to "frontalize" the image. This step enables the DeepFace system to use a neural network architecture with locally connected layers without weight sharing as opposed to standard convolutional layers.<sup>6</sup> Deep learning techniques combined with large datasets have allowed research groups to surpass human level performance on the LFW dataset.<sup>3,5</sup>

The high accuracy (99.63% for FaceNet at the time of publishing) and utilization of outside data (hundreds of millions of images in the case of Google's FaceNet) suggest that current face verification benchmarks such as LFW may not be challenging enough, nor provide enough data, for current techniques.<sup>3,5</sup> There exist a variety of organizations with mobile photo sharing applications that would be capable of releasing a very large scale and highly diverse dataset of facial images captured on mobile devices. Such an "ImageNet for Face Recognition" would likely receive a warm welcome from researchers and practitioners alike.

**Keywords:** Deep Learning, Feature Learning, Representation Learning, Facial Recognition, Face verification, Face identification, biometrics

## 1. INTRODUCTION

The application of deep learning and representation learning to the domain of facial recognition has been the driving force behind recent advances in the state-of-the-art. The most accurate techniques of today leverage datasets of increasing size in conjunction with convolutional neural networks.<sup>1,4</sup>

This paper presents a brief historical overview of face recognition, an overview of the field of representation learning and deep learning, a look at how those fields are influencing the state-of-the-art of face recognition, and proposes future work to develop a new benchmark and dataset for face recognition research.

## 2. BACKGROUND

Previous image recognition and facial recognition pipelines relied on hand-engineered features such as SIFT, LBP, and Fisher vectors. One only needs to look at the techniques used in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2011 to see engineered features at the top of the list.<sup>1</sup>

This changed at the end of 2011, first with a demonstration by Le et al. of large scale feature learning with a sparse autoencoder. This autoencoder was trained using asynchronous Stochastic Gradient Descent (SGD) on 1,000 machines (16,000 cores) at Google using data from YouTube. It was then used to initialize the weights of a DNN which set a new record for performance on ImageNet.<sup>7</sup> Then, in 2012, Krizhevsky, Sutskever, and Hinton

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showed that networks with similar performance could be trained with one computer and two GPUs. Their “SuperVision” network resulted in a 37% gain over competing hand engineered features in the 2012 ILSVRC and paved the way for large scale feature learning without large scale server infrastructure.<sup>8</sup> This marked the beginning of deep learning as the de-facto feature extraction algorithm in the field of visual object recognition. These advances were applied with much success to facial recognition by Taigman, et al. in their 2014 “DeepFace” paper.<sup>6</sup>

### 3. DEEP LEARNING

#### 3.1 Feature Engineering vs. Feature Learning

Computer vision and signal processing algorithms often have two steps: feature extraction, followed by classification. For example, an image feature extractor, such as Haar, SIFT, or SURF, takes in raw input in the form of pixels and transforms it into a feature vector that can be classified by a general classification algorithm such as a Support Vector Machine (SVM). These feature extractors are custom-built, “engineered” features. In LBP facial recognition, weights are applied to specific portions of the face to emphasize or de-emphasize certain regions.<sup>9</sup> This type of feature engineering results in brittle, over-specialized feature extractors that cannot be applied to other problem domains, let alone other modalities. Feature learning methods, on the other hand, *learn* a feature extractor based on the statistics of the training data and have been successfully applied to a variety of different domains and modalities.<sup>1–3</sup>

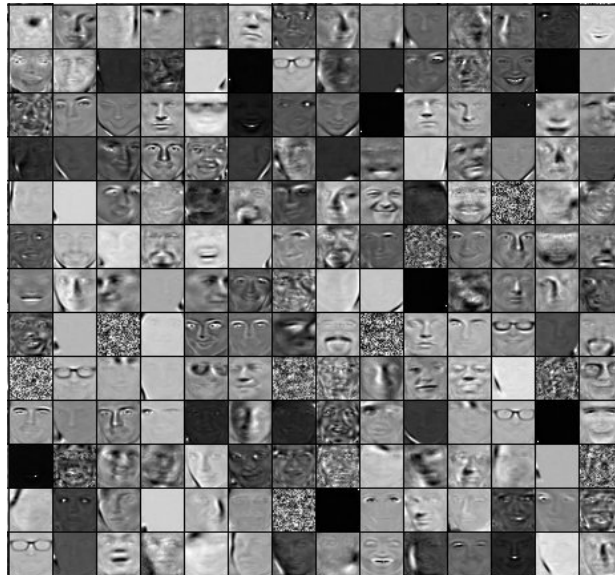


Figure 1. Features learned by training a Stacked Denoising Autoencoder with unlabeled face data. Note the rich variety of learned features including glasses, facial hair, toothy smile, and even sunglasses.

#### 3.2 A quick introduction and review of gradient based learning

Deep learning and feature learning problems share a common structure:

1. The creation of some layered architectures parameterized on  $\theta$ . (Autoencoders, DNNs, CNNs, etc.)
2. The definition of a loss functional\*,  $\mathcal{L}$ .
3. The minimization of the loss functional with respect to  $\theta$  using an optimization algorithm and training data.

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\*The loss functional is a functional because it is a function from a vector space onto its underlying scalar field.

Gradient based optimization methods are commonly used to perform the optimization in step 3.<sup>10,11</sup> Stochastic Gradient Descent (SGD) is a modification of “batch” gradient descent where parameter updates are made after calculating a stochastic approximation of the gradient. This approximation is made using a random subset of the training data,  $\mathbf{m} \subseteq x$  of size  $B$ , called a *mini-batch*. The assumption made by SGD is that the stochastic approximation of the gradient, which is a random variable, has the same *expected* value as the deterministic gradient.  $B$  is also known as the *batch size*. The parameters being optimized,  $\theta$ , are updated after each mini-batch using the formula below.

$$\theta_{t+1} \leftarrow \theta_t - \epsilon(t) \frac{1}{B} \sum_{b=0}^{B-1} \frac{\partial \mathcal{L}(\mathbf{m}_b, \theta)}{\partial \theta}$$

The reason that we average the gradients as opposed to simply summing is due to the fact that the sum of the mini-batch gradients would change significantly as a function of  $B$ , thus changing the optimal learning rate schedule  $\epsilon$ . By averaging, the variance of the stochastic approximation of the gradient becomes inversely proportion to  $B$ . So, if  $B$  decreases, the variance of the approximation goes up which would lead to a slight reduction of the optimal learning rate, and vice versa for an increase in  $B$ .<sup>10</sup> Different values of  $B$  lead to different types of gradient descent:

1. Online stochastic gradient descent:  $B = 1$ .
2. Mini-batch stochastic gradient descent:  $B > 1$  but  $B < |x|$ .
3. “Batch” gradient descent,  $B = |x|$ . Note that in this case the gradient is no longer a random variable and is deterministic.

For a more thorough treatment of the topic of training deep architectures with gradient descent, and an analysis of all of the hyperparameters involved, see Yoshua Bengio’s tutorial “Practical recommendations for gradient-based training of deep architectures.” (Ref. 10.)

### 3.3 Autoencoders & Deep Neural Networks

A deep neural network is a neural network with more layers than is traditionally used. Layered neural networks are also known as multi-layer neural networks or multi-layer perceptrons (MLPs), although the latter is a misnomer. A single layer MLP can be formally described as a function  $f : \mathbb{R}^D \rightarrow \mathbb{R}^P$  parameterized by  $\theta = (\mathbf{W}_0, \mathbf{b}_0, \mathbf{W}_1, \mathbf{b}_1, \sigma_0, \sigma_1)$ . Where  $D$  is the number of dimensions of the input  $\mathbf{x} \in \mathbb{R}^D$  and  $P$  is the number of dimensions of the output layer.

$$f(\mathbf{x}) = \sigma_1(\mathbf{W}_1(\sigma_0(\mathbf{W}_0\mathbf{x} + \mathbf{b}_0)) + \mathbf{b}_1)$$

The function  $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ , is referred to as the *activation function*, or, *nonlinearity*, because it often is a non-linear function such as tanh, sigmoid, or a rectified linear unit (ReLU)<sup>†</sup>. The parameter set,  $\theta$  is then optimized to minimize the training loss  $\mathcal{L}$  using SGD, L-BFGS, or another optimization algorithm.<sup>12</sup>

#### 3.3.1 Unsupervised Learning

Unsupervised feature learning is a set of unsupervised learning techniques that transform the input into a form that is easier to work with for other tasks such as clustering, classification, or regression.<sup>11</sup> Autoencoders are one form of unsupervised learning algorithm.

Formally, an autoencoder is a set of two functions: an *encoder* and a *decoder*. The encoder function parameterized by  $\theta$ ,  $f_\theta$ , maps the input vector  $\mathbf{x} \in \mathbb{R}^D$  onto a hidden layer, or *code*,  $\mathbf{y} \in \mathbb{R}^H$  and the decoder function parameterized by  $\theta'$ ,  $g_{\theta'}$ , maps the code  $\mathbf{y}$  onto a reconstructed vector  $\mathbf{z} \in \mathbb{R}^D$ .<sup>13</sup> The job of the learning algorithm is to modify the parameters  $(\theta, \theta')$  of the encoder and decoder to better reconstruct the original input from

<sup>†</sup>Rectified Linear Units are defined as  $r(x) = \max(0, x)$

the code. Modifications to the autoencoder scheme include denoising autoencoders, contractive autoencoders, and sparse autoencoders.<sup>7, 14–16</sup> Denoising autoencoders are a simple modification of a standard autoencoder. They add noise to the input vector  $\mathbf{x}$  to get  $\tilde{\mathbf{x}}$  and then attempt to reconstruct the original vector with the noisy input  $\mathbf{z} = g_{\theta'}(f_{\theta}(\tilde{\mathbf{x}}))$ .<sup>14</sup>

The loss functional for an autoencoder  $\mathcal{L}$  can range from squared error  $\mathcal{L}(\mathbf{x}, \mathbf{z}) = \|\mathbf{x} - \mathbf{z}\|^2$  to the cross-entropy of the reconstruction  $\mathcal{L}(\mathbf{x}, \mathbf{z}) = \sum_{i=1}^d [\mathbf{x}_i \log \mathbf{z}_i + (1 - \mathbf{x}_i) \log(1 - \mathbf{z}_i)]$ . The choice of the loss functional depends on the assumed distribution of the input code,  $\mathbf{y}$ .<sup>13</sup> Autoencoders can be used to *pretrain* (initialize the weights of) a DNN which is then *fine-tuned* with labeled data, i.e. trained in a supervised manner.<sup>14, 15</sup> This technique is known as unsupervised pretraining.<sup>17</sup>

Creating your own unsupervised face dataset is relatively straightforward due to the robustness of face detection software. All that is needed to form an unlabeled face dataset is a large collection of photos of people and a face detector. With the torrent of images available online, it's easy to gather a large unlabeled dataset for pretraining DNNs.

Because input images to autoencoders and DNNs are flattened, mapped from  $\mathbb{R}^{w \times h} \rightarrow \mathbb{R}^{wh}$ , autoencoders and multi-layer NNs lose out on the inherent local 2D structure of images. Convolutional neural networks (CNNs), on the other hand, take advantage of this 2D structure.

### 3.4 Convolutional Neural Networks

Convolutional neural networks date back to 1980 with Fukushima's Neocognitron.<sup>18</sup> They were improved and successfully applied to handwritten digit recognition by Yann LeCun in the late 90s; early applications to face recognition appeared around the same time.<sup>19</sup>

Unlike DNNs, which operate by performing a dot product between 1D input vectors and the network's weight matrix followed by an element-wise nonlinearity,  $\sigma, \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$ , a CNN operates by performing a 2D convolution of the filters in its filter bank with a 2D input vector:  $\sigma(\mathbf{W} * \mathbf{x} + \mathbf{b})$ . Nearly every method that performs well on LFW utilizes CNNs. (See Table 1.) Another major advantage of CNNs falls out from the nature of the convolution operation: a linear translation in the input data causes a linear translation in the feature map. This provides some degree of translation-invariance which is not found in DNNs and autoencoders.

## 4. THE STATE-OF-THE-ART IN FACIAL RECOGNITION

The standard pipeline for facial recognition has changed drastically over the past few years. We've seen a transition from hand engineered features to learned features, a transition from face-specific alignment to rough alignment and centering, and a transition from datasets with tens of thousands of images to datasets with hundreds of millions of images. The various phases of this transition are shown below:

1. No alignment needed, hand engineered features, dataset size  $\approx 1\text{e}3$ , dataset gathered in highly controlled lab environment.<sup>9, 20, 21</sup>
2. Domain specific alignment, hand engineered features, SVMs, dataset size  $\approx 1\text{e}4$ .
3. Domain specific alignment (face-specific frontalization and deep funneling), learned features, dataset size  $\approx 1\text{e}6$ .<sup>6, 22</sup>
4. Domain specific alignment (rough alignment), learned features, dataset size  $\approx 1\text{e}7$ .<sup>5</sup>

Despite the move from engineered features to deep CNNs, all of the state-of-the-art methods still utilize face specific alignment techniques. This ranges from rough centering in Schroff, Florian and Kalenichenko 2015 to the use of a 3D face mask estimate and re-projection of the 2D image as in Hassner, Tal, et al. 2014.<sup>5, 31</sup>

Table 1. State-of-the-art methods on LFW at time of publishing. (Sorted by accuracy descending.)

Name	Method	Images (Millions)	Accuracy
Baidu <sup>23</sup> (Announced)	CNN	-	0.9985 $\pm$ -
<b>Google FaceNet<sup>5</sup></b>	<b>CNN</b>	<b>200.0</b>	<b>0.9963 <math>\pm</math> 0.0009</b>
DeepID3 <sup>24</sup>	CNN	0.29	0.9953 $\pm$ 0.0010
MFRS <sup>25</sup>	CNN	5.0	0.9950 $\pm$ 0.0036
DeepID2+ <sup>26</sup>	CNN	0.29	0.9947 $\pm$ 0.0012
DeepID2 <sup>3</sup>	CNN	0.16	0.9915 $\pm$ 0.0013
DeepID <sup>27</sup>	CNN	0.2	0.9745 $\pm$ 0.0026
DeepFace <sup>6</sup>	CNN	4.4	0.9735 $\pm$ 0.0025
FR+FCN <sup>28</sup>	CNN	0.087	0.9645 $\pm$ 0.0025
TL Joint Bayesian <sup>29</sup>	Joint Bayesian	0.099	0.9633 $\pm$ 0.0108
High-dim LBP <sup>30</sup>	LBP	0.099	0.9517 $\pm$ 0.0113

Table 2. An overview of known public and private face datasets. (Sorted by images descending.)

Dataset	Identities	Images (Millions)	Availability
Google Face Dataset <sup>5</sup>	8,000,000	260+	<b>Private</b>
Megavii Face Classification (MFC) <sup>25</sup>	20,000	5.0	<b>Private</b>
Social Face Classification (SFC) <sup>6</sup>	4,030	4.4	<b>Private</b>
CASIA-WebFace <sup>32</sup>	10,575	0.494	Public
CelebFaces <sup>33</sup>	10,177	0.202	<b>Private</b>
CACD <sup>34</sup>	2,000	0.163	Public
WDRRef <sup>30</sup>	2,995	0.099	Public (features only)
LFW <sup>4</sup>	5,749	0.013	Public

## 5. DATASETS

### 5.1 Datasets today

Nearly all of the top algorithms on the LFW benchmark are trained using outside data. LFW offers just 13,233 images. That amount of data is insufficient to properly train modern deep networks. Table 1 shows the top results of LFW, the accuracy achieved for the face verification task, and the amount of data used to train the system.

Table 1 shows not only the dominance of deep convolutional neural networks but also the importance of large datasets for training these networks. Table 2 shows the private nature of the largest face datasets. This trend is disconcerting. If these large datasets remain private, it's possible that progress in facial recognition research might be restricted to those with access to large amounts of proprietary data. According to estimates in 2013 by Kleiner, Perkins, Caufield & Byers (KPCB), over 1.8 billion images are uploaded and shared per day on mobile photo sharing networks.<sup>35†</sup>

Publicly available datasets with tens of millions of images could be compiled and would remove a significant roadblock for progress in the field. The optimal size and structure of such a dataset is outside the scope of this paper, however, Schroff, Florian, et al. (See Ref. 5) suggest that the current generation of deep networks benefit from training sets with tens of millions of images and saturate thereafter.<sup>5</sup> The results of their study on the effect of training data on performance is reproduced below in Table 4.

<sup>†</sup>KPCB's analysis only covered companies in the mobile photo sharing market. Other companies, such as Tencent (WeChat), Google, Dropbox, Apple, and Yahoo also upload millions of photos on a daily basis. However, those numbers remain unpublished.

Table 3. Billions of images are uploaded and shared every day.

Company	Daily Uploads
Snapchat	700 M / day
WhatsApp (Acquired by Facebook in 2014)	500 M / day
Facebook	350 M / day
Instagram (Acquired by Facebook in 2012)	60 M / day

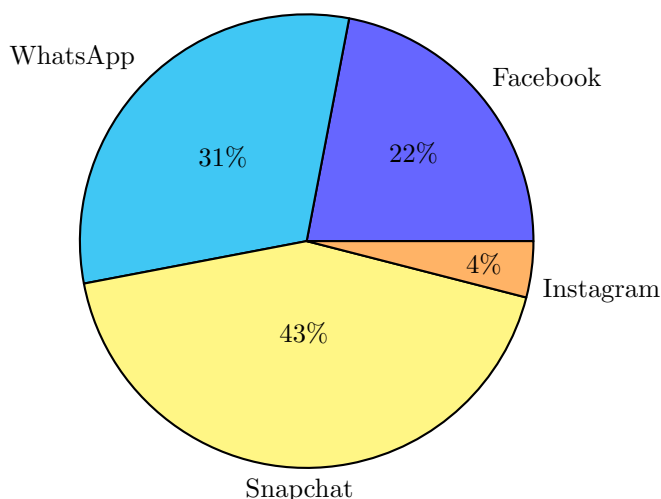


Figure 2. Who's uploading the most?

## 5.2 The problem with today's datasets and benchmarks

### 5.2.1 False Accept Rates (FARs) that are too high.

Yi et al. 2014 noted that the accuracy of state-of-the-art methods may be saturating LFW; the author shares this opinion.<sup>32</sup> Yi et al. suggest BLUFR, which has a focus on lower false accept rates, as a more challenging alternative to LFW. While a benchmark which focuses on lower FARs is needed, a look at the current state-of-the-art also shows the need for a very large scale public dataset.

### 5.2.2 Lack of variety and poor generalization.

Previous generation datasets like AT&T and Yale were captured under highly controlled laboratory environments.<sup>20, 21</sup> Datasets such as LFW and CACD claim to be "in the wild", but are taken almost exclusively by professional photographers with DSLRs in well lit environments. Training on such datasets will likely lead to poor generalization error when the models are confronted with a less constrained operating environment such as a photo stream from a mobile phone.

### 5.2.3 Not enough data.

Deep neural networks require large amounts of data, preferably tens of millions of images.<sup>5</sup> As demonstrated in Table 1, all top performing methods on LFW take advantage of large, supplementary datasets. LFW by itself is simply not enough data given the capacity of modern deep architectures.

## 5.3 Proposal for a new kind of facial recognition dataset

Much like the transition that occurred from Caltech 101 to ImageNet within the visual object recognition field, the author posits that a similar transition will occur within the field of face recognition from LFW to a large scale dataset and corresponding challenge. The companies featured in Table 3 would be in a solid position to create and publish such a dataset.

Table 4. The effect of training set size on the performance of a model after 700 hours of training on 96x96 pixel input images.<sup>5</sup>

#images	validation rate
2.6M	76.3%
26M	85.1%
52M	85.1%
260M	86.2%

## 6. CONCLUSIONS

Deep learning has already been integrated into most state-of-the-art facial recognition pipelines. This shift has lead to a massive increase in the accuracy of facial recognition systems and has caused the current “standard” benchmark for face recognition, LFW, to become saturated. In addition, the data requirements for deep networks highlights the need for a new, very large scale (tens of millions of images), public dataset for face recognition research.

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