Asian Journal of Applied Sciences (ISSN: 2321 – 0893)
Volume 03 – Issue 02, April 2015

Unconstrained Facial Recognition Systems: A Review

Marwa Yousif Hassan[1], Othman O. Khalifa[1*] Azhar Abu Talib[2] and Aisha Hassan Abdulla[1]

[1]International Islamic University Malaysia, Faculty of Engineering
[2]TMIMOS Berhad.

Corresponding author's email: khalifa [AT] iium.edu.my

ABSTRACT— ***Face recognition presents a challenging problem in the field of image analysis and computer vision, and as such has received a great deal of attention over the last few years because of its applications in various domains. Face recognition under controlled environment that is where pose, illumination and other factors are controlled, has well been developed in the literature and near perfection accuracy results have been achieved. However, the unconstrained counterpart, where these factors are not controlled, still under heavy research. Recently, newly developed algorithms in the field that are based on deep learning technology have made significant progress. In this paper, an overview of the newly developed unconstrained facial recognition systems is presented.***

Keywords— Face Recognition, Deep Learning, Representation learning, feature learning.

1. INTRODUCTION

A face recognition system is a computer application that automatically identifies or verifies an identity from a digital image or a video frame. Humans perform face recognition task several times every day and are considered good in doing so. However, the machine recognition of faces is a challenging problem and has been studied for decades. Typically used for security purposes among other applications. The system recognizes faces by comparing selected facial features from the image and a facial database [1].

Controlled Face recognition, i.e. when illumination, pose and face expressions are controlled, has reached maturity as many algorithms have achieved impressive results of near perfection accuracy. It is typically used as a biometric where subjects voluntarily and willingly position themselves to the identification system. Challenges arise when facial recognition is required for a different application such as video surveillance, where sufficient qualities of images and video frames are not available due to different illumination sets, expressions and pose variations not to mention disguise by persons who do not want to be recognized for various reasons. Applications under such uncontrolled conditions are known as *Unconstrained Face Recognition*.

Recent breakthroughs have been made in the area of unconstrained face recognition in academia and industry. Facial recognition systems that are based on 3D face models are more capable of compensating for pose and illuminations problems. Face.com, an Israeli based company, which has been recently acquired by the internet giant Facebook, have achieved about 91.3% accuracy on the Labeled Faces in the Wild "LFW" benchmark for its proprietary 3D model- based method [2, 3]. LFW is a database for studying face recognition in unconstrained environment. The database is aimed at providing a set of labeled face photographs spanning the range of conditions typically encountered by people in their everyday lives. The database offers natural variability in pose, lighting, focus, resolution, facial expression, age, gender, race, accessories, make-up, occlusions, background, and photographic quality [4]. However, the technology that has led the way for recent breakthroughs and impressive results on the LFW benchmark is *deep learning*. It has been recognized as one of the 10 technology breakthroughs of the year 2013 by MIT technology review [5]. It is a relatively new area in machine learning that harnesses multiple layers of neural networks to learn about and solve for complicated tasks.

The breakthroughs that have been achieved by this technology were not only in the area of unconstrained face recognition; other applications such as Natural language processing NLP, Speech Recognition, and the wide area of Object Recognition have witnessed recognizable advancements. For example, Microsoft has released in 2012 a new version of their MAVIS (Microsoft Audio Video Indexing Service) speech system based on deep learning .They managed to reduce the word error rate on four major benchmarks by about 30% compared to state-of-the-art models based on Gaussian mixtures for the acoustic modeling and trained on the same amount of data (309 hours of speech) [6].A breakthrough has also been achieved in the area of object classifications and recognition on ImageNet dataset in the year of 2012 by a team from the University of Toronto, led by Alex Krizhevsky and includes the computer science professor Geoffrey Hinton, bringing down the state-of-the-art error rate from 26.1% to 15.3% [6]. Geoffrey Hinton has recently joined google to assist in its AI and Deep Learning research [5].

Those breakthroughs have made technology giants such as Google, Facebook and Microsoft in competition to monopolize talents and acquire startups in the area of machine learning in general, and particularly in the field of Deep Learning. Google on the beginning of 2014, in a deal of multi hundreds of millions of dollars, has acquired "*DeepMind Technologies*", a startup based in London that had big concentration of researchers working on deep learning. The acquisition, aimed at adding skilled experts rather than specific products [7]. Facebook has won one of the premier scientists in the area of AI and deep learning at the University of New York, Professor Yan LeCun, who has joined the company in September, 2013 to lead its Artificial Intelligence Research Lab. Among his team at Facebook are Yaniv Taigman and Lior Wolf, former Face.com researchers which has been acquired by Facebook earlier. Their joint effort has innovated DeepFace, an algorithm for unconstrained face verification that has become one of the leading algorithms in the field by reaching near human performance of 97.23%% accuracy on LFW benchmark [3, 8].

2. FACE RECOGNITION EXISTING TECHNIQUES

Over the past three decades, a large number of face recognition methods have been proposed in computer vision and most of them have achieved encouraging performance when face images were captured under controlled conditions. All Face Recognition Methods can be classified into 1- holistic methods, in which complete face region is taken into account as input data into face catching system; 2-feature- based (structural) methods, in which Local features such as eyes, nose and mouth are first of all extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier; and 3- hybrid methods, in which hybrid face recognition systems use a combination of both holistic and feature extraction methods. Generally 3D Images are used in hybrid methods [9].

Also, face recognition techniques can be broadly divided into three categories based on the face data acquisition methodology [10]:

I. Methods that operate on intensity images:

Face recognition methods for intensity images fall into two main categories: feature-based and holistic-based. Feature-based approaches first process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., as well as other fiducially marks, and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features. Standard statistical pattern recognition techniques are then employed to match faces using these measurements. Holistic approaches schemes can be subdivided into two groups: statistical and AI approaches. AI approaches utilize tools such as neural networks and machine learning techniques to recognize faces.

II. Those that deal with video sequences:

The major applications of face recognition are surveillance for security purposes, which involves Real time recognition of faces from an image sequence that captured from a video camera. A video based face recognition system consists of 3 modules: Detection, Tracking, and Recognition. Most of these systems choose a few good frames and then apply one of the recognition techniques for intensity images to those frames in order to identify the individual.

III. Those that require other sensory data such as 3D information or infra-red imagery:

Though the bulk of the research on face recognition has been focused on identifying individuals from 2D intensity images, in recent years some attention has nevertheless been directed towards exploiting other sensing modalities, such as 3D or range data and infra-red imagery, for this purpose.

3. FACE RECOGNITION TECHNICAL CHALLENGES

The performance of many state-of-the-art face recognition methods deteriorates with changes in lighting, pose and other factors. The key technical challenges are:

3.1 Large Variability in Facial Appearance: Whereas shape and reflectance are intrinsic properties of a face object, the appearance (i.e. texture) is subject to several other factors, including the facial pose, illumination, facial expression

3.2 Highly Complex Nonlinear Manifolds: The entire face manifold (distribution) is highly nonconvex and so is the face manifold of any individual under various changes. Linear methods such as PCA, independent component analysis (ICA) and linear discriminant analysis (LDA) project the data linearly from a high-dimensional space (e.g. the image space) to a low-dimensional subspace. As such, they are unable to preserve the nonconvex variations of face manifolds necessary to differentiate among individuals.

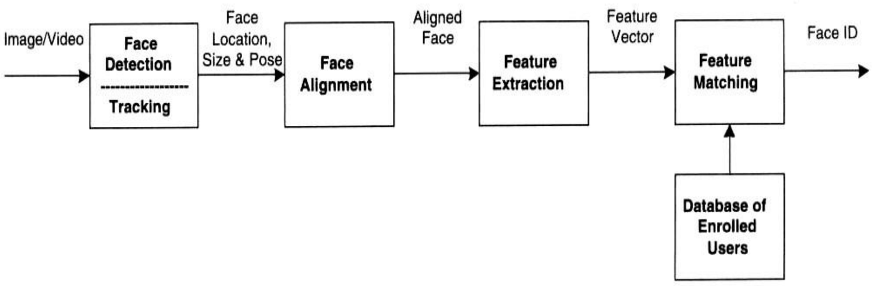

Figure 1 Face recognition processing

3.3 In a linear subspace, Euclidean distance and Mahalanobis distance do not perform well for classifying between face and nonface manifolds and between manifolds of individuals. This limits the power of the linear methods to achieve highly accurate face detection and recognition.

3.4 High Dimensionality and Small Sample Size: Another challenge is the ability to generalize as illustrated in figure. A canonical face image of 112 × 92 resides in a 10,304-dimensional feature space. Nevertheless, the number of examples per person (typically fewer than 10) available for learning the manifold is usually much smaller than the dimensionality of the image space; a system trained on so few examples may not generalize well to unseen instances of the face.

4. LEARNING DEP REPRESENTATIONS FOR FACE RECOGNITION

Machine Learning: The science of Machine learning plays a key role in the fields of statistics, data mining and artificial intelligence, intersecting with areas of engineering and other disciplines. It is about learning from data. As an example, we have an outcome measurement, usually quantitative (such as a stock price) or categorical (such as Match/ Mismatch in face verification), that we wish to predict based on a set of features (such as distance between the eyes, width of the nose, and the length of the jaw line measurements). We have a training set of data, in which the outcome and feature measurements are observed for a set of objects (such as faces). Using this data we build a prediction model, or learner, which will enable us to predict the outcome for new unseen objects. A good learner is one that accurately predicts such an outcome [11]. The core of machine learning deals with representation and generalization. The performance of a machine learning method heavily depends on the choice of data representation (or features). Generalization is the property that the system will perform well on unseen data instances [1]

Supervised and Unsupervised Learning: the discussion above describes what is called the supervised learning problem. It is called “supervised” because of the presence of the outcome variable to guide the learning process. In the unsupervised learning problem, it is only observed the features and has no measurements of the outcome. The task is rather to describe how the data are organized or clustered. The unsupervised problem is less developed in the literature [11].

Deep Learning: A sub-field of machine learning that is based on learning several levels of representations, corresponding to a hierarchy of features or factors or concepts, where higher-level concepts are defined from lower-level ones, and the same lower-level concepts can help to define many higher-level concepts. Deep learning is part of a broader family of machine learning methods based on learning representations. An observation (e.g., an image) can be represented in many ways (e.g., a vector of pixels), but some representations make it easier to learn tasks of interest (e.g., is this the image of a human face?) from examples, and research in this area attempts to define what makes better representations and how to learn them [12]. Figure 2 depicts a general concept of deep learning for face recognition.

A group of researchers and pioneers in deep learning led by Yann LeCun and includes Leon Bottou, Yoshua Benjio and Patrick Haffner at Bell Research Laboratories have made a significant breakthrough in the area when they have implemented a deep convolutional neural network for the purpose of hand written digit recognition at the end of the last millennium [13]. Convolutional Networks (ConvNets) are a biologically inspired trainable architecture that can learn invariant features. Each stage in a ConvNets is composed of a filter bank, some non- linearity, and feature pooling layers. With multiple stages, a ConvNet can learn multi-level hierarchies of features [13, 14]. Their discovery was deployed commercially and used to verify several millions bank checks per day [13]; however, a great effort was needed to transfer and copy their success into other recognition areas such as natural language processing and object/ face recognition.

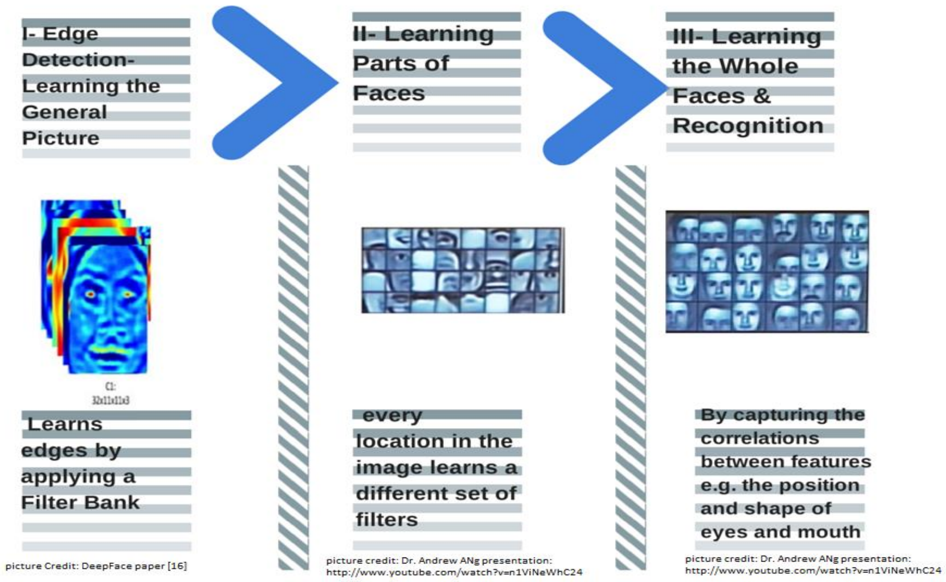

Figure 2 Deep Learning for Face Recognition: General Concept

Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton -a team from the University Of Toronto, Canada- have trained a large, deep convolutional neural network to classify a 1.2 million high-resolution images in the ImageNet LSVRC-2012 contest into one thousand different classes [15]. The neural network consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax (the last layer for decision making- deciding to which of the 1000 classes the query image belongs). To make training faster, the researchers used an efficient GPU implementation of the convolution operation. They have achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

Although their achievement was a breakthrough at the time and despite the fact that the classification problem-classifying objects into groups- is much harder than the verification problem- which is the proof that whether two faces belongs to the same person. However, for applications such as face recognition for video surveillance and homeland security, a much more accuracy is needed.

Yaniv Taigman and Lior Wolf, researchers from face.com- a company that has recently been acquired by FACEBOOK- have achieved an accuracy of 91.3% 0.3 on the test set under the unrestricted LFW protocol for their unconstrained, previously was commercially available, facial recognition system [2]. The system utilizes a 3 D model to rectify poses on query faces and the results were published in a paper entitled "*Leveraging Billions of Faces to Overcome Performance Barriers in Unconstrained Face Recognition*". The accuracy rate is relatively high, however, it is a purely commercial system and on LWF benchmark it is mentioned that in commercial recognition systems, algorithms have not been published and peer-reviewed [3].

DeepFace is an unconstrained face recognition algorithm which was developed by Facebook through Yaniv Taigman and Lior Wolf, the researchers of the newly acquired company Face.com, in addition to Ming Yang and Marc'Aurelio Ranzato, from Facebook's AI research laboratory. The team was led by the Deep Learning's pioneer and legend Yann LeCun. The work was presented at IEEE conference on Computer Vision and Pattern Recognition on June, 2014. The aim of the project is "Face Verification", which is the proof that whether two images belong to the same face. Those images were taken in uncontrolled environments as you might expect from a database of a social network users' photos [16].

Among the 4 general steps of detect, align, represent, and classify, the researchers have revisited the "alignment" and "representation" steps of Face Recognition. They have addressed the alignment problem by employing a 3 D face modeling and a piecewise affine transformation. They derive a face representation using a 9- layers deep Neural Networks. Four million photos of faces belonging to almost 4,000 people of Facebook's users were used to train the neural network. A success rate of 97.23% is achieved, which is closely reaching a human performance of 97.53% [16].

The accuracy rate is impressing and promising; however, this success is difficult to replicate by others who have not got such an enormous resources represented by the huge labeled dataset that Facebook owns, enabling them to achieve such a high rate in the supervised learning mode.

Joint effort between Google.com and Stanford University led by Andrew Ng., the professor from Stanford and the director of Google Brain at the time, a project at Google.com, have addressed the question of *if it is possible to learn a face detector using only unlabeled images* [17]. To answer this, they trained a 9- layered neural network on a large dataset of images (the dataset has 10 million 200x200 pixel images downloaded from the Internet). They have trained this network using model parallelism and asynchronous SGD on a cluster with 1,000 machines (16,000 cores) for three days. The experimental results revealed that it is possible to train a face detector without having to label images as containing a face or not. They have also found that the same network is sensitive to other high-level concepts such as cat faces and human bodies. Starting with these learned features, the network is trained to obtain 15.8% accuracy in recognizing 22,000 object categories from ImageNet, a leap of 70% relative improvement over the previous state-of-the-art [17].

Although their model was a big leap in the unsupervised learning mode, but still there is a long way to go to transform and improve the model for practical applications that need lot more than 15.3% accuracy. Also, this experiment is difficult to replicate by others since small number of entities have Google resources of 16,000 cores.

Professor Andrew Ng with a team from Stanford University addressed the fact of limited resources available to a non-Google enabled entity and have achieved the same result of 15.3% accuracy in the unsupervised learning mode using Commodity OF -The-Shelf High Performance Computing (COTS HPC) technology: a cluster of GPU servers. The system is able to train 1 billion parameter networks on just 3 machines in a couple of days, and they have shown that it can scale to networks with over 11 billion parameters using just 16 machines [18]. However, the system cannot yet be utilized for practical applications because of the low accuracy rate.

5. SUMMARY OF REVIWED METHOD

No.	Method	Description (Main Features)	*Strength's*	Limitations
1-	Gradient-Based Learning Applied to Document Recognition [13].	-Hand written digit recognition using multi- layers convolutional neural network for learning representation	*-Was an innovation, a breakthrough at the time,* *- Was successfully used commercially (verified need for the application)*	-Needs a large labeled dataset for training purposes;
2-	ImageNet Classification with Deep Convolutional Neural Networks [15].	- trains a large, deep convolutional neural network to classify a 1.2 million high-resolution images in the ImageNet - LSVRC-2012 contest into one thousand different classes	*- Was a breakthrough at the time for images category (error rate 15.3%)* *- Using a freely available large labeled dataset* *- Efficient GPU implementation*	-Needs a large labeled dataset for training purposes; - A more accuracy is needed for more sensitive applications.
3-	Leveraging Billions of Faces to Overcome Performance Barriers in Unconstrained Face Recognition [2].	- Uses a 3 D model to rectify poses on query faces and provide a frontal faces as inputs to the facial recognition system.	*- Relatively high accuracy rate (91.3%)*	- The system is commercial- the algorithm has not been published or peer reviewed [3].
4-	DeepFace: Closing the Gap to Human-Level Performance in Face Verification [16].	1- Uses a 3 D model to rectify poses on query faces and provide a frontal faces as inputs to the facial recognition system 2- Uses Deep learning convolutional neural networks to train the facial recognition system in the supervised learning mode utilizing their proprietary huge labeled dataset	*- High accuracy rate (near human performance)* *- Efficient GPU implementation*	- Difficult to replicate, not everyone has huge labeled dataset as Facebook.
5-	Building High-level Features Using Large Scale Unsupervised Learning [17].	- Addresses the question of if it is possible to learn a face detector using only unlabeled images - Uses model parallelism	*- a breakthrough on purely unsupervised training mode,* *- Promising and encouraging further research*	- The accuracy rate (15.3%) is not suitable for practical applications, - Difficult to

		and asynchronous SGD on a cluster with 1,000 machines (16,000 cores).		replicate, not everyone has Google resources of 16000 cores.
6-	Deep learning with COTS HPC systems [18].	-Addresses the question of if it is possible to learn a face detector using only unlabeled images using Commodity OF -The-Shelf High Performance Computing (COTS HPC) technology.	*- They were able to use attainable resources to achieve the same result as Google Brain (15.3% accuracy).*	- Yet, the accuracy rate (15.3%) is not suitable for practical applications.

From the above reviewed methods, we have concluded that it might be possible to train a model in a mixed mode (supervised and unsupervised), so we can still take advantage of the huge unlabeled data available freely on the Internet, and use a relatively small labeled dataset to get improved accuracy results. We will focus in the future on developing such an algorithm and examining its performance.

6. CHALLENGES IN UNCONSTRAINED FACE RECOGNITION

The main challenges in face recognition are due to the non-rigid structure of the human face, challenges in imagery, and practical issues with modeling of face recognition problem. Here is a brief description of each of such challenges:

6.1 Illumination

Variations due to the illumination sometimes result in larger image differences than the variations due to identity. If we do not design the algorithms to handle the illumination variations, recognition is difficult. The system will eventually recognize face images based on the similarity due to illumination instead of the facial features and identity. There has been a lot of work to address the issues due to varying lighting conditions. However, the illumination variation still remains a challenge in uncontrolled face recognition such as '24 hour surveillance.

6.2 Scale/Resolution

Scale is critical in unconstrained face recognition system. Consider an example of a surveillance system. This system clearly should work over multiple scales because the subjects may be at different distances from the camera. A subject 2 meter away from the camera has a scale change of 10x when compared to a subject 20 meter away from the camera. This is can use interpolation methods to resize the images to a standard scale. Though we can increase the digital resolution by doing so, the images still suffer from However, superresolution and hallucinating face algorithms have been used to enhance the quality of low resolution images.

6.3 Noise

Noise is the random variation of the intensity or color information in the captured images which is not present in the actual object or scene being imaged. Noise is produced due to the sensor of the camera capturing the image. The ubiquitous nature of the camera in today's world and the quality of camera sensors, make the noise in the images unavoidable. Face images with noise have a huge negative effect in face recognition.

6.4 Blur

The motion and atmospheric blur are the main sources of blur in face images. In situations like surveillance, people are constantly moving. In situations like maritime environment, blur is present in face images due to the relative motion between the camera and the subject.

6.5 Pose

Pose mainly refers to out-of-plane rotation. It is a challenge in face recognition systems due to the 3D nature of a face. The differences due to pose are, sometimes, larger than inter-person differences within the images. In applications such as law enforcement and passport verification systems, images are required to conform to a certain set of specifications. However, in non-intrusive, uncontrolled settings such as surveillance, a subject can be found looking up, down, left or right, causing an out-of-plane rotation. Local region-based approaches such as EBGM and LBP are more robust to pose variations than holistic approaches such as PCA and LDA. This is because local approaches are less affected by changes in pixel-wise correspondence between the gallery and probe images. However, their tolerance to pose variations is limited to small in-depth rotations.

6.6 Occlusion

The non-invasive nature of face recognition confronts the occlusion problem. People use accessories such as sunglasses, scarfs, and hats which partially occlude the face region. Objects in between the camera and the subject as well as the movement of the subject itself, such as hand movement, can create occlusion. Part of the information is lost or replaced during occlusion. Local region-based methods have been successfully used in partial occlusion problem. The work in [50] shows the effect of occlusion on face recognition. They also mention that face recognition performance is more affected by the occlusion of the upper facial region than the occlusion of the lower facial region.

6.7 Expression: Facial expression changes the geometry of the face and impacts recognition accuracy. Opening and closing of the eyes and mouth in smiling and frowning faces are a few examples of expressions. Texture in the local region changes due to the expressions on the face. Local region-based or patch-based methods that use a histogram of features have been successfully used for expression invariant face recognition.

6.8 Age:

As humans age, the facial texture and shape vary. There is a change in shape of the cranium from infancy to teenage and changes in skin texture during adulthood. This is an issue even on controlled face recognition because the passport and visa face images are not updated frequently.

6.9 Face Image Spoofing:

Some of the face recognition systems can be easily fooled by spoofing face images. For example, a mobile device unlock feature based on face recognition can easily be spoofed with an image of the person. Since face images are easily available over the internet and in social networking sites, it is a challenging problem. Several techniques have recently been used to detect the liveness of a face images. Liveness detection is a new and ongoing research area.

7. PROPSED FRAMEWORK

The biologically inspired convolutional neural nets (ConvNet) are integrated in many outstandingly successful supervised recognition systems. Among those is Facebook's DeepFace. ConvNet were innovated by Yann LeCunn, the head of Facebook's AI research lab, and his team. He was inspired by the Human Visual System "HVS" and its hierarchal architecture. For any algorithm development in the future, HVS is a great source of inspiration.

In an unsupervised learning setting, ConvNet has not yet proved an efficient performance. However, many other feature learning methods are available in academia and industry under that setting. Among those is sparse autoencoder. Unsupervised feature learning is another source of inspiration and solutions for those who are challenged by huge labeled dataset requirement in a supervised learning mode.

Starting from DeepFace, We propose the following framework (Figure 3) for adapting the algorithm to accommodate unlabeled dataset:

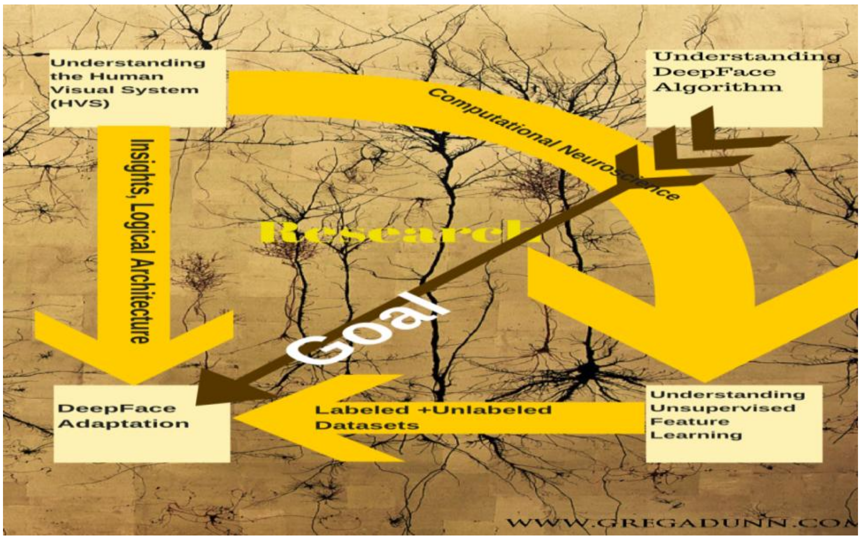

Figure 3 A frame work for adapting DeepFace for unlabeled dataset

A possible architecture of the solution could be as depicted in fig. 3 below.

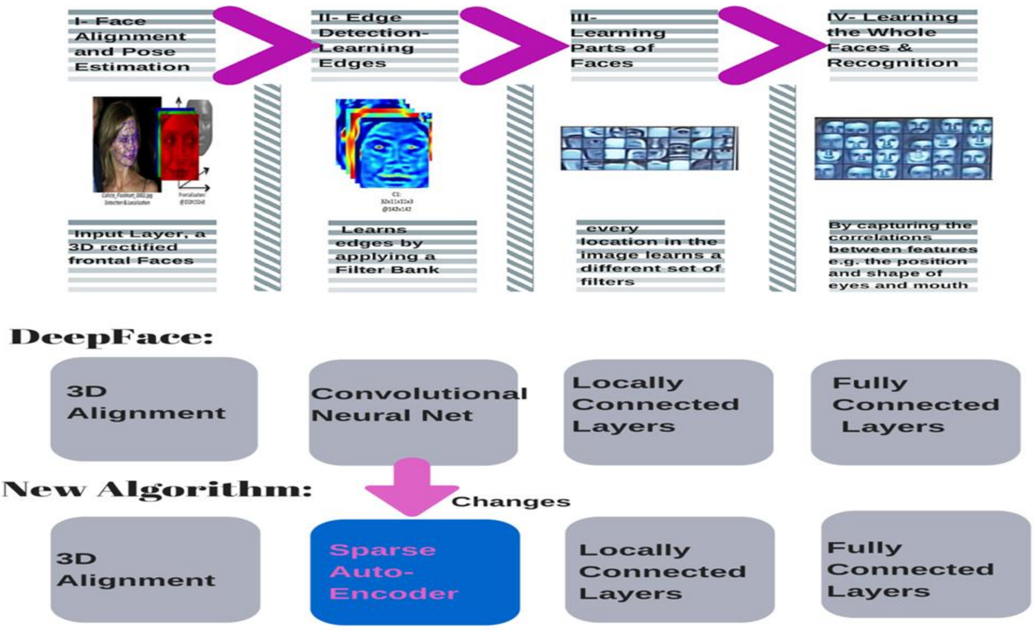

Figure 4 Possible architecture of the solution

8. CONCLUSION AND FUTURE DIRECTION

Currently, the face images captured with cameras that have huge variations due to camera sensors, motion of the subject, distance, etc. However, unconstrained face recognition still challenges in academia and industry. Recently developed algorithms based on the relatively new technology, Deep Learning, have made significant breakthroughs in the field. The progress in accuracy results was made by algorithms in both supervised learning mode, that is where the training dataset is labeled, and unsupervised learning, that is where the training dataset is unlabeled. However, the ones that have achieved the most accurate results for practical applications were those which were trained using labeled datasets. The challenge is to get a huge labeled dataset that reaches millions of labeled samples in order to achieve high accuracy rates in the supervised learning mode.

We have reviewed methods either in the supervised learning mode with high accuracy rates and huge labeled datasets, or in the unsupervised counterpart that does not need labeled dataset but research in this direction have not yet achieved reasonable accuracy rates. We have proposed that it might not be an either/ or situation; that we can possibly train a model in a mixed mode (supervised and unsupervised) to achieve reasonable accuracy without the need to invest as much as before in acquiring huge labeled dataset utilizing the freely available unlabeled ones on the internet.

9. REFERENCES

[1] Facial recognition system, http://en.wikipedia.org/wiki/Facial_recognition_system
[2] Yaniv Taigman and Lior Wolf, "*Leveraging Billions of Faces to Overcome Performance Barriers in Unconstrained Face Recognition*", Face.com, 2011.
[3] Rabia Jafri and Hamid R. Arabnia, A Survey of Face Recognition Techniques, Journal of Information Processing Systems, Vol.5, No.2, June 2009
[4] Cui Y, Fan L. Feature extraction using fuzzy maximum margin criterion[J]. Neurocomputing, 2012, 86: 52-58.
[5] [10] Koç M, Barkana A. A new solution to one sample problem in face recognition using FLDA[J]. Applied Mathematics and Computation, 2011, 217(24): 10368-10376
[6] Gao J, Fan L, Xu L. Median null (Sw)-based method for face feature recognition[J]. Applied Mathematics and Computation, 2013, 219(12): 6410-6419.
[7] Gary B. Huang, Manu Ramesh, Tamara Berg, and Erik Learned-Miller, "*Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments*", http://vis-www.cs.umass.edu/lfw/lfw.pdf;
[8] Zhao, W. & Chellappa, R. (2005). Face Processing: Advanced Modeling and Methods, Elsevier.
[9] Zhao, W., Chellappa, R., Phillips, P. J. & Rosenfeld, A. (2003). Face recognition: A literature survey.

[10] Robert D. Hof, "*10 Breakthrough Technologies 2013: Deep Learning*", MIT Technology Review, http://www.technologyreview.com/featuredstory/513696/deep-learning/, April 23, 2013.
[11] Yoshua Bengioy, Aaron Courville, and Pascal Vincen, "*Representation Learning: A Review and New Perspectives*", 2014.f[20].
[12] Antonio Regalado, "*Is Google Cornering the Market on Deep Learning*?", MIT Technology Review, http://www.technologyreview.com/news/524026/is-google-cornering-the-market-on-deep-learning/, January 29, 2014.
[13] Cade Metz, "Facebook Taps 'Deep Learning' Giant for New AI Lab", http://www.wired.com/2013/12/facebook-yann-lecun/; September 12,2013.
[14] Divyarajsinh N. Parmar, Brijesh B. Mehta2, "Face Recognition Methods & Applications", Divyarajsinh N Parmar et al ,Int.J.Computer Technology & Applications,Vol 4 (1),84-86, 2013;
[15] Rabia Jafri and Hamid R. Arabnia, "A Survey of Face Recognition Techniques", Journal of Information Processing Systems, Vol.5, No.2, June 2009.
[16] Trevor Hastie, Robert Tibshirani, Jerome Friedman, "*The Elements of Statistical Learning: Data Mining, Inference, and Prediction*", Springer, 2008.
[17] Li Deng and Dong Yu, "*DEEP LEARNING: METHODS AND APPLICATIONS*", Microsoft Research, NOW PUBLISHERS, 2014.
[18] Yann LeCun, Leon Bottou, Yoshua Benjio and Patrick Haffner, *"Gradient-Based Learning Applied to Document Recognition*", IEEE, November 1998.
[19] Yann LeCun, Koray Kavukcuoglu and Cl´ement Farabet, "*Convolutional Networks and Applications in Vision*", Proceedings of 2010 IEEE International Symposium on Circuits and Systems (ISCAS), June, 2010;
[20] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, "*ImageNet Classification with Deep Convolutional Neural Networks*", Neural Information Processing Systems proceedings, 2012.
[21] Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, Lior Wolf, "*DeepFace: Closing the Gap to Human-Level Performance in Face Verification*", facebook.com, June, 2014.
[22] Jiwen Lu, Gang Wang, Weihong Deng, and Kui Jia, Reconstruction-Based Metric Learning for Unconstrained Face Verification, IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, VOL. 10, NO. 1, JANUARY 2015, pp. 79-89.