Human Identity Recognition based on Facial Images via Supervised Autoencoder Features Representation

Saddam M. Eragi
College of Computer Science and Information Tech.,
Sudan University of Science and Technology,
Sudan
saddam.eragi@ieee.org

Wael Ouarda
REGIM-Lab.: REsearch Groups in Intelligent Machines, University of Sfax, National Engineering School of Sfax (ENIS), BP 1173, Sfax, 3038, Tunisia
wael.ouarda@ieee.org

Adel M. Alimi
REGIM-Lab.: REsearch Groups in Intelligent Machines, University of Sfax, National Engineering School of Sfax (ENIS), BP 1173, Sfax, 3038, Tunisia
adel.alimi@ieee.org

***Abstract*— Face recognition is still a challenging field due to the wide range of its applications like security, surveillance, criminal justice systems, witness face reconstruction etc. Recently, Researchers achieve an excellent performance on this task by using deep learning. In this paper, we propose a novel approach of features representation of facial images using Supervised Autoencoder. The main goal of this paper is the representation of facial images by a combination of descriptors, such as Viola and Jones technique as a face detector, LBP, HOG, Gabor, Curvelet and Wavelet for features representation, Stacked Autoencoder to transform features and finally Linear SVM as a classifier. The experimental results on Japanese Female Facial Expression Database (JAFFE) and Cohn-Kanade database (CK) have shown the robustness of the Autoencoder as technique for features representation and transformation in nonlinear space. Experiments performed on these databases highlight the effectiveness of our proposed approach by enhancing the Recognition Rate of state of the art to 98.6% on (JAFFE) database and 99.4% on (CK) database.**

Keywords- Face recognition; Face detection; Recognition rates; feature extraction;

I. INTRODUCTION

Image analysis applications have become most popular computer vision research area nowadays. They are mainly used in security issues, however they are also used increasingly in a collection of other applications, such as mobile payment systems, employees attendance [1], smart phone applications and presidential election systems [2]. Face detection and recognition system also plays an essential role in many biometric, surveillance, forensic and human-computer interaction systems.

Face recognition problem can be defined as the identification or verification of one or more individuals in the still or video image by analyzing and comparing patterns using a predefined faces database. This process takes place by utilizing algorithms and techniques of pattern recognition or machine learning to extract features from facial images that are classified by finding the best match among stored database [3].

In face detection, two major approaches are identified: local-feature-based and image-vector-based. Right from the beginning the features are extracted from images. The features could be either hand-designed or learned from training images. Then the most effective part of the extracted features is selected to expedite smooth classification. Eventually, the extracted features are inserted to a pre-specified classifier for training. Most of this work uses different hand-made features extraction: Gabor filter [4], Haar features Transform [5], Local Binary Patterns (LBP) [6], Principal Component Analysis (PCA) [7, 8, 9] and Scale Invariant Feature Transform (SIFT) [10]. They are improving recognition performance by working on small blocks in the image. In the other hand, unsupervised feature learning approaches that based on sparse coding extract features from image and show great success in face recognition. Examples of some techniques used for extracting features: dense local feature extraction with Speeded Up Robust Features (SURF) [11], Histogram of oriented gradients (HOG) and Principal Component Analysis (PCA). The detection takes place by matching an image bit by bit. Regarding the classification algorithms, one could apply many of them, such as: Supervised learning techniques like Support Vector Machine (SVM), deep neural techniques and decision trees.

This area of research is improving quickly and accurately and has overcome many current problems, like: profile faces, occlusion, facial expression and insufficient light. A 3D model is one of the novel methods that proposed to solve such variations. As a result of applying such attracting and successful approaches, many great companies and organizations have adopted face detection and recognition systems: Federal Bureau of Investigation (FBI), Kinect, Facebook … etc. However, these face recognition systems are far from perfect and struggle to perform under particular conditions. Moreover, it sometimes misidentifies persons.

In this paper, we will take advantage of Supervised Autoencoder to represent and classify features from two image datasets, the first one is Japanese Female Facial Expression

(JAFFE) database [12] and the second is Cohn-Kanade (CK) database [13]. In other words, we will combine a package of pre-defined descriptors to represent the features perfectly, the package consists of various extraction techniques.

This paper is organized as follows: The second section will focus on the related work done in the field of Face Recognition, essentially on the same benchmarks that we have used in our paper. The next section will detail the proposed model based on the facial features representation using a combination of texture descriptors followed by an Auto-Encoder architecture. Then, we will present our experimental results in the following section to highlight the robustness of our approach compared to related work. The last section consists to discuss found results and to summarize work done in this paper.

II. Related Work

Amazing progress has been accomplished in last few years regarding face recognition. A lot of papers discussed various facial feature extraction and classification techniques [14]. Among those techniques, neural approaches are always getting the most attraction, they are useful tools for solving many issues: gender classification, face recognition and facial expression classification.

Liu *et al.* [15] introduced Boosted Deep Belief Network (BDBN) that performs three training process steps: learning and selecting the features then constructing the classifier in a statistical way. In (BDBN), face detection process is performed back and forth using joint fine-tune process through six layers framework that obtained recognition rate of 93% on JAFFE database and 96.7% on CK database.

In face recognition, there are two major procedures: offline training and online recognition. Different Online learning algorithms spend long time in training. Therefore, a model integrated between curvelet transform and online sequential extreme learning machine (OSLEM) is introduced by Ucar *et al.* [16] to minimize this limitation. Recognition rate of this model results in 94.65% on JAFFE and 95.15% on CK.

SIFT features is invariant to scale, shift, rotations and illumination changes, it locates the points in an image properly. In 2016, Neeru and Kaur [17] proposed Modified Scale Invariant Feature Transform (MSIFT) approach to enhance SIFT recognition performance. They start by using Gaussian DWT to smooth the image, then reduce the computational complexity by reducing average from each image, lastly Coefficient of Correlation (CoC) is used to create the algorithm. This method resulted in 97.65 % recognition rate on JAFFE database.

Advantages of SIFT inspired Ge *et al.* [18] to use SIFT features and Difference of Gaussian (DoG) filters all over the image to demonstrate the performance of such model on (PIE) (pose, illumination and expression) conditions. It obtained 95.6% on JAFFE database.

III. Proposed Model

Comprehensive practical studies have been carried out to find the optimal combination of feature extraction techniques. Two popular databases: Japanese Female Facial Expression (JAFFE) and Cohn-Kanade (CK) have been used in our model to show the improvement in facial recognition compared to the state-of-the-art methodologies.

Figure 1. demonstrates the general architecture of the proposed model. It consists of 6 steps sequentially:

1- Detect the face region from an input image.
2- Scale image to the desired resolution.
3- Represent image features by the combination of feature extraction techniques illustrated in Figure 1.
4- Vector Normalization and Fusion.
5- Feature Transformation and Selection.
6- Feature Classification.

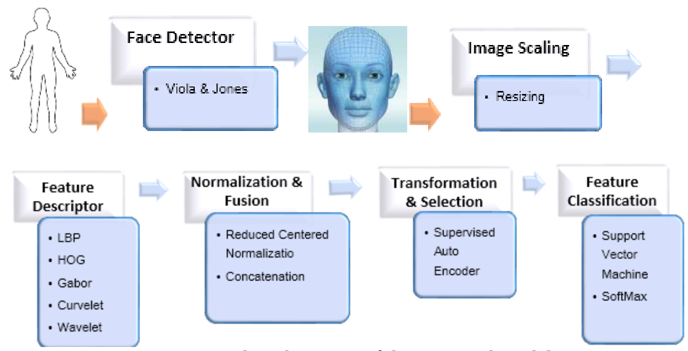

Figure 1. General Architecture of the proposed model

A. Viola and Jones Detection

Viola and Jones [5] technique is used for detecting face regions and for taking out any scale and positional variance based on Haar feature which obtained by computing the difference between black and white rectangles. These rectangles are scanned across the image at multiple scales and locations, and variance normalized to minimize the effect of different lighting conditions [19]. Finally, the detected sub-windows combine overlapping detections into a single detection [20]. This technique shows clearly how a huge cascade of simple classifiers can yield substantial results and was probably the most widely spread technique for locating faces since then.

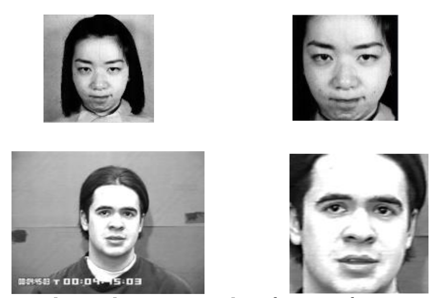
Figure 2. Face detected on two samples of images from JAFFE (upper) and CK Databases (down) using Viola and Jones technique

Figure 2. shows the implementation of Viola and Jones technique on two samples of faces from JAFFE and CK databases. Faces of JAFFE were cropped to 160*160 resolution while CK faces cropped to 281*281 resolution. Then, in order to search for the image size that gives the best recognition performance and moreover to reduce the feature vector of the

image, we tried original size cropped by Viola and Jones technique, 128*128 and 64*64 resolution. We found that the latter (64*64) is the best in case of CK database, while in JAFFE a different resolution was used in correspondence to each feature descriptor.

B. Feature Descriptors

A feature descriptor is a representation of an image that makes the image simple by extracting useful information [21] and putting away inessential information. Our methodology performs the feature representation stage through a combination of five widely known descriptors. In this section we will introduce them briefly:

1) Local Binary Patterns (LBP)

Local Binary Patterns are a type of visual descriptor introduced by Ojala *et al.* [22], it constructs a local representation of gray scale image by the comparison performed between each cell and its neighbors. This process is repeated for each pixel in the image. An array of 2D is built then consisting of LBP values that are calculated and stored in the array. Finally, a histogram of this LBP 2D array is computed as shown in Figure 3.

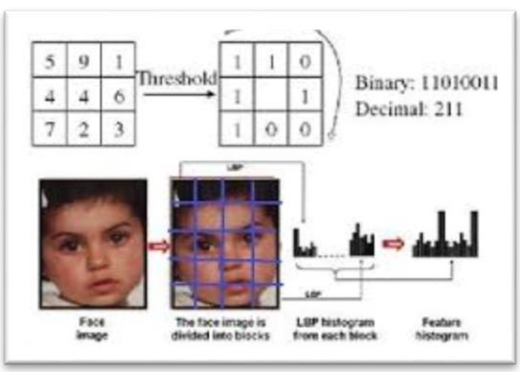

Figure 3. Description of facial expressions with local binary pattern: if the centered pixel of window has a high gray level intensity the neighbor takes 0 else it takes 1, then the obtained window will be multiplied by given window code pixel by pixel to get the LBP code of center pixel. Finally, computing the histogram of valued found and obtaining the LBP features vector [23].

The important feature of LBP is that clear image details are always captured. Moreover, LBP patterns are invariant to many conditions and can also add additional rotation level.

2) Histogram of Oriented Gradient (HOG)

The Histogram of Oriented Gradient (HOG) is a feature descriptor tool used in field of computer vision and image processing. It is first described by Robert K. McConnell in 1986 [24]. This technique counts the occurrences of gradient orientation in portions of an image as in Figure 4.

The main objective of this tool is to make features extraction resistant to any small changes in pose or appearance whilst producing a good encoding that is sensitive to local image content. Normalized block descriptors are referred to as Histogram of Oriented Gradient (HOG) descriptors.

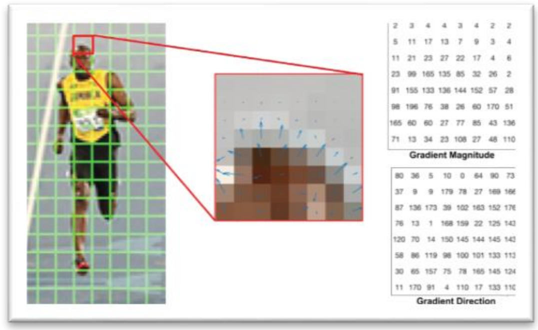

Figure 4. Center : The RGB patch and gradients represented using arrows.
Right : The gradients in the same patch represented as numbers [25]

3) Gabor Filters

Gabor filters are orientation sensitive linear extraction tools, used for analyzing edge and texture. It is named after a brilliant Nobel Prize winning physicist, Dennis Gabor. It perform analysis to unveil any specific frequency content in specific directions in a localized region around the point or region of analysis [4]. In other words, it is mathematically structured so it can distinguish between distinct shapes, sizes and smoothness levels as illustrated in Figure 5.

Figure 5. Application of Gabor filters to an image in the CK dataset [26]

Gabor Filters attracts more attention for its great capability to resemble visual system of the human.

4) Wavelet transform

Wavelet transform is similar to the Fourier transform with different characteristic function [27]. In General, wavelet transform can be expressed as below equation [28]:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^{*}_{(a,b)}(x)\, \mathrm{d}x \qquad (1)$$

where the * in (1) is the complex conjugate symbol and function ψ is some function.

As it shown in the equation, the Wavelet transform is an infinite set of many transforms, depending on the function used for its computation (Figure 6). There are two types of transforms having special properties for each, discrete wavelet transform and continuous wavelet transform.

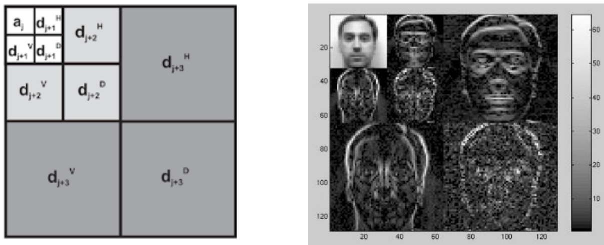

Figure 6. Two-dimensional Wavelet Coefficients [28]

5) Curvelet transform

The Curvelet transform is an efficient tool to achieve localization and properly capture the curves and lines in the image [29]. It is considered as a higher dimensional generalization of the Wavelet transform. Very few coefficients are needed to transform the features properly in Curvelet.

C. Normalization

Normalization [30] is the process of reducing unwanted variation either within or between arrays. Simply, it adjusts the values that is measured on several scales to a general scale before averaging:

$$Normalized\ (e_i) = \frac{e_i - E_{min}}{E_{max} - E_{min}} \quad [31] \quad (2)$$

E_{min} = the minimum value for variable E

E_{max} = the maximum value for variable E

Normalization is sometimes more complicated and sophisticated and sometimes is just rescaling the values.

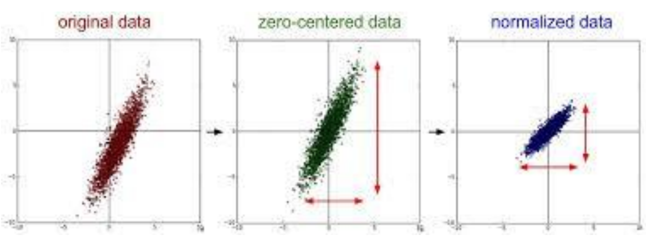

Figure 7. Centralizing and Normalizing Data [31]

D. Auto-Encoder (AE)

An Auto-Encoder (AE) is a Neural Network architecture learned through a back propagation setting the output values to be similar to the input. Its goal is to minimize reconstruction error based on a loss function, such as the mean squared error [32]:

$$\mathcal{L}(\mathbf{x}, \mathbf{x}') = \|\mathbf{x} - \mathbf{x}'\|^2 = \|\mathbf{x} - f(\mathbf{W}'(f(\mathbf{W}\mathbf{x} + \mathbf{b})) + \mathbf{b}')\|^2 \quad (3)$$

Figure 8. shows how the Auto-encoder tries to learn an approximation of the identity function in order to reconstruct the inputs in the output layer. The AE neural network is forced to learn a compressed representation of features vectors entered in inputs [33].

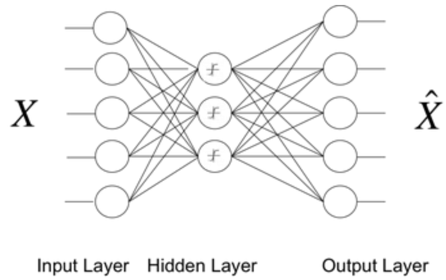

Figure 8. An example of latent features learned by an Auto Encoder

The Auto-Encoder (AE) contains three types of layer: First Layer (LF) used as encoder, Last Layer (LL) used as decoder and Hidden Layer (LH).

E. Linear Support Vector Machines (Linear SVMs)

Support Vector Machine (SVM) is a very efficient technique for classification, regression and outliers detection tasks based on boundary decision. It builds up hyper planes to separate between cases in multiple classes in multidimensional space. SVM has the strength to handle categorical and continuous variables. Either 0 or 1 as a dummy value is used to process categorical variables.

A linear classifier as shown in Figure 9. has the form [34]:

$$f(\mathbf{x}) = \mathbf{w}^\top \mathbf{x} + b \quad (4)$$

the discriminant in 2D is a line and W is known as the weight vector.

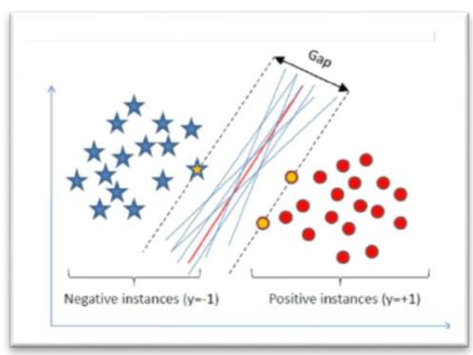

Figure 9. An example of Linear Support Vector Machine (Linear SVM)

IV. Experimental Results

To evaluate the performance of our proposed face identification system, a simple and effective measure is used. This measure is *Recognition Rate.*

Recognition Rate determines how the algorithm is accurate at learning a set of faces from training images and then correctly identifying the same people from a test set of different images of the same people, in other words, the total number of correctly identified probe images divided by the total number of probe images [35]:

$$\text{Recognition Rate} = \frac{\sum True\ Positive + \sum True\ Negative}{Total\ population} \quad (5)$$

Where:

True Positive: True is identified True.

True Negative: False is identified False.

Confusion matrixes are very helpful in evaluating this sort of test.

The system was implemented on Matlab using two widely known databases: JAFFE database and CK database.

A. *Experiment on JAFFE*

The Japanese Female Facial Expression (JAFFE) database was planned and assembled by Lyons *et al.* [12] in Kyushu University in Japan. JAFFE contains 213 gray scale images in (.tiff) format posed by 10 models (Figure 10.). For experiment purpose, we took 20 images to each model divided as 13 (65%) for training and 7 (35%) for testing. Each original image has a resolution of 256*256. Implementing Viola and Jones technique on images resulted in 156*156 image size (Figure 2.). In order to illustrate and compare the performance of proposed model, we resized the images to 3 resolutions: original, 128*128 and 64*64. After cropping process, the combination of 5 descriptors is used to extract features from the images, these descriptors are: LBP, HOG, Gabor, Curvelet and Wavelet. By conducting comprehensive experiments, it is found that the best resolution is 16*16 for LBP and Wavelet, 128*128 for HOG and Gabor, and 64*64 for Wavelet descriptor.

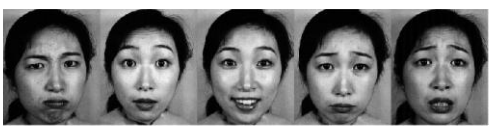

Figure 10. five images from JAFFE database

Concatenation of and Normalization of all 5 vectors took place to construct the whole feature vector which consists of 1650 features. Auto Encoder stage is used for transforming the features, various hidden layers were used to obtain the best result: (300, 400, 600, 700 and 900) hidden layers. We discovered that the best performance was given equally by all of them, hence we decided to use 300 hidden layers considering training and testing time. The last stage is classification; the transformed data were inserted in SVM classifier which gave the performance rate of the proposed model.

Table 1. compares between our model and state-of-the-art algorithms. It reveals clearly that the performance of our model has the better performance with 98.6%.

Table 1. Comparison between different models on JAFFE database

Ref.	Model	Recognition Rate
[15]	BDBN	93.00%
[16]	OSLEM	94.65%
[17]	MSIFT	97.65%
proposed	**(LBP+HOG+Gabor+ Curvelet+Wavelet)+SAE+SVM**	**98.6%**

B. *Experiment on CK*

Cohn-Kanade (CK) database [13] contains 486 gray scale images in (.png) format posed by 97 posers (Figure 11). In this implementation, we took 30 images to each model divided as 20 (67%) for training and 10 (33%) for testing. Each original image has a resolution of 490*640 and 309*309 after implementing Viola and Jones face detector. As we have done on JAFFE, we also tried the 3 resolutions: original, 128*128 and 64*64. We found that the best resolution that gave the best performance was 64*64 for all descriptors. The concatenated feature vector consists of 1506 features. By implementing Auto Encoder, it has been found for CK database that 300 hidden layers is best too. Finally, the SVM classifier achieved recognition rate of 99.4%.

Figure 11. five images from CK database

The results in Table 2. indicates the advantage of our model over the state-of-the-art techniques.

Table 2. Comparison between different models on CK database

Ref.	Model	Recognition Rate
[15]	BDBN	96.70%
[16]	OSLEM	95.15%
proposed	**(LBP+HOG+Gabor+ Curvelet+Wavelet)+SAE+SVM**	**99.4%**

V. CONCLUSION

As it has been seen, the proposed system achieved the better performance rate among the state-of-the-art methodologies. Since the start, detecting and cropping face region leads to reduction of image features thus minimal training and testing time and better recognition rate. With the ability of supervised Auto Encoder to encode the features, the best results have been obtained. And finally, SVM always shows its great power in classification and recognition.

This proposed model is robust and promising system. In the other hand, face expression recognition is a real challenge to many algorithms in this field. Therefore, we are looking to assure the performance of our model by implementing it to this challenge. Indeed, a lot of work is needed to enhance the model in term of accuracy and elapsed time of training and testing. This will be our vision for the next working package.

AKNOWLEDGEMENT

The authors would acknowledge the use of JAFFE Face Database and Cohn-Kanade Face Database.

References

[1] W.Zhao, R.Chellappa, A.Rosenfeld and P.J.Phillips, "Face recognition: a literature survey," *ACM Comput. Surv.*, vol. 2, pp. 399-458, 2003.

[2] C. Sanderson, Biometric Person Recognition: Face, Speech and Fusion, VDM Publishing, 2008.

[3] W. Wan, Z. Zhou, J. Zhao and F. Cao, "A novel face recognition method: Using random weigh tnetworks and quasi-singular value decomposition," *Neurocomputing,* vol. 151, pp. 1180-1186, 2015.

[4] V. P. Lekshmi and M. Sasikumar, "A Neural Network Based Facial Expression Analysis using Gabor Wavelets," in *Word Academy of Science, Engineering and Technology*, 2012.

[5] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Vision and Pattern Recognition,* pp. 1-9, 2001.

[6] R. S. Smith and T. Windeatt, "Facial expression detection using Filtered local binary pattern features with ECOC Classifiers and Platt scaling," in *JMLR Workshop and Conference proceedings*, 2010.

[7] Madhu and R. Amutha, "A Novel Approach to Face Recognition under Various facial expressions, Occlusion and Tilt Angles," in *International Conference on Emerging Trends in Science*, 2012.

[8] N. Vretos, N. Nikolaidis and I. Pitas, "A model-based facial expression recognition algorithm using principal components analysis," in *the 16th IEEE International Conference on Image Processing (ICIP '09)*, Cairo, Egypt, 2009.

[9] W. Ouarda, H. Trichili, A. M. Alimi and B. Solaiman, "MLP Neural Network for face recognition based on Gabor Features and Dimensionality Reduction techniques," in *Multimedia Computing and Systems (ICMCS)*, Marrakech, Morocco, 2014.

[10] H. Demirel and H. Soyel, "Improved SIFT Matching for Pose Robust Facial Expression Recognition," in *Automatic Face & Gesture Recognition and workshops*, 2011.

[11] H. Bay, T. Tuytelaars and L. V. Gool, "SURF: Speeded Up Robust Features," in *Lecture Notes in Computer Science*, Berlin, Heidelberg, Springer, 2006.

[12] M. J. Lyons, S. Akamatsu and M. K. &. J. Gyoba, "Coding Facial Expressions with Gabor Wavelets," in *Third IEEE International Conference on Automatic Face and Gesture Recognition*, Japan, 1998.

[13] T. Kanade, J. F. Cohn and Y. Tian, "Comprehensive database for facial expression analysis," in *Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition (FG'00)*, Grenoble, France, 2000.

[14] Y. Su, S. Shan, X. Chen and W. Gao, Hierarchial Ensemble of Global and Local Classifiers for Face Recognition, 2007.

[15] P. Liu, S. Han, Z. Meng and Y. Tong, "Facial Expression Recognition via a Boosted Deep Belief Network," in *Computer Vision and Pattern Recognition*, 2014.

[16] A. Ukar, Y. Demir and C. Guzelis, "A new facial expression recognition based on curvelet transform and online sequential extreme learning machine initialized with spherical clustering," *Neural Computing and Application,* vol. 27, pp. 131-142, 2016.

[17] N. Neeru and L. Kaur, "Modified SIFT Descriptors for Face Recognition under Different Emotions," *Journal of Engineering,* 2016.

[18] W. Ge, L. Cai and W. Zhan, "Face recognition with illumination, pose and expression variations using SIFT method," in *International Conference on Information Sciences, Machinery, Materials and Energy*, 2015.

[19] Y. Wang, "An Analysis of the Viola-Jones Face Detection Algorithm," *Image Processing On Line,* vol. 5, pp. 128-148, 2014.

[20] W. Ouarda, H. Trichili, A. M. Alimi and B. Solaiman, "Face Recognition Based on Geometric Features Using Support Vector Machines," in *International Conference of Soft Computing and Pattern Recognition*, Tunis, 2014.

[21] I. Jarraya, W. Ouarda and A. M. Alimi, "A Preliminary Investigation on Horses Recognition Using Facial Texture Features," in *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Kowloon, Hong Kong, 2015.

[22] T. Ojala, M. Pietika and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," *Pattern Recognition,* vol. 29, no. 1, pp. 51-59, 1996.

[23] M. Pietikäinen, A. Hadid, G. Zhao and T. Ahonen, "Local binary patterns for still images," in *Computer Vision Using Local Binary Patterns*, Springer, 2011, pp. 13-47.

[24] R. K. McConnell, "Method of and apparatus for pattern recognition," Wayland Research Inc., USA, 1986.

[25] S. Mallick, "Histogram of Oriented Gradients," Learn OpenCV, 6 December 2016. [Online]. Available: https://www.learnopencv.com/histogram-of-oriented-gradients/. [Accessed 10 August 2017].

[26] A. Kar and A. Mukherjee, "Facial Expression Classification using Visual Cues and Language," Kanpur-India.

[27] "Discrete wavelet transform," Wikipedia, 27 June 2017. [Online]. Available: https://en.wikipedia.org/wiki/Discrete_wavelet_transform. [Accessed August 2017].

[28] E. F. Oliveira, A. G. C. Bianchi, L. S. Martins-Filho and R. Figueiredo, "Granulometric analysis based on the energy of Wavelet Transform coefficients," Scientific Electronic Library Online - SciELO, Brasil, 2010.

[29] D.L.Donoho and M.R.Duncan, "Digitalcurvelettransform: Strategy, implementation and experiments," *Proceedings of SPIE,* vol. 4056, pp. 12-30, 2000.

[30] S. Aksoy and R. Haralick, "Feature normalization and likelihood-based similarity measures for image retrieval," *Pattern Recognition,* no. Special Issue on Image and Video Retrieval, 2000.

[31] S. Raschka, "About Feature Scaling and Normalization," 11 July 2014. [Online]. Available: http://sebastianraschka.com/Articles/2014_about_feature_scaling.html . [Accessed 10 August 2017].

[32] S. Gao, Y. Zhang, K. Jia, J. Lu and Y. Zhang, "Single Sample Face Recognition via Learning Deep Supervised Auto-Encoders," *IEEE Transactions on Information Forensics and Security,* vol. 10, no. 10, pp. 2108 - 2118, 2015.

[33] M. Kan, S. Shan, H. Chang and X. Chen, "Stacked Progressive Auto-Encoders (SPAE) for Face Recognition Across Poses," *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* pp. 1883-1890, 2014.

[34] C.-C. C. a. C.-J. L. Chih-Wei Hsu, "A Practical Guide to Support Vector Classification," datascienceassn.org, Taiwan, 2003.

[35] t. f. e. Wikipedia, "Sensitivity and specificity," Wikipedia , 12 July 2017. [Online]. Available: https://en.wikipedia.org/wiki/Sensitivity_and_specificity. [Accessed 20 August 2017].

[36] G. G. N, S. N. C.L. and P. K. Das, "Face Recognition using MB-LBP and PCA: A Comparative Study," *International Conference on Computer Communication and Informatics,* 2014.

[37] M. M. F. Donia, A. A. A. Youssif and A. Hashad, "Spontaneous facial expression recognition based on histogram of oriented gradients descriptor," *Computer and Information Science,* vol. 7, no. 3, 2014.

[38] M. Rouse, "Definition," whatis.com, December 2016. [Online]. Available: http://whatis.techtarget.com/definition/facial-recognition. [Accessed June 2017].