The Nucleus ***54****, No. 1 (2017) 26-32*

www.thenucleuspak.org.pk

The Nucleus

ISSN 0029-5698 (Print)

ISSN 2306-6539 (Online)

A Facial Image Analysis based Algorithm to Detect Human Personality

M. Waheed, H. Tauseef*, S. Shafique, M.A. Fahiem and S. Farhan

Lahore College for Women University, Lahore, Pakistan

mayra_waheed@yahoo.com; humaiftikhar@hotmail.com; sibghashafiq@ymail.com; itisab@gmail.com; saifar79@hotmail.com

ARTICLE INFO

Article history :
Received : 26 December, 2016
Revised : 22 February, 2017
Accepted : 03 March, 2017

Keywords:
Classification
Feature extraction
Facial analysis
Personality prediction

ABSTRACT

Human personality plays an essential role in many fields of life. Facial features are used for, but are not limited, to different face recognition, pain detection, spontaneous and non-spontaneous action detection and personality detection systems. The main objective of this study is to judge human personality through facial features. Normalized facial images are used as an input. Interest points and features are extracted using Convolution Neural Network and distance metrics. Human personality is predicted using rule based classification. An accuracy of 84% for personality prediction with 8 fold cross validation is achieved.

1. Introduction

Human face is believed to be the mirror of personality. Human facial images and their analysis in the field of image processing is a widely researched area nowadays[1]. Facial expressions are an important tool for verbal or non-verbal communication. Facial features analysis facilitates human personality detection. Human personality can be determined using facial features like face shape, ear length, nose length, forehead length, forehead width, distance between eyes and width of eyes [2, 3]. Human personality and traits depict the behavior of a person towards another person. There are many applications of personality identification using facial images [4]. Some of the key areas are; different recruitment and vocational processes [5-7], fraud detection [8], crime detection [8-10], actor selection for entertainment [11], etc.

The term "physiognomy" is defined as the method of perceiving or judging a person's traits on the basis of his facial features or patterns. In the human body the most complicated signal system is a person's face. There are many ways to detect the human personality. Human personality can be detected by conducting interview with the person whose personality is to be judged or by using regular methods like written test in the form of questionnaire or by conducting a group discussion. These methods are not reliable because the targeted person whose personality is to be judged could pose or prepare himself for such situations.

Human personality is also detected using behavioral analysis. Behavioral analysis can be done by analyzing a person's face. Facial features are extracted using different feature extraction algorithms or by using some learning based algorithms. For processing facial images, the main task is to locate the face in images. Facial expressions are dependent on muscle movement under the skin of face. Facial expression can be either voluntarily or involuntarily. Sometimes it becomes difficult to judge whether the expressions are real or fake. Different techniques can be used to recognize human facial expressions [12] such as Eigen Faces [13], Principal Component Analysis [14], Gabor Wavelet [15], Geometric Features [16], Neural Networks [17], Feed Forward Neural Networks [18], Cascade Neural Network [19] etc.

Different characteristics, qualities, features, traits and habits combine together and form a particular personality. A person can either be an introvert or extrovert [20]. People with introvert personality are shy and are less talkative. They mostly involve themselves in indoor activities. Usually such people are not social and avoid public dealings. They cannot easily adapt to the changes in environment. They have their own world of ideas and have their own psychological thinking. The people with extrovert personality are very open to public dealings. They are full of energy, creativity, confidence and boldness. They like outdoor activities more than indoor activities. Such people are full of life and have recreational habits and are dominant. They adapt to every sort of environment or change in the environment easily without any hesitation.

* Corresponding author

Personality also helps in predicting the person's reaction to different situations, circumstances, events and people. Research shows that face patterns influenced by a person's thinking can be used by the observer for perceiving or judging his personality [21]. Five factor personality model [22] was used for personality assessment in a study by Hu et al. [23]. The neutral 3D facial images of some volunteers were quantitatively analyzed. Principal Component analysis (PCA) along with Partial Least Square Component (PLSC) was then used for identification. The results were finally compared with self-tested personality for the given 3D facial images.

There exists a Big Five Model abbreviated as OCEAN which represents five basic traits. OCEAN stands for Openness, Consciousness, Extraversion, Agreeableness and Neuroticism [24]. Six measurements are included in Openness namely; dream, tasteful affectability, mindfulness to inward sentiments, inclination for assortment, and scholarly curiosity. Conscientiousness is one of the five attributes of the Five Factor Model of identity and is a part of what has customarily been alluded to as having character. Five Factor model has been used in the proposed algorithm of this research work.

Introduction and literature review of the research area is already presented in section 1, an algorithm for personality prediction is proposed in Section 2. Section 3 presents the results and discussion followed by conclusion in Section 4.

2. Proposed Methodology

The main purpose of this study was to find out the personality of a person using facial images. Facial images were taken from Extended Cohen-Kanade database [25]. The data base had 123 facial images for different subjects. The details of the selected dataset used in this study are given in Table 1.

Table 1: Attribute values

Attributes	Values
No. of images	100 images
Age Group	18-50 years
Extension of Image	.png
Image size	640X480 pixels

The input image was normalized in the image normalization phase. Normalized image is then forwarded to the face detection phase for face extraction. After the face detection phase various facial features were extracted from the images. Neural network was trained to detect the interest points. After getting points of interests from the image, the distance between points of interest were calculated to find out the required features. Then on the basis of various extracted features, face shape was detected by classifying an image. After classification personality of a person was predicted. The overview of the proposed algorithm is given in Fig. 1.

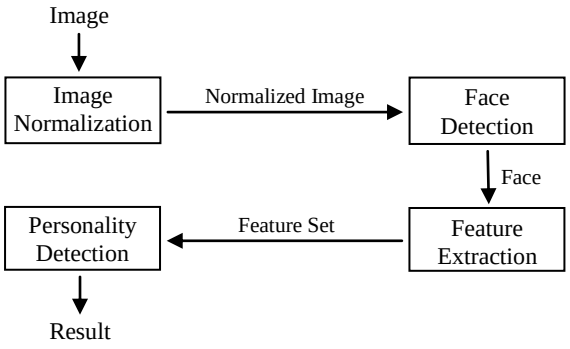

Fig. 1: Schematic of proposed methodology

2.1 Image Normalization

The input image was normalized and the intensity values of pixels were calculated in the image normalization phase. The purpose of normalizing the image was to convert the image to a standard form for further processing. Normalization process involved the following steps:

- Input Image $I = \{X \subseteq R^n\} \rightarrow \{Min, Max\}$ with the intensity values having range {Min, Max}
- New Image $I_N = \{X \subseteq R^n\} \rightarrow \{NewMin, NewMax\}$ with the intensity values having range {NewMin, NewMax}
- Linearly normalized image was obtained using Eq. (1).

$$I_N = (I - Min)\frac{(NewMin - NewMax)}{Max - Min} + NewMin \quad (1)$$

2.2 Face Detection

This normalized image was used for face detection in the next phase. The detection of face was done through Viola-Jones face detection algorithm [26]. Steps used to detect a face are as follows :

- Selection of Haar Features
- Producing an integral image
- Training using Adaboost
- Cascade training of classifiers

All people had some similar or common facial features that could be calculated using Haar features such as region of eyes is brighter than region of upper cheeks. After calculating Haar features integral image was produced. Integral image was the image that consisted of the rectangular features' values which were calculated in a constant time. For any point a, b in an image, the integral image at position (a, b) was the total sum of the pixel values that lay above and on the left side of (a, b).

The Adaboost algorithm was used to train the classifier using best features. Adaboost used a combination of many weak classifiers that made one strong classifier. Suppose, W_t (x) was a weak classifier then the summation of multiple weak classifiers produced a strong classifier as given in Eq. (2).

$$S(x) = \text{Sign}\left(\sum_{t=1}^{T} \alpha_t w_t(x)\right) \quad (2)$$

In the process of cascading there was a strong classifier at each stage. So, all the stages had a classifier for different features and at the end of cascading process all features were grouped together. The basic target of each classifier was to detect whether the given sub window was 100 percent not a face or it was a face. To train the cascade a set of positive and negative examples were both fed.

2.3 Feature Extraction

After the face was detected using Voila-Jones face detection algorithm, the extracted face was passed on to next phase for feature extraction. The selected facial features were forehead, face length, cheek bones, ears and jaw lines. These features were used for interest point calculation. The point of interest for measuring the forehead length was the point the peak of both eyebrow arcs where eyebrow arises and hence the distance was calculated. The length of face was determined from the tip of chin and the centre of hair line. The length of cheek bones was determined using the sharp bump of cheek under the corner of right eye and the sharp bump of cheek under the left eye. The points of interest for calculating ear to ear distance were the end points of both ear lobes. The point of interest for calculating length of jaw line was top of chin and the point below the ear where jaw angles upwards.

In feature extraction the basic task was to detect the points of interest or key points for extraction of required features. Neural Network was used to find these key points [27]. The Neural Network approach that was used was "Convolutional Neural Network". The facial points extracted are stated in Table 2.

First of all three deep Convolutional network layers were employed which are as follows

- Whole face (F1)
- Hair line to Nose (HN1)
- Nose to Chin (NC1)

Each network layer predicted various points at a time. The variance for each facial point was reduced by taking the average. The second and third layer covered lesser region of face as compared to the first one. The networks at their second and third level took the prediction of the previous layer as an input and only minor changes were allowed to be made at each level. Along the cascade, the size of given patches kept reducing as well as search range was also reduced side by side.

Table 2: Interest points

Facial features	Points of interest / Key points
Forehead	Left eye eyebrow arc Right eye eyebrow arc
Face length	The tip of the chin The center of the hair line
Cheek bones	Corner of left eye Corner of right eye Right cheek bump Left cheek bump
Jaw line	Tip of the chin The point below the ear where jaw angle upwards
Facial Features	Points of Interest / Key Points
Ear to ear	The point below the left ear where jaw angle upwards The point below the right ear where jaw angle upwards

The prediction made by the last two levels, remained restricted because the local prediction was often unreliable. The target of the network at the first level was to firmly evaluate the points of interest with capacity of some large errors while the purpose of the network at the last two levels was to evaluate values accurately.

The implementation of the neural network was done using the following steps :

STEP I: The input layer was represented as *I (w, l)* where, "*w"* represented the width of image and *"l"* represented the length of the input image region.

STEP II: Next was the Convolutional layer *C (s, n, p, q)*, where, "s" was the side length of the convolution filter, "*n*" represented the number of maps, "*p*" and "*q*" represented the parameters used for weight sharing.

STEP III: In the convolution layer each map was divided into *p* by *q* regions and each map shared weight locally. By default filter stride was set equal to 1 pixel in both directions.

STEP IV: Previous layer size was taken as (*l, w, m*) where, "*m*" represented number of maps for next layer and each map had size equal to "*l*" by "*w*".

STEP V: An operation on *C (s, n, p, q)* was performed using Eq. (3).

$$y_{i,j}^{(t)} = \tanh\left(\sum_{r=0}^{m-1}\sum_{k=0}^{s-1}\sum_{h=0}^{s-1} x_{i+k,j+h}^{(r)} \cdot w_{k,h}^{(r,u,v,t)} + b^{(u,v,t)}\right) \quad (3)$$

Where,

$$i = \Delta l\,.u, \ldots\ldots, \Delta l\,.u + \Delta l - 1$$

$$j = \Delta w.\, v, \ldots\ldots, \Delta w\,.v + \Delta w - 1$$

$$t = 0, \ldots.., n\text{-}1$$

$$\Delta l = \frac{l - s + 1}{p}$$

$$\Delta w = \frac{w - s + 1}{q}$$

u = 0,……, p – 1

v = 0,…., q – 1

x and ***y*** were the outputs of previous and current layers.

STEP VI: Max pooling was used to remove non-maximal values. So pooling layer was formulated using Eq. (4).

$$y_{i,j}^{(t)} = tanh(g^{(u,v,t)} \cdot \max_{0 \leq k,h < s} \{x_{i.s+k,j.s+h}^{(t)}\} + b^{(u,v,t)}) \quad (4)$$

STEP VII: In the last step **F1** took input in the form of full image and gave all the interest points as output. **HN1** took the input of upper and middle part of face and output the centre of hair line, left and right eye corners, left and right cheek bumps. **NC1** took the lower part of face as an input and output the values of tip of chin, and the points below the left and right ear where the jaw angled upwards.

The extracted interest points are shown in Fig. 2.

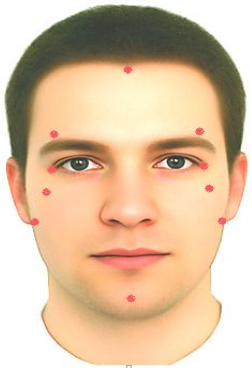

Fig. 2: Image representation of interest points

After getting the values of points of interest, facial features as mentioned in Table 2 were calculated using Euclidean distance as given in Eq.(5).

$$Euclidean\ Distance = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2} \quad (5)$$

The facial features calculated for classification of face are shown in Fig. 3.

2.4 Personality Detection

After extracting required features, the next phase was personality prediction. Human facial features extracted were used to predict the person's personality. Classification was done to find the face shape and then on the basis of face shape the person's personality was mapped. The rules used for defining personality are summarized in Table 3.

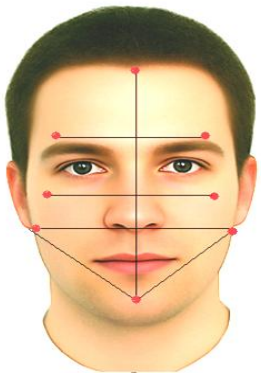

Fig. 3: Extracted features for classification

Table 3: Rules for classification

Face shape	Rules for classification
Oval	FH > EE, FL > CB
Round	FH ≈ EE < CB ≈ FL
Square	FH ≈ EE≈CB
Diamond	FL > CB > FH > EE
Oblong	FL > AND CB ≈FH ≈EE
Triangular	EE > CB > FH

Where FH= Forehead, EE= Ear Distance, FL= Face length, CB= Cheek bone.

Personality mapping on the base of face shape [28] is summarized in Table 4.

Table 4: Personality prediction

Face shape	Personality
Oval	Balanced and diplomats
Round	Sensitive and caring
Square	Bold, decisive mind, intelligent and analytical
Diamond	Dominant with less force
Oblong	Practical and methodical
Triangular	Creative and fiery temperament

Classification of face shape was done on the basis of rules described in Table 3 and mapping on the basis of Table 4. Multiple classifiers were used for classification.

The person with Oval face was considered to be "Balanced and Diplomat". The person with balanced and diplomatic personality would be able to enjoy relationships in his life. The person with Round face was mapped as "Sensitive and caring". Such person would show concern for others. The person with Square face was mapped to be "Bold, Decisive Mind, Intelligent and Analytical". The person with this personality would be courageous, brave and will have the ability to do anything. The person with Diamond face was mapped "Dominant with less Force". Such person would have a power of leadership in his gene or inherited power. The person with Oblong face was mapped "Practical and

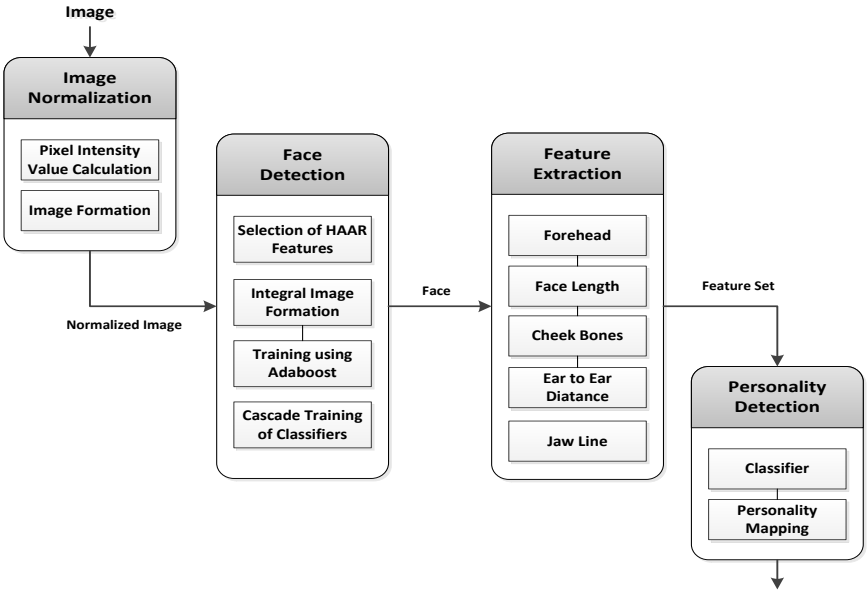

Fig. 4: Detailed description of the proposed algorithm

Methodical". Such person would lose his temperament rapidly. Yet he would have creative mind to invent things.

Detailed diagram of the proposed algorithm is given in Fig. 4.

3. Results and Discussion

After extraction of the desired features; forehead length, face length, cheekbones, ear to ear distance and jaw line, the last step was to classy face shape and calculation of results. Multiple classifiers including Jrip, Simple Logistic, J48, LMT and Random Forests were used for classification. The accuracy achieved in percentage for all classifiers is reported in Table 5. The data was classified into six different classes named oval, square, oblong, round, triangular and diamond. We achieved the highest accuracy of 84% with 8 folds cross validation using Jrip classifier. Jrip is an effective rule based classifier. It was implemented using a propositional rule learner.

Table 5: Accuracy of all classifiers

Classifier	Cross validation			Percentage split
	Fold 8	Fold 10	Fold 12	
Jrip	84	83	83	33
Simple Logistic	79	81	82	32
J48	81	81	81	33
LMT	79	81	82	32
Random Forest	81	82	83	33

Accuracy calculated using Jrip classifier is shown in Fig. 5.

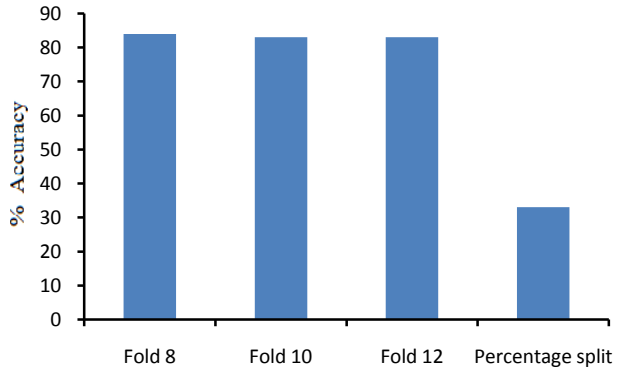

Fig. 5 Accuracy of JRIP classifier

Accuracy calculated using Simple Logistic classifier is shown in Fig. 6.

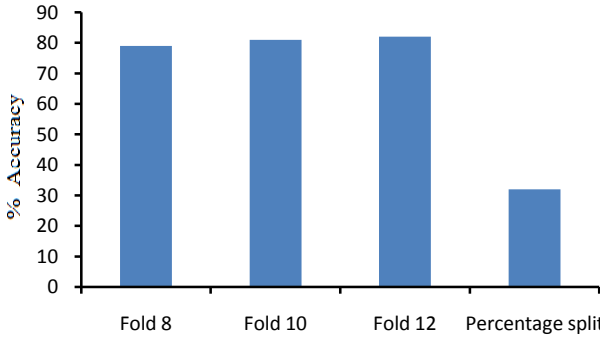

Fig. 6: Accuracy of simple logistic classifier

Accuracy calculated using J48 classifier is given in Fig. 7.

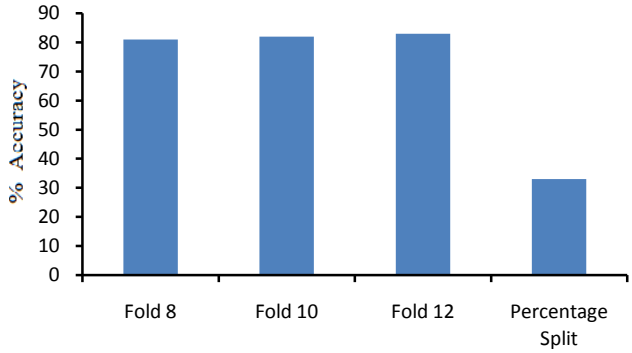

Fig. 7: Accuracy of J48 classifier

Accuracy calculated using LMT classifier is given in Fig. 8.

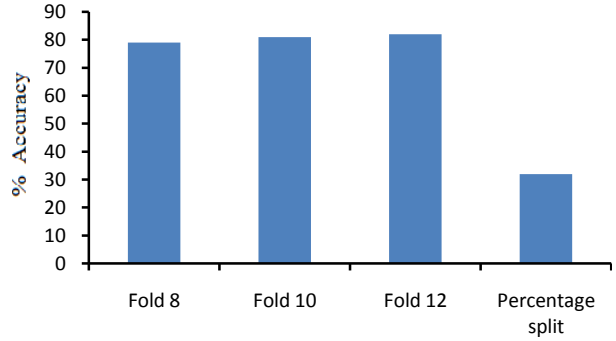

Fig. 8: Accuracy of LMT classifier

The accuracy calculated using Random Forest classifier is given in Fig. 9.

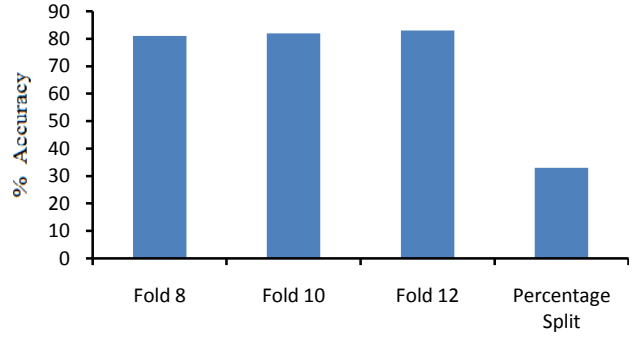

Fig. 9: Accuracy of random forest classifier

The results achieved using multiple classifiers are collectively shown in Fig. 10. The results clearly show that percentage split produced the overall worst results for classification while Jrip gave best accuracy. Jrip and Random forest produced similar accuracy.

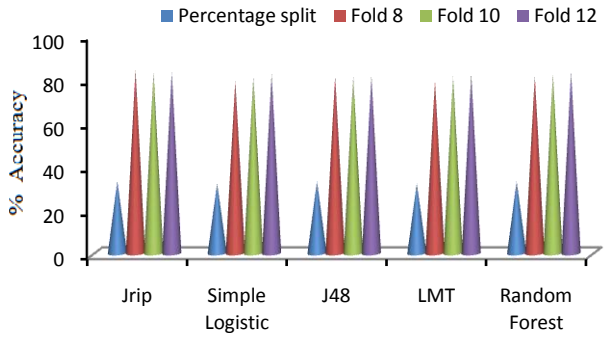

Fig. 10: Accuracies achieved using multiple classifiers

4. Conclusion

An individual's face tends to reveal his personality and his attitude towards life. In this paper we have proposed an algorithm for personality prediction using images. Images were processed for face ectraction and facial features extraction. Facial features were classified for face shape. Classified face shape was used for personality prediction. The accuracy achieved is 84% using Jrip classifier. Future implications can be to incorporate more features for shape classification and personality prediction. The factors that could be used may include digital footprints (digital activities, actions and communications) and behavioral analysis of a person to enhance the automated prediction of human personality.

References

[1] X. Jiang and Y.-F. Chen, "Facial image processing", Appl. Pattern Recogn., Springer. p. 29-48, 2008.

[2] M. G. Rothstein and R. D. Goffin, "The use of personality measures in personnel selection: What does current research support?", HRMR, vol. 16, no. 2, pp. 155-180, Month 2006.

[3] C. R. Kumar, P. G. Chandra, and R. Narayana, "Future path way to biometric", IJBB), vol. 5, no. 3, pp. 180, Month 2011.

[4] P. Ekman, T. S. Huang, T. J. Sejnowski, and J. C. Hager, "Final report to NSF of the planning workshop on facial expression understanding", Human Interaction Laboratory, University of California, San Francisco, vol. 378, Month 1993.

[5] R.P. Tett and N.D. Christiansen, "Personality assessment in organizations", Pers. Measure. Assess, pp. 720-742, Month 2008.

[6] G. Louch, J. O'Hara, P. Gardner and D. B. O'Connor, "The daily relationships between staffing, safety perceptions and personality in hospital nursing: A longitudinal on-line diary study", Int. J. of Nursing Studies, vol. 59, pp. 27-37, Month 2016.

[7] J. M. Williamson, J. W. Lounsbury and L. D. Han, "Key personality traits of engineers for innovation and technology development", J. Engg. and Tech. Manage., vol. 30, no. 2, pp. 157-168, Month 2013.

[8] J. Cohen, Y. Ding, C. Lesage and H. Stolowy, "Corporate fraud and managers' behavior: Evidence from the press", Entrepreneurship, Governance and Ethics 2012, Springer. p. 271-315.

[9] J. L. Van Gelder and R. E. De Vries, "Traits and states: Integrating personality and affect into a model of criminal decision making", Criminology, vol. 50, no. 3, pp. 637-671, 2012.

[10] K. Z. Hussain, M. Durairaj, and G. R. J. Farzana, "Criminal behavior analysis by using data mining techniques", IEEE Int.

Conf. Advances in Engineering, Science and Management (ICAESM), pp. 656-658, 2012.

[11] O. Scekic, M. Riveni, H.-L. Truong and S. Dustdar, "Social interaction analysis for team collaboration", Encyclopedia of Social Network Analysis and Mining, Springer. pp. 1807-1819, 2014.

[12] A. V. Smith, L. Proops, K. Grounds, J. Wathan, and K. McComb, "Functionally relevant responses to human facial expressions of emotion in the domestic horse (Equus caballus)", Biol. Lett., vol. 12, vol. 2, pp. 20150907, 2016.

[13] M. Turk, "Over twenty years of eigenfaces", ACM TOMM, vol. 9, no. 1s, pp. 45, 2013.

[14] J. H. Shah, M. Sharif, M. Raza, and A. Azeem, "A Survey: Linear and Nonlinear PCA Based Face Recognition Techniques", Int. Arab J. Inf. Technol., vol. 10, no. 6, pp. 536-545, 2013.

[15] Z. Chai, Z. Sun, H. Méndez-Vázquez, R. He, and T. Tan, "Gabor ordinal measures for face recognition", IEEE T. Inf.. Foren. Sec., vol. 9, no. 1, pp. 14-26, 2014.

[16] E. Hjelmås and B. K. Low, "Face detection: A survey", Comput. Vis. Image Und., vol. 83, no. 3, pp. 236-274, Month 2001.

[17] H. A. Rowley, S. Baluja and T. Kanade, "Neural network-based face detection", IEEE T Pattern Anal., vol. 20, no. 1, pp. 23-38, 1998.

[18] L. Ma and K. Khorasani, "Facial expression recognition using constructive feedforward neural networks", IEEE T Syst. Man Cyb., Part B (Cybernetics), vol. 34, no. 3, pp. 1588-1595, 2004.

[19] S. Qatawneh, S. S. Ipson, R.S. Qahwaji and H. Ugail, "3D face recognition based on machine learning", 2008.

[20] C. Nass and K. M. Lee, "Does computer-synthesized speech manifest personality? Experimental tests of recognition, similarity-attraction, and consistency-attraction", J. Exper. Psychol-Appl., vol. 7, no. 3, pp. 171-181, 2001.

[21] V. Bruce and A. Young, "Understanding face recognition", Brit. J. Psychol., vol. 77, no. 3, pp. 305-327, 1986.

[22] R. R. McCrae and P. T. Costa, "Validation of the five-factor model of personality across instruments and observers", J. Pers. Soc. Psychol., vol. 52, no. 1, pp. 81-90, 1987.

[23] S. Hu, J. Xiong, P. Fu, L. Qiao, J. Tan, L. Jin, and K. Tang, "Signatures of personality on dense 3D facial images", bioRxiv, pp. 055590, Month 2016.

[24] T. A. Judge and J. E. Bono, "Five-factor model of personality and transformational leadership", J. Appl. Psychol., vol. 85, no. 5, pp. 751, 2000.

[25] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar and I. Matthews, "The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression", IEEE Computer Society Conference on Computer Vision and Pattern Recognition-Workshops, pp. 94-101, 2010.

[26] M. Viola, M. J. Jones, and P. Viola, "Fast multi-view face detection", Proc. of Computer Vision and Pattern Recognition, Citeseer, pp. 14-21, 2003.

[27] M. Bhelande, A. Krishnan, A. Bharadwaj, N. Palecha, and Y. Tawade, "Prediction of Facial Key points in Images Using Neural Networks", IJARCCE, vol. 5, no. 4, pp. 93-94, 2016.

[28] T. Bradberry, The Personality Code: Unlock the Secret to Understanding Your Boss, Your Colleagues, Your Friends--and Yourself: Penguin, 2007 (Book).