



APPLICATION OF FACIAL EXPRESSION RECOGNITION IN HEALTHCARE INDUSTRIES – A REVIEW

Dr.Masood Ikram¹, Elanthendral.R² and Dr.Swaminathan.S³

¹Managing Director –MellonAI Pvt Ltd, 18/5, Parameswari Colony, Andavar Nagar, Kodambakkam, Chennai-600024, South India

²Quality Manager, Colorimeter Consulting Pvt Ltd. Ramana Nursing HomeComplex, No.320A/47A, Velachery Main Road, Velachery, Chennai- 600042, South India

³Director of Lab Services, Research and Development, Colorimetr Consulting Pvt Ltd . Ramana Nursing Home Complex, No.320A/47A, Velachery Main Road, Velachery, Chennai- 600042, South India

ARTICLE INFO

Article History:

Received 4th January, 2020

Received in revised form 25th

February, 2020

Accepted 23rd March, 2020

Published online 28th April, 2020

Key words:

AI, Facial Recognition, PD, FER, FE, ML

ABSTRACT

The applications of Artificial intelligence (AI) are now well developed in software algorithms, embedded and hardware for use in a vast number of healthcare fields. AI which emphasis on deep learning, as well as Machine Learning (ML) holds great promise and they are already being successfully applied to basic research, diagnosis, drug discovery, and clinical trials. Rare diseases (RDs) are rarely undertaken in basic and application of AI technologies could accelerate such fields. Computer-aided facial analysis could be a great boon in the diagnosis of genetic syndromes. Another extension of AI is facial Expression (FE) as a preferable biometric trait for automatic human authentication as it is intuitive and non-intrusive. FE are important in facilitating human communication and interactions. FE are fundamental to interpersonal communication, including social interaction, and allow people of different ages, cultures, and languages to quickly and reliably convey emotional information. Increasing evidence suggests that the visual representations of different emotional facial expressions may overlap and help to identify varieties of human disorders.

Copyright©2020 Dr.Masood Ikram, Elanthendral.R and Dr.Swaminathan.S. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

The review articles highlight the various findings in the application of facial expressions, recognitions to identify human diseases and to help clinicians to proceed further as laboratory related diagnosis. The old philosophy “ Face is the Index of mind” holds good when FE and FR are applied not only to human disorders, but in all types of human life.both FE and FR are very much useful in work places, Industries, Human Resources Development , Competency Evaluation to name a few.

AI has been developing rapidly in recent years in terms of software algorithms, hardware implementation, and applications in a vast number of areas. It could be asserted that, just like AI itself, the application of AI in biomedicine is still in its early stage. New progress and breakthroughs will continue to push the frontier and widen the scope of AI application, and fast developments are envisioned in the near future^[1].

Essential information about the application of AI to radiology includes a description of the available algorithms with a glossary; a review of the issues raised by healthcare data, notably those pertaining to imaging

(imaging data and co-variables, metadata); High-quality care in radiology and opportunities for managing large datasets are two avenues relevant to the development of a precise, personalized, and participative radiology practice characterized by improved predictive and preventive capabilities^[2].

The amount of data collected and managed in (bio) medicines are ever-increasing. Thus, there is a need to rapidly and efficiently collect, analyze, and characterize all these information's.. AI with an emphasis on deep learning holds great promise in this area and is already being successfully applied to basic research, diagnosis, drug discovery, and clinical trials. Rare diseases (RDs), which are severely underrepresented in basic and clinical research, could particularly benefit from AI technologies. The ability of AI technologies to integrate and analyze data from different sources (e.g., multi-omics, patient registries, and so on) could be used to overcome RDs' challenges (e.g., low diagnostic rates, reduced number of patients, geographical dispersion, and so on). Ultimately, RDs' AI-mediated knowledge could significantly boost therapy development^[3].

Facial Recognition/ Expressions

FE is used to assess the utility of computer-aided facial analysis in identifying dimorphic syndromes. A software aided Facial Recognition (FR) predicted the correct diagnosis in 72.5% of patients as the first in the top ten. However, the

***Corresponding author: Dr.Masood Ikram**

Managing Director –MellonAI Pvt Ltd, 18/5, Parameswari Colony, Andavar Nagar, Kodambakkam, Chennai-600024, South India

software did not suggest a correct diagnosis. Computer-aided Facial Analysis (FA) is a method that could aid in the diagnosis of genetic syndromes. When more clinicians start using this software, its accuracy will certainly be expected to improve^[4]. Parkinson's Disease–Mild Cognitive Impairment (PD-MCI) patients showed reduced Facial Emotional Recognition (FER) with specific impairment of anger recognition. Although the scanned area of PD patients with intact cognition was significantly restricted, they did not differ in FER from healthy subjects. While healthy subjects and cognitively intact PD patients scanned faces with preference for mouth and eyes, patients with PD-MCI tended to look at the center of the face and spent significantly less time fixating the mouth. Ineffective visual exploration may contribute to impaired emotion recognition in PD. Visual scanning of emotional faces is altered in PD even in the absence of cognitive impairment. The progression to PD-MCI may result in further deterioration of scanning behavior and FER impairment^[5].

Face stands out as a preferable biometric trait for automatic human authentication as it is intuitive and non-intrusive. Human face also undergoes irreversible changes due to aging. These factors makes the process of face recognition as non trivial and hard. Applications of FR in the forensic domain sometimes needs identification using a scanned facial image. The scenario is quite useful to get investigative leads^[6].

Skin colour detection is a technique used in most of the face detectors to find faces in images or videos. However, there is not a common opinion about which colour space is the best choice to do this task. 10 of the most commonly used colors showed different comparisons among them, and hence difficult to choose an option for human skin color detection. 15 truth images were identified about the skin colour of a face in clearly separated from the rest of the image (background, eyes, lips, hair, etc.). Thus, we could compare at level pixel each color model, doing a detailed study of each format. The most appropriate colour spaces for skin color detection are HSV model and the models YCbCr and YDbDr^[7].

Rhesus macaques are widely used in biomedical research. Automated behavior monitoring can be useful in various fields (including neuroscience), as well as having applications to animal welfare but current technology lags behind that developed for other species. One difficulty facing developers is the reliable identification of individual macaques within a group especially as pair- and group-housing of macaques becomes standard. A classification accuracy of between 90 and 96% was achieved for four different groups. Group size, number of training images and challenging image conditions such as high contrast all had an impact on classification accuracy. Comparison with existing method(s): FR methods have been reported for humans and other primate species such as chimpanzees but not rhesus macaques. The classification accuracy with this method is comparable to that for chimpanzees. FR has the advantage over other methods for identifying rhesus macaques such as tags and collars of being non-invasive. This is the first reported method for rhesus macaques, has high classification accuracy and can be implemented in real time^[8].

Emotion recognition (ER) has attracted major attention in numerous fields because of its relevant applications in the contemporary world: marketing, psychology, surveillance, and

entertainment are some examples. It is possible to recognize an emotion through several ways; a clear difficulty in translating the high FER accuracy in controlled environments to uncontrolled and pose-variant environments. The future efforts in the FER field should be put into multimodal systems that are robust enough to face the adversities of real world scenarios. A thorough analysis on the research done on FER on Computer Vision based could be very useful^[9].

Over the past two decades, automatic FER has received enormous attention. This is due to the increase in the need for behavioral biometric systems and human–machine interaction where the FER and the intensity of emotion play vital roles. The existing works usually do not encode the intensity of the observed facial emotion and even less involve modeling the multi-class facial behavior data jointly. The results verified that the comparative study could be further used in real-time behavioral facial emotion and intensity of emotion recognition^[10].

FE are important in facilitating human communication and interactions. Also, they are used as an important tool in behavioral studies and in medical rehabilitation. Facial image-based mood detection techniques may provide a fast and practical approach for non-invasive mood detection. Several facial parameters were extracted from a facial image and were used to train several generalized and specialized neural networks. Based on initial testing, the best performing generalized and specialized neural networks were recruited into decision making committees which formed an integrated committee neural network system. The integrated committee neural network system was then evaluated using data obtained from subjects not used in training or in initial testing. The system identified the correct FE in 255 of the 282 images (90.43% of the cases), from 62 subjects not used in training or in initial testing. Committee neural networks offer a potential tool for image-based mood detection^[11].

FE are fundamental to interpersonal communication, including social interaction, and allow people of different ages, cultures, and languages to quickly and reliably convey emotional information. Historically, FE research has followed from discrete emotion theories, which have limited number of distinct affective states that are represented with specific patterns of facial action. Much less work has focused on dimensional features of emotion, particularly positive and negative affect intensity. This is likely, in part, because achieving inter-rater reliability for facial action and affect intensity ratings is painstaking and labor-intensive. Computer Vision Machine Learning (CVML) could determine the importance of different facial actions that human coders use to derive positive and negative affective ratings when combined with interpretable machine learning methods, and efficiently automate positive and negative affect intensity coding on large facial expression databases. Further, CVML could be applied to individual human judges to infer which facial actions they use to generate perceptual emotion ratings from Fes^[12].

Automated FER will greatly improve the human–machine interface. Many DL approaches have been applied in recent years due to their outstanding recognition accuracy by using large amounts of data. The preprocessing methods are :resizing the mean, normalization, standard deviation, scaling and edge detection. Face detection as single pre-processing phase

achieved significant result with 100 % of accuracy, compared with another pre-processing phase and raw data ^[13].

Three anger expression types in nurses were found: low-anger expression, anger-in, and anger-in/control type. From the results of multivariate analysis of variance, there were significant differences between anger expression types and interpersonal problems. Additionally, anger-in/control type was found to have the most difficulty with interpersonal problems by Duncan's post hoc test. Based on this research, the development of an anger expression intervention program for nurses is recommended to establish the means of expressing the suppressed emotions, which would help the nurses experience less interpersonal problems ^[14].

In a letter detection task 50% of the subjects were led to believe that they could avoid an aversive tone, while the other group was led to believe that they could not avoid the tone. Increases in systolic blood pressure, heart rate, and pulse transit time were consistent with the prediction of higher sympathetic cardiovascular activation during active coping. Anxiety and anger were aroused under both conditions. Only for anxiety, there was an association between the physiological and affective responses. On the level of traits, subjects tending not to express their anger revealed higher activation. The results are discussed with respect to a possible relationship between the expression of anger and different parameters of cardiovascular reactivity ^[15].

A significant interaction between family risk and a disposition towards anger inhibition was observed, with the greatest systolic blood pressure responses to tasks being recorded in high risk boys who reported high levels of anger inhibition. This effect was maintained after controlling for initial blood pressure level, age and body mass. The cardiac baroreceptor reflex was inhibited during tasks and was lower in high than low family risk subjects. The results suggest that the tendency to inhibit anger expression interacts with familial factors in determining reactivity patterns that may be indicative of raised risk of future cardiovascular disease ^[16].

Stress is an inevitable part of life that can profoundly impact social and emotional functioning, contributing to the development of psychiatric disease. One key component of emotion and social processing is FE, which humans can readily detect and react to even without conscious awareness. FE have been the focus of philosophic and scientific interest for centuries. Historically, FE have been relegated to peripheral indices of fixed emotion states. More recently, affective neuroscience has undergone a conceptual revolution, resulting in novel interpretations of these muscle movements. Stress shapes FE focus on the consequence of genetic variation within the endocannabinoid system, a neuromodulatory system implicated in stress and emotion, and its impact on stress-induced facial muscle activity, and hence these interpretations may contribute to a broader understanding of FE ^[17].

Increasing evidence suggests that the visual representations of different emotional FE overlap. Participants categorized faces morphed from neutral to anger or neutral to disgust after adaptation to expressions of anger, disgust, and fear. Adaptation to expressions of both anger and disgust was found to bias perception of anger expressions away from anger. For disgust expressions, adaptation to disgust biased perception away from disgust, whereas fear adaptation biased perception

towards disgust. Adaptation to anger had no measurable effect. Covering the mouth region of the disgust adaptation face was found to severely diminish the effect of disgust adaptation on perception of anger targets whereas covering the nose- or eye-region had no effect. Adaptation to anger had a substantial effect on perception of anger targets when the mouth-region of the anger face was covered; indicating that the results are not an artifact of the stimuli and procedures used. These results indicate that the visual representations of anger, disgust and fear expressions overlap to a considerable degree. Furthermore, the nature of this overlap appears related to the communicative functions of these expressions ^[18].

Intentional FE of emotion is critical to healthy social interactions. Patients with neurodegenerative disease, particularly those with right temporal or prefrontal atrophy, show dramatic socioemotional impairment. Patients' performance on emotion expression tasks was correlated with gray matter volume using Voxel-Based Morphometry (VBM) across the entire sample. Intentional emotional imitation scores were related to fundamental socioemotional deficits; patients with known socioemotional deficits performed worse than controls on intentional emotion imitation; and intentional emotional expression predicted caregiver ratings of empathy and interpersonal warmth. Whole brain VBMs revealed a rightward cortical atrophy pattern homologous to the left lateralized speech production network was associated with intentional emotional imitation deficits. Results point to a possible neural mechanism underlying complex socioemotional communication deficits in neurodegenerative disease patients ^[19].

Experiences affect mood, which in turn affects subsequent experiences. Recent studies suggest two specific principles. First, mood depends on how recent reward outcomes differ from expectations. Second, mood biases the way we perceive outcomes (e.g., rewards), and this bias affects learning about those outcomes. The two-way interaction serves to mitigate inefficiencies in the application of reinforcement learning to real-world problems. Mood represents the overall momentum of recent outcomes, and its biasing influence on the perception of outcomes 'corrects' learning to account for environmental dependencies ^[20].

Automatic early detection of acromegaly is theoretically possible from facial photographs, which can lessen the prevalence and increase the cure probability. Several popular machine learning methods including LM, KNN, SVM, RT, CNN, and EM were used to automatically identify acromegaly from the detected facial photographs, extracted facial landmarks, and synthesized frontal faces. The trained models were evaluated using a separate dataset, of which half were diagnosed as acromegaly by growth hormone suppression test. The best result oriented proposed methods showed a PPV of 96%, a NPV of 95%, a sensitivity of 96% and a specificity of 96%. AI application could automatically detect acromegaly with a high sensitivity and specificity ^[21].

Cushing's syndrome (CS) and acromegaly are endocrine diseases that are currently diagnosed with a delay of several years from disease onset. Novel diagnostic approaches and increased awareness among physicians are needed. Face classification technology has recently been introduced as a promising diagnostic tool for CS and acromegaly in pilot studies. It has also been used to classify various genetic

syndromes using regular facial photographs. Image analysis is based on applying mathematical functions evaluating geometry and image texture to a grid of nodes semi-automatically placed on relevant facial structures, yielding a binary classification result $t^{[22]}$.

CONCLUSION

- ✓ AI, FR and FE technologies have been developing rapidly in recent years in terms of software algorithms, hardware implementation, and applications in a vast number of areas.
- ✓ The amount of data collected and managed in the field of AI and FR are ever-increasing. Hence, there is a need to rapidly and efficiently collect, analyze, and characterize all the information's.
- ✓ Computer-aided facial analysis is a method that could aid in diagnosis of genetic syndromes and when more clinicians start to use this software, its accuracy is expected to improve.
- ✓ PD-MCI patients showed reduced FER with specific impairment of anger recognition.
- ✓ The progression to PD-MCI may result in further deterioration of scanning behavior and FER impairment
- ✓ Face stands out as a preferable biometric trait for automatic human authentication as it is intuitive and non-intrusive.
- ✓ Applications of FR in the forensic domain sometimes needs identification using a scanned facial image. The scenario is quite useful to get investigative leads
- ✓ ER has attracted major attention in numerous fields because of its relevant applications in the contemporary world: marketing, psychology, surveillance, and entertainment are some examples
- ✓ Facial expressions are important in facilitating human communication and interactions. Also, they are used as an important tool in behavioral studies and in medical rehabilitation. Facial image based mood detection techniques may provide a fast and practical approach for non-invasive mood detection.
- ✓ The development of an anger expression intervention program for nurses is recommended to establish the means of expressing the suppressed emotions, which would help the nurses experience less interpersonal problems.
- ✓ Intentional facial expression of emotion is critical to healthy social interactions. Patients with neurodegenerative disease, particularly those with right temporal or prefrontal atrophy, show dramatic socio emotional impairment

Conflict of Interest : None

Reference

1. Guoguang Rong, Arnaldo Mendez, Elie Bou Assi, Bo Zhao, Mohamad Sawan, Artificial Intelligence in Healthcare: Review and Prediction Case Studies, Engineering, 2020, ISSN 2095-8099.
2. SFR-IA Group; CERF; French Radiology Community. Artificial intelligence and medical imaging 2018: French Radiology Community white paper. *Diagn Interv Imaging*. 2018;99 (11):727–742.
3. Brasil S, Pascoal C, Francisco R, Dos Reis Ferreira V, Videira PA, Valadão AG. Artificial Intelligence (AI) in Rare Diseases: Is the Future Brighter?. *Genes (Basel)*. 2019;10 (12):978.
4. Wang K, Luo J. Detecting Visually Observable Disease Symptoms from Faces. *EURASIP J Bioinform Syst Biol*. 2016;2016 (1):13.
5. Josefine Waldthaler, Charlotte Krüger-Zechlin, Lena Stock, Zain Deeb, Lars Timmermann, New insights into facial emotion recognition in Parkinson's disease with and without mild cognitive impairment from visual scanning patterns, *Clinical Parkinsonism & Related Disorders*, 2019: 2019(1); 102-108.
6. Umarani Jayaraman, Phalguni Gupta, Sandesh Gupta, Geetika Arora, Kamlesh Tiwari, Recent Development in Face Recognition, *Neurocomputing* (2020).
7. Jose M. Chaves-González, Miguel A. Vega-Rodríguez, Juan A. Gómez-Pulido, Juan M. Sánchez-Pérez, Detecting skin in face recognition systems: A colour spaces study, *Digital Signal Processing*, 2010 : 20 (3); 806-823.
8. Witham CL. Automated face recognition of rhesus macaques. *J Neurosci Methods*. 2018;300:157–165.
9. Canedo, Daniel & Neves, António. (2019). Facial Expression Recognition Using Computer Vision: A Systematic Review. *Applied Sciences*. 9. 10.3390/app9214678.
10. Mehta D, Siddiqui MFH, Javaid AY. Recognition of Emotion Intensities Using Machine Learning Algorithms: A Comparative Study. *Sensors (Basel)*. 2019 Apr 21;19(8):1897.
11. Kulkarni, Saket & Reddy, Narender & Hariharan, S. I. Facial expression (mood) recognition from facial images using committee neural networks. *Biomedical engineering online*. 2009; 8:16.
12. Haines N, Southward MW, Cheavens JS, Beauchaine T, Ahn WY. Using computer-vision and machine learning to automate facial coding of positive and negative affect intensity [published correction appears in *PLoS One*. 2019 Mar 7;14 (3):e0213756]. *PLoS One*. 2019;14 (2):e0211735.
13. K.Sravanthi, G.Jaya Suma. A Prediction of Emotions for Recognition of Facial Expressions Using Deep Learning. 2019; 2S11 (8): 1076-1079.
14. Han A, Won J, Kim O, Lee SE. Anger Expression Types and Interpersonal Problems in Nurses. *Asian Nurs Res (Korean Soc Nurs Sci)*. 2015;9 (2):146–151.
15. Volker Hodapp, Stephan Bongard, Ulrich Heiligtag. Active coping, expression of anger, and cardiovascular reactivity. *Personality and Individual Differences*. 1992; 13(10):1069-1076.
16. Vögele C, Steptoe A. Anger inhibition and family history as modulators of cardiovascular responses to mental stress in adolescent boys. *J Psychosom Res*. 1993;37 (5):503–514.
17. Leah M. Mayo, Markus Heilig. In the face of stress: Interpreting individual differences in stress-induced facial expressions. *Neurobiology of Stress*.2019;10; 100166;1-8
18. Philip J. Pell, Anne Richards. Cross-emotion facial expression aftereffects, *Vision Research*; 2011:51(17); 1889-1896.
19. Gola KA, Shany-Ur T, Pressman P, et al. A neural network underlying intentional emotional facial

- expression in neurodegenerative disease. *Neuroimage Clin.* 2017;14:672–678.
20. Eran Eldar, Robb B. Rutledge, Raymond J. Dolan, Yael Niv, Mood as Representation of Momentum, *Trends in Cognitive Sciences*, 2016;20(1);15-24.
21. Kong X, Gong S, Su L, Howard N, Kong Y. Automatic Detection of Acromegaly From Facial Photographs Using Machine Learning Methods. *EBio Medicine.* 2018;27:94–102.
22. Kosilek RP, Frohner R, Würtz RP, *et al.* Diagnostic use of facial image analysis software in endocrine and genetic disorders: review, current results and future perspectives. *Eur J Endocrinol.* 2015;173(4):M39–M44.

How to cite this article:

Dr.Masood Ikram, Elanthendral.R and Dr.Swaminathan.S (2020) 'Application of Facial Expression Recognition in Healthcare Industries – A Review', *International Journal of Current Advanced Research*, 09(04), pp. 21859-21863.
DOI: <http://dx.doi.org/10.24327/ijcar.2020.21863.4303>
