iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** XII **Month of publication:** December 2021

DOI: https://doi.org/10.22214/ijraset.2021.39424

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XII Dec 2021- Available at www.ijraset.com

A Review Paper on Emotion Recognition Analysis on Real Time Video by Using the Concept of Computer Vision

Rewati Saha[1], Sachin Meshram[2]
[1, 2]*Electronics & Comminucaion, CEC, Bilaspur, India*

Abstract: ***As we know we are living in the era of digital world where everything is based on data analysis, now a days after covid it's really difficult to do the analysis on real world, so there is need of an algorithm which is able to do the analysis on virtual world, suppose there is any application which is able to identify the user feedback based on there emotion, so there is need of a novel algorithm which is work on the concept of the emotion analysis, in this paper basically we did the study about the previous existing work on emotion analysis and try to find out the research gaps and there future scope.***
Keywords: Computer Vision, Machine Learning, Emotion Analysis, Deep Learning

I. INTRODUCTION

In some cases speech or high level scene context can also be useful to infer emotion. Most of the time there is a considerable overlap between emotion classes making it a challenging classication task. In this paper we present a deep learning based approach to modeling different input modalities and to combining them in order to infer emotion labels from a given video sequence. The Emotion recognition in the wild (EmotiW 2015) challenge [9] is an extension of a similar challenge held in 2014 [8]. The task is to predict one of seven emotion labels: angry, disgust, fear, happy, sad, surprise and neutral. The dataset used in the challenge is the Acted Facial Expressions in the Wild (AFEW) 5.0 dataset, which contains short video clips extracted from Hollywood movies. The video clips present emotions with a high degree of variation, e.g. actor identity, age, pose and lighting conditions. The dataset contains 723 videos for training, 383 for validation and 539 test clips. Traditional approaches to emotion recognition were based on hand-engineered features [17, 28]. With the availability of big datasets, deep learning has emerged as a general approach to machine learning yielding state-of-the-art results in many computer vision and natural language processing tasks [22, 19]. The basic principle of deep learning is to learn hierarchical representations of input data such that the learned representations improve classi cation performance. The primary contribution of this work is to model the spatio-temporal evolution of facial expressions of a person in a video using a Recurrent Neural Network (RNN) combined with a Convolutional Neural Network (CNN) in an underlying CNN-RNN architecture. In addition to this, we also employed an Autoencoder based activity recognition pipeline for modelling user activity and a simple Support Vector Machine (SVM) based approach over energy and spectral features for audio. We also present a neural network-based feature level fusion technique to combine di erent modalities for the nal emotion prediction for a short video clip. Previous work [18, 25] has achieved state-of-the-art results in the emotion recognition challenge using deep learning techniques which includes our work that won the 2013 Emotion challenge. In contrast to [18, 16], which use an averaging-based aggregation method for visual features in video, here we employ an RNN to model the temporal evolution of facial features in video. We also explore feature level fusion of our modality-specific models and show that this increases performance. Emotional aspects have huge impact on Social intelligence like communication understanding, decision making and also helps in understanding behavioral aspect of human. Emotion play pivotal role during communication. Emotion recognition is carried out in diverse way, it may be verbal or non-verbal .Voice (Audible) is verbal form of communication & Facial expression, action, body postures and gesture is non-verbal form of communication. [1] While communicating only 7% effect of message is contributes by verbal part as a whole, 38% by vocal part and 55% effect of the speaker's message is contributed by facial expression. For that reason automated & real time facial expression would play important role in human and machine interaction. Facial expression recognition would be useful from human facilities to clinical practices. Analysis of facial expression plays fundamental roles for applications which are based on emotion recognition like Human Computer Interaction (HCI), Social Robot, Animation, Alert System & Pain monitoring for patients. This paper presents brief introduction of facial expression in section Facial expression presents key mechanism to describe human emotion. From starting to end of the day human changes plenty of emotions, it may be because of their mental or physical circumstances.

©IJRASET: All Rights are Reserved

Although humans are filled with various emotions, modern psychology defines six basic facial expressions: Happiness, Sadness, Surprise, Fear, Disgust, and Anger as universal emotions [2]. Facial muscles movements help to identify human emotions. Basic facial features are eyebrow, mouth, nose & eyes. In AI, design acknowledgment and in picture handling, highlight extraction begins from an underlying arrangement of estimated information and manufactures inferred values (highlights) planned to be enlightening and non-excess, encouraging the consequent learning and speculation steps, and now and again prompting better human elucidations. Highlight extraction is identified with dimensionality decrease. At the point when the information to a calculation is too enormous to possibly be prepared and it is suspected to be excess (for example a similar estimation in the two feet and meters, or the tedium of pictures displayed as pixels), at that point it tends to be changed into a decreased arrangement of highlights (additionally named an element vector). Deciding a subset of the underlying highlights is called include selection.[1] The chose highlights are relied upon to contain the pertinent data from the info information, so the ideal errand can be performed by utilizing this decreased portrayal rather than the total introductory information. Highlight extraction includes decreasing the quantity of assets required to portray a huge arrangement of information. When performing examination of complex information one of the serious issues comes from the quantity of factors included. Examination with countless factors for the most part requires a lot of memory and calculation control, likewise it might make a characterization calculation overfit to preparing tests and sum up inadequately to new examples. Highlight extraction is a general term for techniques for developing mixes of the factors to get around these issues while as yet portraying the information with adequate precision. Many MACHINE LEARNING experts accept that appropriately enhanced component extraction is the way to successful model construction.[2]The remainder of the paper is sorted out as follows. Vital writing overview related past research on leaf deficiency identification are given in II recognition based past work are given in segment ii though area III portrays explore issue and future degree philosophy and IMPLEMENTATION FOR THE PREVIOUS EXISTING APPROACHES. IV portrays philosophy and IMPLEMENTATION FOR THE PREVIOUS EXISTING APPROACHES. Trial results and its examination are given in area V. At long last, area VI closes the paper.

II. LITRECTURE REVIEW

Encoding and understanding feelings is especially significant in instructive settings [3,31]. While eye to eye instruction with a fit, taught, and sympathetic instructor is ideal, it is additionally not generally imaginable. Individuals have been checking out instructing without educators since the time the innovation of books and with the new advances in innovation, for instance by utilizing recreations [43,66]. We have additionally seen huge advances in distance learning stages and frameworks [22,52]. In any case, while mechanization brings many benefits, like arriving at a wide populace of students or being accessible at areas where eye to eye training may not be imaginable, it additionally brings new difficulties [2,9,50,61]. One of them is the normalized look-and-feel of the course. One design doesn't fit all students, the speed of the conveyance ought to be dealt with, the assignments ought to shift contingent upon the level of the student, and the substance ought to be additionally aligned to the singular necessities of students. Full of feeling Agents: Some of these difficulties have been tended to by intuitive educational specialists that have been found powerful in improving distance learning [6,40,47,57]. Among them, vivified instructive specialists assume a significant part [12,39], in light of the fact that they can be effectively controlled and their conduct can be characterized by strategies regularly utilized in PC liveliness, for instance by giving satisfactory motions [25]. Educational specialists with passionate capacities can upgrade associations between the student and the PC and can further develop learning as shown by Kim et al. [30]. A few frameworks have been executed, for instance Lisetti and Nasoz [37] joined look and physiological signs to perceive a students feelings. DMello and Graesser [15] presented AutoTutor and they shown that students show an assortment of feelings during learning and they additionally shown that AutoTutor can be intended to recognize feelings and react to them. A virtual specialist SimSensei [42] takes part in meetings to evoke practices that can be consequently estimated and examined. It utilizes a multimodal detecting framework that catches an assortment of signs that survey the clients full of feeling state, just as to illuminate the specialist to give criticism. The control of the specialists emotional states essentially impacts learning [68] and affects student self-adequacy [30]. Be that as it may, a powerful academic specialist needs to react to students feelings that should be first identified. The correspondence ought to be founded on genuine contribution from the student, academic specialists ought to be sympathetic [11,30] and they ought to give passionate associations the student [29]. Different method for feeling discovery have been proposed, for example, utilizing eye-tracker [62], estimating internal heat level [4], utilizing visual setting [8], or skin conductivity [51] however a huge assortment of work has been zeroing in on distinguishing feelings in discourse [28,35,65]. Looks: While the previously mentioned past work gives very great outcomes, it may not be consistently appropriate in instructive setting. Discourse is frequently not needed while speaking with instructive specialists, and approaches that require appended sensors may not be great for the student. This leaves the discovery of looks and their examination as a decent choice. Different methodologies have been proposed to identify looks.

©IJRASET: All Rights are Reserved

Early works, for example, the FACS [16], center around facial definition, where the highlights are distinguished and encoded as an element vector that is utilized to track down a specific feeling. Late methodologies utilize dynamic forms [46] or other computerized strategies to identify the elements naturally. An enormous class of calculations endeavors to utilize math based methodologies, for example, facial remaking [59] and others distinguish notable facial elements [20,63]. Different feelings and their varieties have been considered [45] and ordered [24], and some attention on miniature articulations [17]. Novel approaches utilize robotized highlight recognition by utilizing AI techniques for example, support vector machine [5,58], however they share a similar reasonableness to the facial locator as the previously mentioned approaches (see likewise an audit [7]). One of the critical parts of these methodologies is a face global positioning framework [60] that ought to be fit for a vigorous identification of the face and its elements even in changing light conditions and for various students [56]. Nonetheless, existing strategies frequently require cautious adjustment, comparable lighting conditions, and the alignment may not move to different people. Such frameworks give great outcomes to head position or direction following, however they might neglect to distinguish unobtrusive changes in temperament that are significant for feeling location. Profound Learning: Recent advances in profound learning [34] brought profound neural organizations additionally to the field of feeling location. A few methodologies have been presented for powerful head pivot discovery [53], recognition of facial highlights [64], discourse [19], or even feelings [44]. Among them, EmoNets [26] recognizes acted feelings from films by all the while breaking down both video and sound transfers. This methodology expands on the past work for CNN facial identification [33]. Our work is roused by crafted by Burket et al. [10] who presented profound learning network called DeXpression for feeling location from recordings. Specifically, they utilize the Cohn-Kanade data set (CMU-Pittsburg AU coded information base) [27] furthermore, the MMI Facial Expression [45].Recurrent Neural Networks for Emotion Recognition in Video ,2015 In this work author present a complete system for the 2015 Emotion Recognition in the Wild (EmotiW) Challenge. We focus our presentation and experimental analysis on a hybrid CNN-RNN architecture for facial expression analysis that can outperform a previously applied CNN approach using temporal averaging for aggregation.

Deep Facial Expression Recognition: A Survey, 2018: In this paper, author provide a comprehensive survey on deep FER, including datasets and algorithms that provide insights into these intrinsic problems. First, we introduce the available datasets that are widely used in the literature and provide accepted data selection and evaluation principles for these datasets. We then describe the standard pipeline of a deep FER system with the related background knowledge and suggestions of applicable implementations for each stage. For the state of the art in deep FER, we review existing novel deep neural networks and related training strategies that are designed for FER based on both static images and dynamic image sequences, and discuss their advantages and limitations. Competitive performances on widely used benchmarks are also summarized in this section. We then extend our survey to additional related issues and application scenarios. Finally, we review the remaining challenges and corresponding opportunities in this field as well as future directions for the design of robust deep FER systems.

III. RESEARCH ISSUE & FUTURE SCOPE

In this section basically we talk about research gap which need to be solved, as per the all previous work there is no any researcher who solve the most important and critical factors and that are:

1) Most of the time accuracy of emotion detection is very
2) Quality of emotion analysis is low
3) Time complexity is a main issue
4) Lack in real time analysis

A. Future Objective

In this future our main is to resolve all previous existing issue and create a balanced system which will give a quality result in all parameters:

1) Most of the time accuracy of emotion detection is very low so we will try to improve that
2) Quality of emotion analysis is low so we will try to improve that
3) Time complexity is a main issue so we will try to improve that
4) There is need of balance algorithm which is able to manage time & quality.
5) Real time video-based analysis

©IJRASET: All Rights are Reserved

IV. CONCLUSION

Human emotion analysis is a challenging machine learning task with a wide range of applications in human-computer interaction, e-learning, health care, advertising and gaming. Emotion analysis is particularly challenging as multiple input modalities, both visual and auditory, play an important role in understanding it. Given a video sequence with a human subject, some of the important cues which help to understand the user's emotion are facial expressions, movements and activities. In this paper basically we did the detailed study about the all-previous existing approaches and based on that we found multiple future scope on this area.

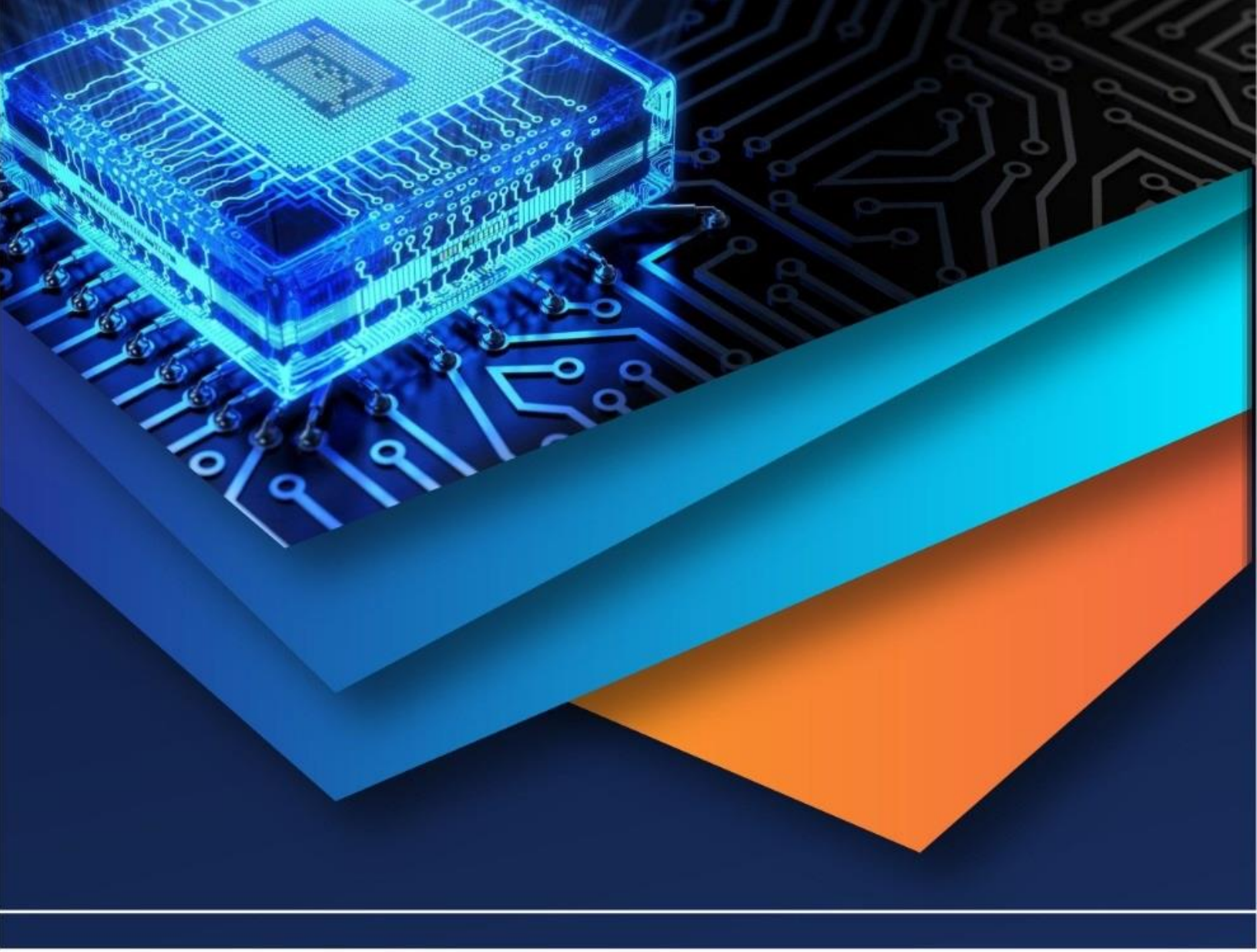
REFERENCES

[1] Aifanti, N., Papachristou, C., Delopoulos, A.: The MUG facial expression database. In: 11th International Workshop on Image Analysis for Multimedia Interactive Services, WIAMIS 2010, pp. 1–4. IEEE (2010)
[2] Allen, I.E., Seaman, J.: Staying the Course: Online Education in the United States. ERIC, Newburyport (2008)
[3] Alsop, S., Watts, M.: Science education and affect. Int. J. Sci. Educ. 25(9), 1043– 1047 (2003)
[4] Ark, W.S., Dryer, D.C., Lu, D.J.: The emotion mouse. In: HCI (1), pp. 818–823 (1999)
[5] Bartlett, M.S., Littlewort, G., Fasel, I., Movellan, J.R.: Real time face detection and facial expression recognition: development and applications to human computer interaction. In: 2003 Conference on Computer Vision and Pattern Recognition Workshop, vol. 5, p. 53. IEEE (2003)
[6] Baylor, A.L., Kim, Y.: Simulating instructional roles through pedagogical agents. Int. J. Artif. Intell. Educ. 15(2), 95–115 (2005)
[7] Bettadapura, V.: Face expression recognition and analysis: the state of the art. arXiv preprint arXiv:1203.6722 (2012)
[8] Borth, D., Chen, T., Ji, R., Chang, S.F.: SentiBank: large-scale ontology and classifiers for detecting sentiment and emotions in visual content. In: Proceedings of the 21st ACM International Conference on Multimedia, pp. 459–460 (2013)
[9] Bower, B.L., Hardy, K.P.: From correspondence to cyberspace: changes and challenges in distance education. New Dir. Community Coll. 2004(128), 5–12 (2004)
[10] Burkert, P., Trier, F., Afzal, M.Z., Dengel, A., Liwicki, M.: DeXpression: deep convolutional neural network for expression recognition. arXiv preprint arXiv:1509.05371 (2015) 330 W. Zhou et al.
[11] Castellano, G., et al.: Towards empathic virtual and robotic tutors. In: Lane, H.C., Yacef, K., Mostow, J., Pavlik, P. (eds.) AIED 2013. LNCS (LNAI), vol. 7926, pp. 733–736. Springer, Heidelberg (2013). https://doi.org/10.1007/978-3-642-39112- 5 100
[12] Craig, S.D., Gholson, B., Driscoll, D.M.: Animated pedagogical agents in multimedia educational environments: effects of agent properties, picture features and redundancy. J. Educ. Psychol. 94(2), 428 (2002)
[13] Dimberg, U.: Facial reactions to facial expressions. Psychophysiology 19(6), 643– 647 (1982)
[14] Dimberg, U., Thunberg, M., Elmehed, K.: Unconscious facial reactions to emotional facial expressions. Psychol. Sci. 11(1), 86–89 (2000)
[15] D'Mello, S., Graesser, A.: Emotions during learning with autotutor. In: Adaptive Technologies for Training and Education, pp. 169–187 (2012)
[16] Ekman, P.: Biological and cultural contributions to body and facial movement, pp. 34–84 (1977)
[17] Ekman, P.: Telling Lies: Clues to Deceit in the Marketplace, Politics, and Marriage, Revised edn. WW Norton & Company, New York (2009)
[18] Ekman, P., Keltner, D.: Universal facial expressions of emotion. In: Segerstrale, U., Molnar, P. (eds.) Nonverbal Communication: Where Nature Meets Culture, pp. 27–46 (1997)
[19] Fayek, H.M., Lech, M., Cavedon, L.: Evaluating deep learning architectures for Speech Emotion Recognition. Neural Netw. 92, 60–68 (2017)
[20] Gourier, N., Hall, D., Crowley, J.L.: Estimating face orientation from robust detection of salient facial features. In: ICPR International Workshop on Visual Observation of Deictic Gestures. Citeseer (2004)
[21] Gross, R., Matthews, I., Cohn, J., Kanade, T., Baker, S.: Multi-PIE. Image Vis. Comput. 28(5), 807–813 (2010)
[22] Gunawardena, C.N., McIsaac, M.S.: Distance education. In: Handbook of Research on Educational Communications and Technology, pp. 361–401. Routledge (2013)
[23] Happy, S., Patnaik, P., Routray, A., Guha, R.: The indian spontaneous expression database for emotion recognition. IEEE Trans. Affect. Comput. 8(1), 131–142 (2015)
[24] Izard, C.E.: Innate and universal facial expressions: evidence from developmental and cross-cultural research (1994)
[25] Cheng, J., Zhou, W., Lei, X., Adamo, N., Benes, B.: The effects of body gestures and gender on viewer's perception of animated pedagogical agent's emotions. In: Kurosu, M. (ed.) HCII 2020. LNCS, vol. 12182, pp. 169–186. Springer, Cham (2020)
[26] Kahou, S.E., et al.: EmoNets: multimodal deep learning approaches for emotion recognition in video. J. Multimodal User Interfaces 10(2), 99–111 (2016). https:// doi.org/10.1007/s12193-015-0195-2
[27] Kanade, T., Cohn, J.F., Tian, Y.: Comprehensive database for facial expression analysis. In: IEEE International Conference on Automatic Face and Gesture Recognition, pp. 46–53. IEEE (2000)
[28] Kim, S., Georgiou, P.G., Lee, S., Narayanan, S.: Real-time emotion detection system using speech: multi-modal fusion of different timescale features. In: 2007 IEEE 9th Workshop on Multimedia Signal Processing, pp. 48–51. IEEE (2007)
[29] Kim, Y., Baylor, A.L.: Pedagogical agents as social models to influence learner attitudes. Educ. Technol. 47(1), 23–28 (2007)
[30] Kim, Y., Baylor, A.L., Shen, E.: Pedagogical agents as learning companions: the impact of agent emotion and gender. J. Comput. Assist. Learn. 23(3), 220–234 (2007) Learning-Based Emotion Recognition from Real-Time Videos 331
[31] Kirouac, G., Dore, F.Y.: Accuracy of the judgment of facial expression of emotions as a function of sex and level of education. J. Nonverbal Behav. 9(1), 3–7 (1985). https://doi.org/10.1007/BF00987555
[32] Langner, O., Dotsch, R., Bijlstra, G., Wigboldus, D.H., Hawk, S.T., Van Knippenberg, A.: Presentation and validation of the Radboud Faces Database. Cogn. Emot. 24(8), 1377–1388 (2010)
[33] Le, Q.V., Zou, W.Y., Yeung, S.Y., Ng, A.Y.: Learning hierarchical invariant spatiotemporal features for action recognition with independent subspace analysis. In: CVPR 2011, pp. 3361–3368. IEEE (2011)
[34] LeCun, Y., Bengio, Y., Hinton, G.: Deep learning. Nature 521(7553), 436–444 (2015)

©IJRASET: All Rights are Reserved

[35] Lee, C.M., Narayanan, S.S.: Toward detecting emotions in spoken dialogs. IEEE Trans. Speech Audio Process. 13(2), 293–303 (2005)
[36] Levi, G., Hassner, T.: Emotion recognition in the wild via convolutional neural networks and mapped binary patterns. In: Proceedings of the 2015 ACM on International Conference on Multimodal Interaction, pp. 503–510 (2015)
[37] Lisetti, C.L., Nasoz, F.: MAUI: a multimodal affective user interface. In: Proceedings of the Tenth ACM International Conference on Multimedia, pp. 161–170 (2002)
[38] Lyons, M., Kamachi, M., Gyoba, J.: Japanese Female Facial Expression (JAFFE) Database, July 2017. https://figshare.com/articles/jaffe desc pdf/5245003
[39] Martha, A.S.D., Santoso, H.B.: The design and impact of the pedagogical agent: a systematic literature review. J. Educ. Online 16(1), n1 (2019)
[40] Miles, M.B., Saxl, E.R., Lieberman, A.: What skills do educational "change agents" need? An empirical view. Curric. Inq. 18(2), 157–193 (1988)
[41] Mollahosseini, A., Hasani, B., Mahoor, M.H.: AffectNet: a database for facial expression, valence, and arousal computing in the wild. IEEE Trans. Affect. Comput. 10(1), 18–31 (2017)
[42] Morency, L.P., et al.: SimSensei demonstration: a perceptive virtual human interviewer for healthcare applications. In: Twenty-Ninth AAAI Conference on Artificial Intelligence (2015)
[43] Neri, L., et al.: Visuo-haptic simulations to improve students' understanding of friction concepts. In: IEEE Frontiers in Education, pp. 1–6. IEEE (2018)
[44] Ng, H.W., Nguyen, V.D., Vonikakis, V., Winkler, S.: Deep learning for emotion recognition on small datasets using transfer learning. In: Proceedings of the 2015 ACM on International Conference on Multimodal Interaction, pp. 443–449 (2015)
[45] Pantic, M., Valstar, M., Rademaker, R., Maat, L.: Web-based database for facial expression analysis. In: 2005 IEEE International Conference on Multimedia and Expo, pp. 5–pp. IEEE (2005)
[46] Pard`as, M., Bonafonte, A.: Facial animation parameters extraction and expression recognition using hidden Markov models. Sig. Process. Image Commun. 17(9), 675–688 (2002)
[47] Payr, S.: The virtual university's faculty: an overview of educational agents. Appl. Artif. Intell. 17(1), 1–19 (2003)
[48] Pekrun, R.: The control-value theory of achievement emotions: assumptions, corollaries, and implications for educational research and practice. Educ. Psychol. Rev. 18(4), 315–341 (2006). https://doi.org/10.1007/s10648-006-9029-9
[49] Pekrun, R., Stephens, E.J.: Achievement emotions: a control-value approach. Soc. Pers. Psychol. Compass 4(4), 238–255 (2010)
[50] Phipps, R., Merisotis, J., et al.: What's the difference? A review of contemporary research on the effectiveness of distance learning in higher education (1999) 332 W. Zhou et al.
[51] Picard, R.W., Scheirer, J.: The Galvactivator: a glove that senses and communicates skin conductivity. In: Proceedings of the 9th International Conference on HCI (2001)
[52] Porter, L.R.: Creating the Virtual Classroom: Distance Learning with the Internet. Wiley, Hoboken (1997)
[53] Rowley, H.A., Baluja, S., Kanade, T.: Rotation invariant neural network-based face detection. In: Proceedings of the 1998 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No. 98CB36231), pp. 38–44. IEEE (1998)
[54] Russakovsky, O., et al.: ImageNet large scale visual recognition challenge. Int. J. Comput. Vis. 115(3), 211–252 (2015). https://doi.org/10.1007/s11263-015-0816-y
[55] Russell, J.A.: Core affect and the psychological construction of emotion. Psychol. Rev. 110(1), 145 (2003)
[56] Schneiderman, H., Kanade, T.: Probabilistic modeling of local appearance and spatial relationships for object recognition. In: Proceedings of the 1998 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No. 98CB36231), pp. 45–51. IEEE (1998)
[57] Schroeder, N.L., Adesope, O.O., Gilbert, R.B.: How effective are pedagogical agents for learning? A meta-analytic review. J. Educ. Comput. Res. 49(1), 1–39 (2013)
[58] Tian, Y.I., Kanade, T., Cohn, J.F.: Recognizing action units for facial expression analysis. IEEE Trans. Pattern Anal. Mach. Intell. 23(2), 97–115 (2001)
[59] Tie, Y., Guan, L.: A deformable 3-D facial expression model for dynamic human emotional state recognition. IEEE Trans. Circ. Syst. Video Technol. 23(1), 142–157 (2012)
[60] Viola, P., Jones, M., et al.: Robust real-time object detection. Int. J. Comput. Vis. 4(34–47), 4 (2001)
[61] Volery, T., Lord, D.: Critical success factors in online education. Int. J. Educ. Manag. 14(5), 216–223 (2000)
[62] Wang, H., Chignell, M., Ishizuka, M.: Empathic tutoring software agents using real-time eye tracking. In: Proceedings of the 2006 Symposium on Eye Tracking Research & Applications, pp. 73–78 (2006)
[63] Wilson, P.I., Fernandez, J.: Facial feature detection using Haar classifiers. J. Comput. Sci. Coll. 21(4), 127–133 (2006)
[64] Yang, S., Luo, P., Loy, C.C., Tang, X.: From facial parts responses to face detection: a deep learning approach. In: Proceedings of the IEEE International Conference on Computer Vision, pp. 3676–3684 (2015)

©IJRASET: All Rights are Reserved



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)