Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp. 4729-4742
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764879

Machine Learning-Based Development Of A Real-Time Emotions Recognition System Applying Facial Expressions

Simrat Kaur Rakhraj
M. Tech. Scholar
School of Engineering and I.T., MATS University, Raipur
Apurv Verma
Assistant Professor
School of Engineering and I.T., MATS University, Raipur
Dr. Abhishek Badholia
Associate Professor
School of Engineering and I.T., MATS University, Raipur

ABSTRACT:

The purpose of the research is just to discuss the benefits and capabilities of facial expression recognition. Facial expression is a type of non-verbal communications that plays an important part in both verbal and non-verbal communications. It expresses a person's point of view or attitude, as well as his or her mental state. Over the last 20 years, a significant amount of experimentation had already been conducted for optimize Human Computer Interaction (HCI). This article covers the following topics: an introduction to facial emotion recognition systems, their applications, a comparison of popular face expression identification approaches, and the stages of an automatic facial expression identification system. Emotions factors have a significant influence on social intelligence, such as interaction understandings, making decisions, and comprehending human behaviour at the time of conversation, emotion is really important. Emotions recognition could be done in a variety of ways, including verbal and nonverbal methods. Voices (Audio) are a type of spoken conversation. Nonverbal conversation includes facial expressions, actions, bodily orientations, and gestures. [1] When speaking, the spoken component overall provides just 7% of the statement's impact, the audible component provides 38%, and also the subject's facial expression provides 55% of the message's consequences. As a result, automatic and significant facial expressions will be advantageous in human-machine interaction. From human services to healthcare operations, facial expressions interpretation might be beneficial. Facial expressions interpretation is beneficial for technologies including HCI, Friendly Robots, Animations, Surveillance Systems, and Pain Detecting in Healthcare that are mainly focused around emotional identification.

Keywords: Facial expressions, Emotion recognition, Human Computer Interface, gestures.

I. INTRODUCTION

Facial expressions are the variations on a particular person face in reaction to their inner sentimental experiences, goals, or human interactions. Behavioural researchers have been studying facial expression interpretation over a long time. simply tracing the movements of 25 recognised points around an image series, showed an earlier experiment to autonomously identify facial emotions. Further all these, even more advancement might have been achieved in developing software applications to aid in our understanding as well as include with this organic pattern of human interactions. Facial expressions analysis refers to machine which intent to autonomously analyse and recognise faces movements and transformations in facial features from graphical data. Mostly in computer vision area, facial expression interpretation is mostly misunderstood with emotional interpretation. Greater understanding is necessary for emotional interpretation. for instance, Facial expressions, could reflect emotions as well as purpose, cognitive processes, physical effort, and other intra- or interpersonal understandings. Situation, gestures, speech, individual characteristics, and social aspects, as well as face structure and timing, all help interpretation.

Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp. 4729-4742
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764879

Computerized face recognition interpretation programs must be able to evaluate faces motions in a variety of situations, including situation, region, sexual orientation, etc.

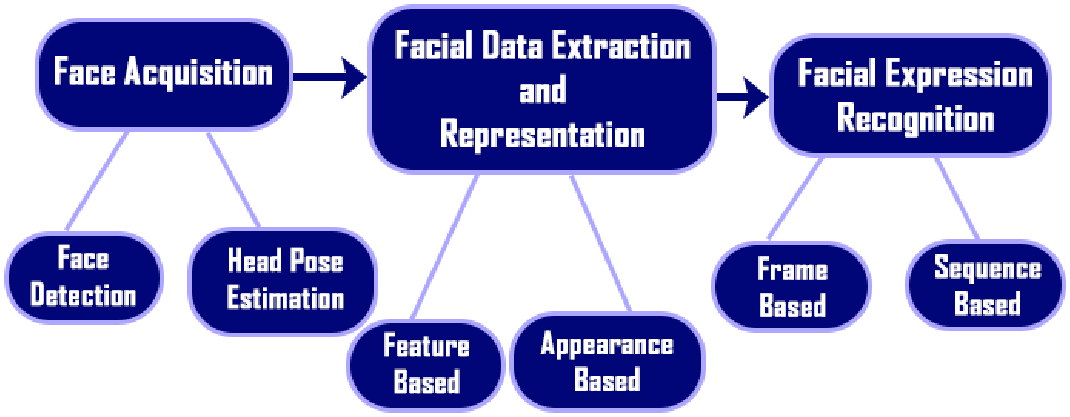

Figure -1: Facial expression analysis system

Automatic facial expression analysis is feasible because to advances in related fields such as psychology research, human movement analysis, face detection, face tracking, and identification. Emotions and paralinguistic communications, clinical psychology, psychiatry, neuroscience, pain assessment, deception detection, intelligent settings, and multimodal human machine interfaces are just few of the domains where automated facial expressions methodology may be used.

Table 1: Universal Emotion Identification

Emotion	Definition	Motion of facial Part
Disgust	Disgust is a feeling of dislike. Human may feel disgust from any taste, smell. sound or tough.	Lip corner depressor, nose wrinkle .lower lip depressor, Eyebrows pulled down
Fear	Fear is the emotion of danger. It may be because of danger of physical or Psychological harm. Secondary emotions of fear are Horror, nervousness, panic, worry and dread.	Outer eyebrow down, inner eyebrow up, mouth open, law dropped
Sadness	Sadness is opposite emotion of Happiness. Secondary emotions are suffering. hurt, despair. petty and hopelessness,	Outer eyebrow down, Inner corner of eyebrows raised, mouth edge down, closed eye. lip corner pulled down.
Surprise	This emotion comes when unexpected things happens. Secondary emotions of surprise are amazement, astonishment.	Eyebrows up. open eye. mouth open. taw dropped
Anger	Anger is one of the most dangerous emotions. This emotion may be harmful so, humans are trying to avoid this emotion. Secondary emotions of anger are irritation, annoyance, frustrationon, hate and dislike.	Eyebrows pulled down, Open eye, teeth shut and lips tightened, upper and lovrt lips pulled up.
Happiness	Happiness is most desired expression by human. Secondary emotions are cheerfulness, pride, relief,	Open Eyes, mouth edge up. open mouth, lip corner pulled up,

	hope, pleasure, and thrill.	cheeks raised, and wrinkles around eyes.

Emotional factors provide a significant influence on sociocultural intelligence, such as communications comprehension, decision-making, and comprehending human behaviour. In the time of communications, emotions is really important. Emotions detection can be done in a variety of ways, including verbal and nonverbal methods. Voices (Audio) is a type of spoken interaction. Nonverbal communications includes facial expressions, actions, bodily positions, and gestures. While speaking, the verbal component as a whole provides just 7% of the message's affect, the audible component provides 38%, and the author's face expressions provides 55% of the message's influence. As a result, automatic and real-time facial expressions will perform an increasingly crucial role in human-machine interactions. From human facilities to healthcare operations, facial expression recognition might be beneficial. On a comparison analysis of popular methods suggested earlier for Automatic Facial Emotions Identification System, interpretation of face expressions plays fundamental tasks for applications that are premised on emotion recognising like HCI, Social Robot, Motion graphics, Warning System, and Pain analysing for sick people. Stages of the Automated Facial Emotions Identification System are included. Classifying face expressions and their characteristics Facial expression is a crucial tool for expressing human emotion. Humans experience a wide range of emotions during the day, which may be due to their mental or physical situations. Despite the fact that people are capable of a wide range of emotions, contemporary psychology has identified six universal facial expressions: happiness, sadness, surprise, fear, disgust, and anger. The movements of the facial muscles aid in the identification of human emotions. The eyebrow, mouth, nose, and eyes are the most basic facial characteristics.

II. Research Review:

Humans can understand feelings without much latency or difficulty, however computer identification of face expressions is a major difficulty. The following are several most important face expressions identification methodologies:

- **Based on statistical movements:** This study presented distortion and rotational independent face expressions identification relied upon Zernike moments, a statistics motion. For emotion detection, the retrieved features from Zernike moments is fed into the Navie Bayesian Classification algorithm.

  Advantage:
  i) Zernike moments are used to establish rotational constancy.
  ii) For a facial images, the recognising duration is lower than just one sec.
  Disadvantage:
  i) Due to the rotations of face pictures, the emotions detection systems was harmed.

- **Based on auto-illumination Correction:** The location of elements termed Actions Units (AUs) is used to identify facial emotions without tagging it. The skin and chrominance of the retrieved picture are used to recognise the face. The removed eyeballs and lips are linked collectively with a mapping approach. Through applying Haar-Cascaded technique, skin and non-skin particles are divided to differentiate the face from the backdrop. Numerous facial images identification is used in this study.

  Advantage:
  i) The colour consistency algorithm removes the limitations of lighting and autonomously corrects it.
  ii) Facial recognition method with singular & numerous faces.
  Disadvantage:
  i) On identifying several facial photos, a 65% identification accuracy was attained. As a result, greater precision is necessary.

Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp. 4729-4742
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764879

ii) This technique is hampered by a weak lights arrangement.

- **Emotion detection mechanism for a Community Robot based on identification:** This work contains an identifying phase before emotions classifications in attempt to give individualized emotions recognizing [5]. A hybrid strategy was employed to determine face configurations that included Active Space models and Active Appearance models. Facial identification is done with the help of facial trackers. Textured data is made up of a series of vectors that characterise its 3-dimensional modeled faces

Advantage:

i) Recognition of the object as well as previous information of the object improve performance recognizing in terms of classifications accuracy and efficiency

ii) Whenever a faces picture is obtained in a social robot operational scenario with varying lights circumstances and multiple locations & inclinations of the individual face, it has an 83% identification rate.

Disadvantage:

i) Before it could be used as a community robots emotions detection mechanism, it needed to be trained.

ii) In order to reach the entire 5 features space for emotion detection, an suitable format as in monitoring data was needed.

iii)

- **Emotions identifying system centred on E-learning:** This research presented an emotions identification method based on E-learning. Based on the SVM classifier To find a person's face, a Booster approach is utilised. The Ads Booster approach analyzes classifiers by obtaining characteristics from a weak classifiers and comparing them to a powerful classifiers. This is an example of an incremental weights update procedure.

Advantage:

(i) This study examines the use of emotions in a network teaching system.

(ii) Emotions detection is unaffected by putting spectacles upon face.

Disadvantage:

(i) Facial recognizing would be influenced by the distances b/w the webcam and the individual's face.

(ii) Hearing, seating positions, and lighting intensity are all affected by the spatial influence of the person's face on emotions detection accuracy.

- **Cognitive Face Analysis System for Interactive TV System:** Emotions detecting of individuals viewing TV programmes was suggested on the study. Facial expressions identification is used to distinguish individual TV viewers & its interior emotional states. Recognizing using the Ada-LDA technique. Around 16 fps could be performed.

Advantage:

i) This study presented a new paradigm for futuristic interacting television.

ii) The presented methodology is rooted upon a program that recognises emotions in real time.

iii) It has a refresh rate of more than 16 fps.

Disadvantage:

i) The accuracy of detection varies depending on the types of face databases employed.

ii) For real-time applications, recognizing and timeliness efficiency must be improved.

- **Motion detection based facial expression using Optical flow:** In order to estimate the location of face features, active Infra Red (IR) lighting was utilised. For vector collection, Source Vector (SV) was employed, which indicates movement and distortion owing to emotional representations. Emotions are categorised based on the calculated likeness b/w the origin vectors and the executing movement vectors, with the largest degree of correlation indicating a recognised emotions.

Advantage:

i) Face emotion may be detected with a small amount of image frames (three).

ii) It is not required to establish the actual positions of face features; merely the approximated measurements will suffice.

Disadvantage:

i) Fear has a lower identification rates than others moods.

III INTEGRATED FACIAL EXPRESSION RECOGNISING MECHANISM:

The program that recognises facial expressions is known as a face recognizing system. Face expressions identification is performed via image processing. Images processing may be used to obtain valuable details from the images. Images processing involves converting an images to electronic document then performing actions on it in order to retrieve usable details. The processes of a face expressions identification systems are as follows:

- **Image Acquisition:** For facial expression recognition, fixed pictures or picture sequences were also utilised. Even if photos could describe enough details regarding feeling, like stammering, grey scale pictures are the most famous for facial image recognition. Because of the cheap price of colour picture appliance, pictures would be preferred as in long term. Cameras, mobile phones, and other electronic gadgets are utilised to capture images.
- **Pre-processing:** It is an important part of the total workflow. By reducing noise and softening the picture, the pre-processing phase improves the grade of the input picture and identifies data of relevance. It reduces picture duplication while preserving picture detail. Filtration and normalising of the picture are also part of the pre-processing phase, that results in a uniformly sized and turned picture.
- **Segmentation:** Segmentation divides a picture into meaningful categories. On the basis of texture, edges, and sharpness, segments of a picture is a technique of separating the picture into homogeneous, self-consistent sections belonging to distinct items in the picture.
- **Feature Extraction:** It may be thought of as the picture's "interest" element. It contains details on the structure, movement, colour, and texture of a person's face. It pulls the relevant data from a picture. When comparison with its actual picture, feature extraction dramatically decreases that picture's details, giving it a space benefit.
- **C**ategorization**:** The outcome of feature extraction phase is followed by the categorization phase. The categorization step recognises face images and groups them into categories to aid in their accurate identification. Categorization is a complicated procedure that is influenced by a variety of aspects. The categorization phase, often known as feature selection, works with obtained data & groups it accordance to particular criteria.

IV. PRINCIPLES OF FACIAL EXPRESSION ANALYSIS

Measurements of facial movements and identification of expressions are both part of facial expressions interpretation. Facial acquisitions , faces visualisation and interpretation, & facial expressions identification are the three processes in the standard methodology to automated facial expressions interpretation. Facial acquisitions is a phase within that handling of incoming pictures or sequencing that autonomously locates the facial features. This can be a detectors that detects the face across each frames or a detectors that only detects the facial features during the first frame and afterwards tracks the face throughout the video frames. A facial expressions analysis technique can use a head finder, head tracking, and pose estimation to manage massive head movements. The next stage is to extract and portray the facial changes induced by facial expressions after the face has been found. There are two sorts of techniques to face feature extraction for expression analysis: geometric feature-based methods and appearance-based methods. Geometric facial characteristics show the form and placement of face features. To construct a feature vector that reflects the face geometry, the facial components or facial feature points are extracted. To extract a feature vector using appearance-based approaches, image filters such as Gabor wavelets are applied to either the complete face or select areas of a face picture. Face normalisation or feature representation before the stage of emotion recognition can reduce the impacts of in-plane head rotation and varying scales of the faces, depending on the different facial feature extraction methods. The penultimate stage of a system's development is facial expression recognition. Facial action units or prototypic emotional expressions can be found in the facial alterations. Depending on whether or not the temporal data is available,

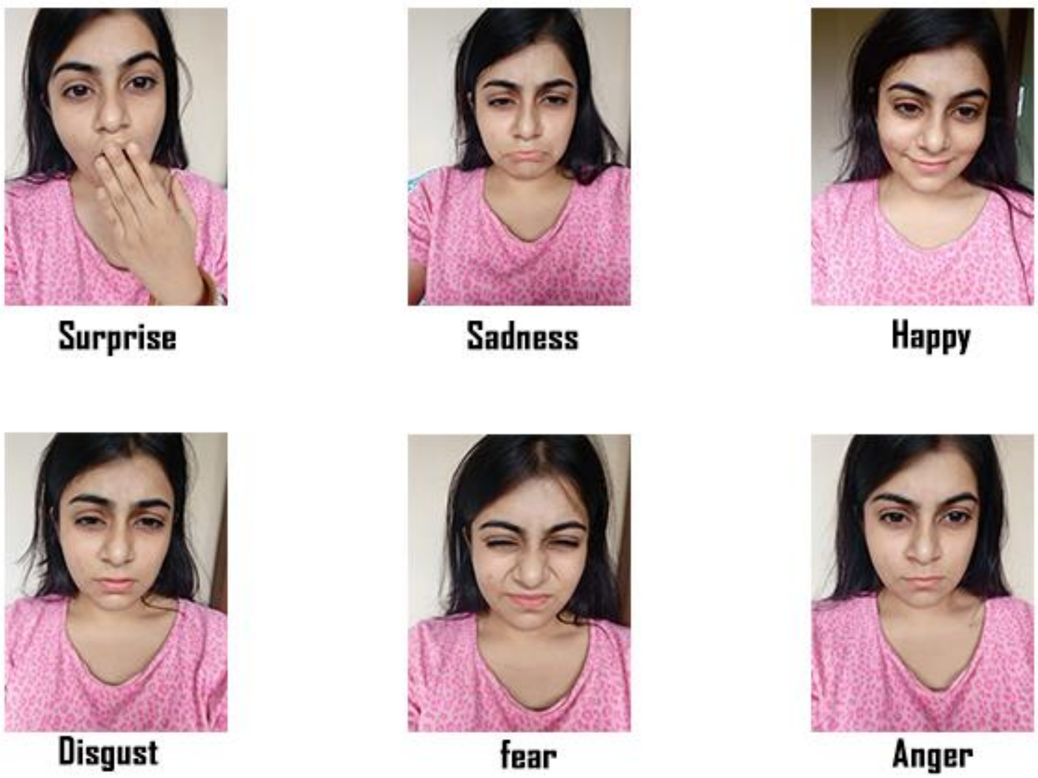

Figure.2: Emotion-specified facial expression

1 surprise, 2 sadness, 3 happy, 4 disgust, 5 fear, 6 anger, used, in this chapter we classify a recognition approach as frame-based or sequence based.

V. ISSUES, NECESSITATES AND PURPOSE

- It is critical to involve a huge data set of persons of different cultural backgrounds, ages, and sexes in order to establish methodologies that are robust to person variation in facial characteristics and behaviour. This contains persons with facial hair, persons wearing jewellery or eyewear, and both common and medically impaired persons.
- To Facial Expression Strength Face form, texture, colour, and face and forehead hairs all differ depending on sex, ethnicity, and age. For example, infants' skin is softer & lesser textures, and they generally absence hair in the eyebrows and forehead.
- The notion that facial expressions are unitary and start and finish with a neutral stance simplifies facial expression analysis. Face expressions is extremely complicated in actuality, particularly at the levels of actions components.
- Facial identification, feature monitoring, and expressions recognizing efficacy may be influenced.

Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp. 4729-4742
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764879

- Numerous factors are involved in the issue of face expression space. All of these elements must be addressed by a best face expressions evaluation system, which produces appropriate identification outcomes.
- To combine multimodal characteristics like face expressions, verbal expressions, gesture, and physical activities to analyse emotional representations.
- To develop more advanced model for face acquisitions, face data retrieval and representation, and facial expressions identification that can manage head movements occlusion, illumination variations, and weaker intensity expressions.

VI. Facial Expression Recognition

The final stage in the process is for the algorithm to recognise facial expressions using the retrieved characteristics. The neural network, support vector machines, linear discriminant analysis (LDA), K-NN, multinomial logistic ridge regression (MLR), hidden Markov models (HMM), tree enhanced naïve Bayes, Rank Boost, as well as other classification algorithms were all used to recognise expressions. A few programs depend just on rule-based classifications premised upon faces reaction definitions. I compare and contrast frames and sequential based gesture identification algorithms in this article. To recognise various gestures in the frames, this frame-based identification approach employs simply the current frame with or without a references picture (which is usually a truthful face images). An sequential based recognizing approach recognises expressions for single or maybe multiple frames by using the sequence' temporal data. The recognizing algorithms, recognition rates, recognizing outcomes, and databases employed in the most current programs are summarised in Table 1. The optimum result for the individual autonomous testing has been chosen for the strategies which employed multiple classifications. Expressions Detection Using Frames, For the given photos, frame-based expressions identification doesn't employ temporal data. It makes use of existing given picture's data, with or without a reference frame. A stable picture or a frame in a series that is processed separately can be used as the input picture. For facial expression recognition, there are several approaches in the literature, including NN, SVM, linear discriminant analysis, Bayesian networks, and rule-based classifications. To detect FACS AUs, Tian et al. [96] used a NN-based recognition system. They employed a typical back propagation approach to distinguish AUs using 3 layer neural networks including 1 secret layer. The top and bottom faces are served by independent network. The normalised geometrical attributes, the visual attribute, or perhaps both could be used as inputs. The identified AUs are the outcomes. The connectivity has been programmed to react to the specific AUs, either they appear individually or in groups.

Table .1 FACS AU or expression recognition of recent advances. SVM, support vector machines; MLR, multinomial logistic ridge regression; HMM, hidden Markov models; BN, Bayesian network; GMM, Gaussian mixture model; Reg Rank Boost, Rank Boost with l1 regularization

System	Recognition Mechnique	Recognition Rate	Recognition Outputs	Database
NNF	Neural Network frame	97.62%	16 single AUs and their combinations	Ekman-Hager Cohn-Kanade
SVM MLR	MLR+SVM FRAME	93.7%	Six facial expression	Cohn-Kanade
RBS	Rule based sequence	99.57%	Blink,nonblink,brownup,down and non- motion	Frank-Ekman
SVM	Adaboost+SVM Sequence	84.72%	Twenty facial expression	Frank-Ekman
HMM,BN	BN+HMM FRAME AND	72.52%	Six facial expression	UIUC-CHEN

	SEQUENCE			
GMM,NN	**GMM+NN-Frame**	**75.09%**	**Six facial expression**	**Cohn-Kanade**
RR Boost	**Frame Reg,Rank Boost**	**91.9%**	**Six facial expression**	**Cohn-Kanade**

Numerous outputs modules get triggered as AUs occurred in combo. Various additional systems attempted to detect AU combos, but each combo was processed as if it were a single AU. A device which could manage AU combos is highly effective, since more than 7200 distinct AU combos have been seen. Normal expressions and 16 AUs showed an average identification rate of 96.1 percent, either they appeared separately or in combos. To recognise stable expression and 6 emotion-specified gestures, a two-stage classification was used. For the pairs classifier, SVMs were utilised first, with each SVM being trained to differentiate between two moods. The researchers next used closest neighbour, a SVM, & MLR to turn the representations generated by the initial phase into a probability distributions among 6 emotion-specific expression and neutral. MLR had the best performance, with a score of 91.5 percent. A two-stage classifier was also used by Wen and Huang [102] to distinguish neutral and 6 emotion-specific phrases. To begin, a neural network is utilised to distinguish between neutral and nonneutral-like objects. [93]. For the other expressions, Gaussian mixture models (GMMs) are utilised. For a people-independent testing, the total avg recognizing accuracy is 70%. For expressions identification, Yang et al. [111] use RankBoost with l1 regularisation. Researchers often use their outcome rating values to determine the levels of gestures. They attained an 89% identification rate for 6 emotion-specific terms inside the Cohn–Kanade data warehouse

VII. Multimodal Expression Analysis

Nonverbal communication can take many forms, including facial expression. Based on the circumstances, the messaging value of distinct modes might fluctuate, and they may be coherent or incompatible with one another. Several recent studies combined facial expression evaluation with additional modalities such as gestures, fluency, and voice. Cohn et al. [20] looked at the relationship among facial gestures and voice phrasing to see whether it might be used to diagnose depression. Using face motions and voice phrasing, we were able to attain the exact 78 % success rate. There were none outcomes for the combo. For 9 emotion identification, Gunes and Piccardi [45] coupled facial activities and body motions. They discovered that recognition using a combination of face and body modalities outperforms recognition using either the face or the body modality alone. Following frame-by-frame face recognition, a mix of appearance (e.g., wrinkles) and geometric features (e.g., feature points) is recovered from the face movies for facial feature extraction. For feature comparison, a reference frame with neutral expression is used. They used the mean shift approach to detect and track head, shoulders, and hands from body films for body feature extraction and tracking. Instances of face and body feature extraction are shown in Figure. Body and face behavioral segmentation was detected using several classification model, including both frame-based and sequence-based approaches, with a sum of 152 properties for facial modalities and 170 properties for body modalities. They tested the method on the FABO dataset and found that merely utilizing facial characteristics resulted in an identification accuracy of 35.22 % and only using body traits resulted in an identification accuracy of 76.87 %. While both body and facial traits were combined, the identification rate climbed to 85 %

Ilkogretim Online - Elementary Education Online, 2020; Vol 19 (Issue 4): pp. 4729-4742
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2020.04.764879

Table 19.8 Summary of databases for facial expression analysis

Databases	Images/ Videos	Subjects	Expressions	Neutral	Spontaneous	Multimodal	3D data
Cohn–Kanade [49]	videos	210	basic expressions	yes	no	frontal face	no
			single AUs			30° face	
			AU combinations			30° face	
FABO [44]	videos	23	9 expressions	yes	no	frontal face	no
			hand gestures			upper body	
JAFFE [59]	images	10	6 basic expressions	yes	no	frontal face	no
MMI [71]	images	19	single AUs	yes	no	frontal face	no
	videos		AU combinations			profile face	
RU-FACS [5]	videos	100	AU combinations	yes	yes	4 face poses	no
			AU			speech	
BU-3DFE [112]	static	100	6 basic expressions	yes	no	face	yes
BU-4DFE [113]	dynamic	101	6 basic expressions	yes	no	face	yes

VII. CONSIDERATION & PROGRESS IN THE FUTURE

Standard datasets are used extensively in this research to train, assess, and compare various face expression analysis algorithms and systems. For doing comparison testing, there are various publicly available expression analysis databases. Table 19.8 summarises a number of commonly used standard databases for facial expression analysis in this chapter. Kanade–Cohn The AU-Coded Face Expression Database is the most widely utilised comprehensive database in facial expression analysis research. The Japanese Female Facial Expression (JAFFE) Database comprises 213 photos of 10 Japanese female participants posing in 6 fundamental facial emotions and neutral poses. This is the first dataset for facial expressions evaluation that may be downloaded. MMI Facial Expression Database (MMI) comprises about 1500 examples of both stable photos and picture frames of faces from 19 participants in frontal and profile views demonstrating diverse facial reactions of sentiment, single AUs, and AU combos in frontal and portrait angles. It also comprises determining the timing sections (onset, peak, offset) of AU and emotional facial expressions that have been presented. The FABO database comprises picture sequences collected by two synchronised cameras; one is for upfront vision face motions and the other for upfront views upper body motions. The RU-FACS Spontaneous Expression Database (RUFACS) is a FACS-coded collection of spontaneous facial activity. The data comes from 100 people who took part in a 'false opinion' paradigm that included speech-related lip motions and out-of-plane head rotations from four different perspectives (frontal, left 45°, right 45°, and up approximately 22°). To date, picture sequences from 33 participants' frontal views have been FACS-coded. The database is currently being prepared for distribution. The Binghamton University 3D Facial Expression Database has 2500 3D facial expressions images from 100 people, containing truthful and simple expressions.

There are two related facial texture photos collected at two viewpoints (approximately +45° and 45°) associated with each 3D emotion model. At a video rate of 25 frames per second, the BU-4DFE database is expanded from a static 3D space (BU-3DFE database) to a dynamic 3D space. The BU-4DFE database has 606 3D facial expression sequencing from 101 people. A face texture movie with a high quality of 1040 x 1329 pixels per frame is associated with each 3D emotion sequence.

VII. Reference

[1] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota, "A Detailed Analysis on NSL-KDD Dataset using various Machine Learning Techniques for Intrusion Detection" Turkish Journal of Computer and Mathematics Education Vol.12 No. 11 (2021), 2954- 2968.

[2] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota, "An Investigation and Analysis of Cyber Security Information Systems: Latest Trends and Future Suggestion" publication in International Journal IT in Industry, Vol. 9, No.2, 2021, pp. 477–492, ISSN: ISSN (Print): 2204-0595 ISSN (Online): 2203-1731.

[3] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota, "Multifactor Authentication Methods: A Framework for Their Selection and Comparison" publication in International Journal of Future Generation Communication and Networking Vol. 13, No. 3, (2020), pp. 2522–2538, ISSN: 2233-7857

[4] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota, "A Novel Hybrid Approach for Cyber Security in IoT network Using Deep Learning Techniques" publication in International Journal of Advanced Science and Technology ISSN:2394-5125, ISSN: 2005-4238

[5] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota, entitled "Development of Real Time Automated Security System for Internet of Things (IoT)" publication in International Journal of Advanced Science and Technology Vol. 29, No. 6s, (2020), pp. 4180 – 4195, ISSN: 2005- 4238.

[6] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota Research paper entitled "An Experimental Analysis of Security Vulnerabilities in Industrial Internet of Things Services" published in International Journal of Information Technology in Industry IT in Industry, Vol. 9, No.3, 2021, pp.592–612, ISSN: 2203-1731.

[7] Tarun Dhar Diwan, Dr. Siddhartha Choubey, Dr.H.S.Hota Research paper entitled "An Investigation and Analysis of Cyber Security Information Systems: Latest Trends and Future Suggestion" published in International Journal of Information Technology in Industry IT in Industry, Vol. 9, No.2, 2021, pp.477–492, ISSN: 2203-1731.

[8] Tasnim, Mashrura, RifatShahriyar, NowshinNahar, and Hossain Mahmud. "Intelligent depression detection and support system: Statistical analysis, psychological review and design implication." In e-Health Networking, Applications and Services (Healthcom), 18th International Conference on, pp. 1-6. IEEE, 2016.

[9] Pampouchidou, Anastasia, Kostas Marias, ManolisTsiknakis, P. Simos, Fan Yang, and FabriceMeriaudeau. "Designing a framework for assisting depression severity assessment from facial image analysis." In Signal and Image Processing Applications (ICSIPA), International Conference on, pp. 578-583. IEEE, 2015.

[10] Maddage, Namunu C., RajindaSenaratne, Lu-Shih Alex Low, Margaret Lech, and Nicholas Allen. "Video-based detection of the clinical depression in adolescents." In Engineering in Medicine and Biology Society, (EMBC). Annual International Conference of the IEEE, pp. 3723-3726. IEEE, 2009.

[11] Meng, Hongying, Di Huang, Heng Wang, Hongyu Yang, Mohammed AI-Shuraifi, and Yunhong Wang. "Depression recognition based on dynamic facial and vocal expression features using partial least square regression." In Proceedings of the 3rd ACM international workshop on Audio/visual emotion challenge, pp. 21-30. ACM, 2013.

[12] Katikalapudi, Raghavendra, Sriram Chellappan, Frances Montgomery, Donald Wunsch, and Karl Lutzen. "Associating internet usage with depressive behavior among college students." IEEE Technology and Society Magazine 31, no. 4 : 73- 80. 2012

[13] Sahla, K. S., and T. Senthil Kumar. "Classroom Teaching Assessment Based on Student Emotions." In The International Symposium on Intelligent Systems Technologies and Applications, pp. 475-486. Springer International Publishing, 2016.

[14] Athira, S., R. Manjusha, and Latha Parameswaran. "Scene Understanding in Images." In The International Symposium on Intelligent Systems Technologies and Applications, pp. 261-271. Springer International Publishing, 2016.

[15] Karthika, R., and LathaParameswaran. "Study of Gabor wavelet for face recognition invariant to pose and orientation." In Proceedings of the International Conference on Soft Computing Systems, Springer, New Delhi, 2016.

[16] Vikram, K., and S. Padmavathi. "Facial parts detection using Viola Jones algorithm." In Advanced Computing and Communication Systems (ICACCS), 4th International Conference on, pp. 1-4. IEEE, 2017.

[17] Haghighat, Mohammad, Saman Zonouz, and Mohamed AbdelMottaleb. "CloudID: Trustworthy cloud-based and cross-enterprise biometric identification." Expert Systems with Applications 42, Vol no. 21, pp. 7905-7916, 2015.

[18] C. Darwin and P. Prodger, 'e Expression of the Emotions in Man and Animals, Oxford University Press, Oxford, MA, USA, 1998.

[19] Y.-I. Tian, T. Kanade, and J. F. Cohn, "Recognizing action units for facial expression analysis," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 97–115, 2001.

[20] R. Donoso, C. San Mart´ın, and G. Hermosilla, "Reduced isothermal feature set for long wave infrared (LWIR) face recognition," Infrared Physics & Technology, vol. 83, pp.114–123, 2017.

[21] T. Liu, H. Liu, Z. Chen et al., "FBRDLR: fast blind reconstruction approach with dictionary learning regularization for infrared microscopy spectra," Infrared Physics & Technology, vol. 90, pp. 101–109, 2018.

[22] Z. Huang, H. Fang, Q. Li et al., "Optical remote sensing image enhancement with weak structure preservation via spatially adaptive gamma correction," Infrared Physics & Technology, vol. 94, pp. 38–47, 2018.

[23] Y. Bi, M. Lv, Y. Wei, N. Guan, and W. Yi, "Multi-feature fusion for thermal face recognition," Infrared Physics & Technology, vol. 77, pp. 366–374, 2016.

[24] H. Liu, Z. Zhang, S. Liu, J. Shu, T. Liu, and T. Zhang, "Blind spectrum reconstruction algorithm with L0-sparse representation," Measurement Science and Technology, vol. 26, no. 8, pp. 085501–085507, 2015.

[25] H. Wu, Y. Liu, L. Qiu, and Y. Liu, "Online judge system and its applications in C language teaching," in Proceedings of the International Symposium on Educational Technology (ISET), pp. 57–60, Beijing, China, July 2016.

[26] T. Liu, Z. Chen, H. Liu, Z. Zhang, and Y. Chen, "Multi-modal hand gesture designing in multi-screen touchable teaching system for human-computer interaction," in Proceedings of the Second International Conference on Advances in Image Processing, pp. 100–109, Chengdu China, June 2018.

[27] P. Ekman and W. V. Friesen, "Constants across cultures in the face and emotion," Journal of Personality and Social Psychology, vol. 17, no. 2, pp. 124–129, 1971.

[28] P. Ekman, "Strong evidence for universals in facial expressions: a reply to Russell's mistaken critique," Psychological Bulletin, vol. 115, no. 2, pp. 268–287, 1994.

[29] P. Ekman and W. V. Friesen, "A new pan-cultural facial expression of emotion," Motivation and Emotion, vol. 10, no. 2, pp. 159–168, 1986.

[30] P. Ekman and W. V. Friesen, "Who knows what about contempt: a reply to Izard and Haynes," Motivation and Emotion, vol. 12, no. 1, pp. 17–22, 1988.

[31] P. Ekman and K. G. Heider, ",e universality of a contempt expression: a replication," Motivation and Emotion, vol. 12, no. 3, pp. 303–308, 1988.

[32] D. Matsumoto, "More evidence for the universality of a contempt expression," Motivation and Emotion, vol. 16, no. 4, pp. 363–368, 1992.

[33] I. J. Goodfellow, D. Erhan, P. L. Carrier et al., "Challenges in representation learning: a report on three machine learning contests," Neural Information Processing, Springer, Berlin, Germany, pp. 117–124, 2013.
[34] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang, "A survey of affect recognition methods: audio, visual, and spontaneous expressions," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 1, pp. 39–58, 2009.
[35] E. Sariyanidi, H. Gunes, and A. Cavallaro, "Automatic analysis of facial affect: a survey of registration, representation, and recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 37, no. 6, pp. 1113–1133, 2015.
[36] B. Martinez and M. F. Valstar, "Advances, challenges, and opportunities in automatic facial expression recognition," in Advances in Face Detection and Facial Image Analysis, pp. 63–100, Springer, Cham, Switzerland, 2016.
[37] H. Gunes and B. Schuller, "Categorical and dimensional affect analysis in continuous input: current trends and future directions," Image and Vision Computing, vol. 31, no. 2, pp. 120–136, 2013.
[38] S. Li and W. Deng, "Deep facial expression recognition: a survey," IEEE Transactions on Affective Computing, In press.
[39] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, extended Cohn-Kanade dataset, a complete dataset for action unit and emotion-specified expression," in Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, pp. 94–101, San Francisco, CA, USA, July 2010.
[40] P. Ekman and W. V. Friesen, "Measuring facial movement," Environmental Psychology and Nonverbal Behavior, vol. 1, no. 1, pp. 56–75, 1976.
[41] S. Bayrakdar, D. Akg¨un, and ˙I. Y¨uceda˘g, "A survey on automatic analysis of facial expressions," Sakarya University Journal of Science, vol. 20, no. 2, pp. 383–398, 2016.
[42] Y. Kim, S. Kang, S. Lee et al., "Efficiently detecting outlying behavior in video-game players," PeerJ, vol. 3, p. e1502, 2015.
[43] A. Agrawal and N. Mittal, "Using CNN for facial expression recognition: a study of the effects of kernel size and number of filters on accuracy," 'e Visual Computer, vol. 36, no. 2, pp. 405–412, 2020.
[44] C. M.Kuo, S. H. Lai, and M. Sarkis, "A compact deep learning model for robust facial expression recognition," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 2202–2208, Salt Lake City, UT, USA, June 2018.
[45] C. Shan, S. Gong, and P. W. McOwan, "Facial expression recognition based on local binary patterns: a comprehensive study," Image and Vision Computing, vol. 27, no. 6, pp. 803–816, 2009.
[46] P. Liu, S. Han, Z. Meng, and Y. Tong, "Facial expression recognition via a boosted deep belief network," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1805–1812, Columbus, OH, USA, June 2014.
[47] A. Mollahosseini, D. Chan, and M. H. Mahoor, "Going deeper in facial expression recognition using deep neural networks," in Proceedings of the IEEE Winter Conference Applications of Computer Vision (WACV), pp. 1–10, Lake Placid, NY, USA, March 2016.
[48] G. Zhao and M. Pietikainen, "Dynamic texture recognition using local binary patterns with an application to facial expressions," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 6, pp. 915–928, 2007.
[49] H. Jung, S. Lee, J. Yim, S. Park, and J. Kim, "Joint fine-tuning in deep neural networks for facial expression recognition," in Proceedings of the IEEE International Conference Computer Vision (ICCV), pp. 2983–2991, Santiago, Chile, December 2015.
[50] X. Zhao, X. Liang, L. Liu et al., "Peak-piloted deep network for facial expression recognition," Computer Vision—ECCV 2016, Springer, Cham, Switzerland, pp. 425–442, 2016.
[51] I. Bhardwaj, N. D. Londhe, and S. K. Kopparapu, "A spoof resistant multibiometric system based on the physiological and behavioral characteristics of fingerprint," Pattern Recognition, vol. 62, pp. 214–224, 2017.
[52] J. Zhao, R. Ma, and X. Zhang, "Speech emotion recognition based on decision tree and improved SVM mixed model," Transactions of Beijing Institute of Technology, vol. 37, no. 4, pp. 386–395, 2017.

[53] M. J. Lyons, S. Akamatsu, M. Kamachi, J. Gyoba, and J. Budynek, “,e Japanese female facial expression (Jaffe) database,” in Proceedings of 'ird International Conference on Automatic Face and Gesture Recognition, pp. 14–16, Nara, Japan, April 1998.
[54] M. Pantic, M. Valstar, R. Rademaker, and L. Maat, “Webbased database for facial expression analysis,” in Proceedings of the IEEE International Conference on Multimedia and Expo, Amsterdam, Netherland, July 2005.
[55] A. Dhall, R. Goecke, S. Lucey, and T. Gedeon, “Collecting large, richly annotated facial-expression databases from movies,” IEEE Multimedia, vol. 19, no. 3, pp. 34–41, 2012.
[56] R. Zhi, M. Flierl, Q. Ruan, and W. B. Kleijn, “Graph-preserving sparse nonnegative matrix factorization with application to facial expression recognition,” IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 41, no. 1, pp. 38–52, 2011.
[57] A. Dhall, R. Goecke, J. Joshi, K. Sikka, and T. Gedeon, “Emotion recognition in the wild challenge 2014: baseline, data and protocol,” in Proceedings of the 16th International Conference on Multimodal Interaction, pp. 461–466, ACM, Istanbul Turkey, November 2014.
[58] J. Li, K. Jin, D. Zhou, N. Kubota, and Z. Ju, “Attention mechanism-based CNN for facial expression recognition,” Neurocomputing, vol. 411, pp. 340–350, 2020.
[59] J. Shao and Y. Qian, “,ree convolutional neural network models for facial expression recognition in the wild,” Neurocomputing, vol. 355, pp. 82–92, 2019.
[60] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” 2014, https:// arxiv.org/abs/1409.1556.
[61] C. Szegedy, W. Liu, Y. Jia et al., “Going deeper with convolutions,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–9, Boston, MA, USA, June 2015.
[62] A. Jahandad, S. M. Sam, K. Kamardin, N. N. Amir Sjarif, and N. Mohamed, “Offline signature verification using deep learning convolutional neural network (CNN) architectures Google Net inception-v1 and inception-v3,” Procedia Computer Science, vol. 161, pp. 475–483, 2019.
[63] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778, Las Vegas, NV, USA, June 2016.
[64] I. Banerjee, Y. Ling, M. C. Chen et al., “Comparative effectiveness of convolutional neural network (CNN) and recurrent neural network (RNN) architectures for radiology text report classification,” Artificial Intelligence in Medicine, vol. 97, pp. 79–88, 2019.
[65] H. Hasan, B. Huang, and G. Tian, “Facial expression recognition based on deep convolution long short-term memory networks of double-channel weighted mixture,” Pattern Recognition Letters, vol. 131, pp. 128–134, 2020.
[66] I. Allen and J. Seaman, “Digital compass learning: distance education enrollment report 2017,” Babson Survey Research Group, Babson Park, MA, USA, 2017.
[67] P. Shea, T. Bidjerano, and J. Vickers, “Faculty attitudes toward online learning: failures and successes,” SUNY Research Network, Albany, NY, USA, 2016.
[68] D. Lederman, Conflicted Views of Technology: A Survey of Faculty Attitudes, Inside Higher Education, Washington, WA, USA, 2018.
[69] C. L. Cason and J. Stiller, “Performance outcomes of an online first aid and CPR course for laypersons,” Health Education Journal, vol. 70, no. 4, pp. 458–467, 2010.
[70] S. Maloney, M. Storr, S. Paynter, P. Morgan, and D. Ilic, “Investigating the efficacy of practical skill teaching: a pilotstudy comparing three educational methods,” Advances in Health Sciences Education, vol. 18, no. 1, pp. 71–80, 2013.
[71] E. Dolan, E. Hancock, and A. Wareing, “An evaluation of online learning to teach practical competencies in undergraduate health science students,” 'e Internet and Higher Education, vol. 24, pp. 21–25, 2015.
[72] F. D. l. Torre, W. Chu, and X. Xiong, “IntraFace,” in Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition, Lille, France, May 2015.
[73] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proceedings of the Advances in Neural Information Processing Systems, pp. 1097–1105, Lake Tahoe, Nevada, December 2012.

[74] W. Wei, B. Zhou, D. Połap, and M. Wozniak, “A regional ´ adaptive variational PDE model for computed tomography image reconstruction,” Pattern Recognition, vol. 92, pp. 64–81, 2019.

[75] L. Zhang, P. Shen, X. Peng et al., “Simultaneous enhancement and noise reduction of a single low-light image,” IET Image Processing, vol. 10, no. 11, pp. 840–847, 2016.

[76] Q. Zhu, J. Zhang, W. Wei et al., “A neuro-heuristic approach for recognition of lung diseases from X-ray images,” Expert Systems with Applications, vol. 126, pp. 218–232, 2019.

[77] C. S. Chin, J. Si, A. S. Clare, and M. Ma, “Intelligent image recognition system for marine fouling using Softmax transfer learning and deep convolutional neural networks,” Complexity, vol. 2017, Article ID 5730419, 9 pages, 2017.

[78] G. Tonguç and B. O. Ozkara, “Automatic recognition of student emotions from facial expressions during a lecture,” Computers & Education, vol. 148, Article ID 103797, 2020.

[79] Sumathy, S., Revathy, M., & Manikandan, R. (2021). Improving the state of materials in cybersecurity attack detection in 5G wireless systems using machine learning. Materials Today: Proceedings. Published. https://doi.org/10.1016/j.matpr.2021.04.171

[80] Mishra, A., Jain, H., Biswas, P., Thowseaf, S., & Manikandan, R. (2021). Integrated solution for optimal generation operation efficiency through dynamic economic dispatch on Software Technological Park of India. Materials Today: Proceedings. Published. https://doi.org/10.1016/j.matpr.2021.05.019