



INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Facial Emotion Detection

Rishabh Kumar, Prashant Kumar Sonkar

“School of Computing Science And Engineering
Galgotia’s University ,Greater Noida”

Abstract :

Facial emotions are mirrors of human thoughts and feelings. It provides a wealth of social cues to the viewer, including the focus of attention, intention, feelings, motivation, and emotion. It is regarded as a potent tool of silent communication. Study of these expressions gives a significantly more profound insight into human behavior. AI-based Facial Emotion Recognition (FER) has become one of the essential research topics in recent years, with applications in dynamic analysis, pattern recognition, mental health monitoring, and many more.

Expression on human faces have been of special use for understanding the feelings or emotions of a person and it has consistently been a simple affair for peoples, yet accomplishing a similar assignment with a AI- based technique or algorithm is very hard and testing. There are different algorithms and techniques to analyze how human emotions works, which are frequently communicated by face demeanor, could be perceived.

This paper provides a comparative study of different strategies and algorithm that have been inspected for detecting emotions on human faces. The study incorporates various forms of literary works and explores led by experts that involves numerous viewpoints identified on facial emotion detection. Such a beginning framework utilizes a rearranged technique called 'Viola Jones Face Detection' for contain of faces and further emotion classification can be achieved using different classifiers. Some other technique Utilizes convolutional neural organizations facial emotion recognition. The technique depends on two-section convolutional neural organization (CNN): initially it eliminates the image background, and the subsequent part focus on the facial component vector extraction. Computer vision has thus paved ways for expression detection through inspecting human faces through various algorithms and techniques. **Keywords—** Computer vision, Facial Emotion Recognition, Face Localization, Feature Extraction, Emotion Classification, Deep Learning, Facial Expression, Face Detection.

1. INTRODUCTION

Facial emotion detection has pulled in the consideration of numerous researchers from various fields. Exploration on

facial emotion detection comprises of outward appearances, vocal, motion and physiological sign detection, etc.

Expressions on the face are the fundamental identifiers for human sentiments, since it is compared to the feelings. In a large portion of the instances (generally in 55% cases) [1], the emotions are expressed in a nonverbal way through facial expressions, and it tends to be considered as solid proof to reveal if an individual is talking reality [32].

The emotion of an individual can be investigated to decide if an individual is fit or not for a delicate undertaking. Robots can also be provided with Facial Expression Detection (FER) capacity in order to improve their utilization. Social Networking organizations may include highlights that recommend status of the client's post relying upon emotion of the transferred photograph. Few cell phone cameras as of now have the component of catching the photograph by recognizing the smiling faces. As everything is getting computerized, so a definitive objective is to enable machines to perceive facial emotions instantly as a human can do. People can perform facial emotion detection in a simpler manner however for PC it is very troublesome. So when a picture is given, we need to recognize and then localize faces. To resolve this issue we perform segregation, feature extraction and verifying the facial emotions using the picture in background. The model utilizes information from input pictures, perceive the expression and characterize the emotion into various classes. Initial step involves discovery of the face it will discover if face show up belongs to a human or not in a target picture. Also whenever showed up discovery of where these faces are found is also clear, the subsequent stage is to extract those human-face. A vector with fixed points is formed with the help of the feature points. The extraction parts get over with subsequent step of finding the emotion communicated by the face.

Automated frameworks for detecting facial emotions need database of faces. From the database pictures are picked and their feature points are attained and stored. At the point when another picture needs to be tried, face from that pictures are obtained to extract the features, a comparison of features is done with those already present in the database and then emotion of the input face is categorized as per the comparison results.

2. FRAMEWORK

Emotion detection through facial expressions has been effectively investigated in the research field of Computer Vision. Ascending in progress, Machine Learning or ML's promotion [29] and procedural steps that pertain to the study of Deep Learning [30], the possibility to assemble insightful frameworks which is responsible to precisely perceive emotions turned into a closer reality. The complexity in detection of emotion through computer vision has increased with the advancement of fields that are straightforwardly connected with detection of emotion, for example, brain research and nervous system science etc.

Usually, a Facial Emotion detection framework comprises of

the accompanying steps to be carried out: image securing, pre-processing of the image, extracting features and classification of emotions. Figure A shows various phases involved in Facial Emotion Recognition.

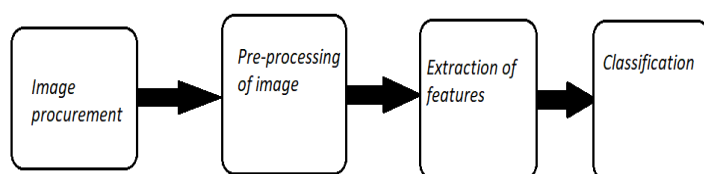


Figure A. Phases of Facial Emotion Recognition

A) Image procurement

For Facial emotion classification, images are extracted from various already present datasets or an image can be provided as an input as well, one of the popular set of such reliable image database is JAFFE i.e. Japanese Female Facial Expression. This image or picture is generally utilized to find the face in the provided image.

B) Image Pre-Processing

Preprocessing of picture is a significant advance for classification of emotions since just the central part of face, for example, nose, eyes, mouth are required for detection of the emotion portrayed by the face present in the picture. Thus localization of face in the image is done using various techniques and algorithm.

C) Extraction of features

Extracting the feature points of face is very important for face detection. Several techniques are existing for extraction of

feature points. Example include Scale Invariant Feature Transform (SIFT), Linear Discriminant Analysis (LDA) [30], Gabor wavelets [31], moments Speeded-Up Robust Features (SURF), and numerous others. Gabor Wavelets are strong and powerful against photometric unsettling influences yet gives feature vector with tremendous measurement. SURF includes just focus on the couple of most grounded features

D) Classification

There are various "random" and "natural" classifiers for classifying emotions. The most commonly used random classifiers are the K-Neighbor Neighbor (KNN) classifiers, Support Vector Machine (SVM) and Random Forest (RF). Actual purpose of this technique is to classify emotions into (fear, anger, surprise, disgust, happiness, sadness and neutrality).

3. RELATED WORK

In order to carry out facial emotion expression, characterize algorithm(s) that examine pictures in a more progressive manner are required than simply an identification to be actualized by computer system utilizing apparatuses gave or planned without anyone else. A considerate number of tools and algorithms have been created or used to achieve this purpose.

One of the studies done talks about an algorithm to achieve the detection of emotions present on the face was led by et al. [3]. Main activity taken by the framework was grouping pictures into face or nonface sections dependent on work that was done by of Viola-Jones[4]. Thereafter Haar Basis capacities were imbibed within the filters though the means of classifiers taken for utilizing highlight determination strategy that depended on Adaboost. The image was scaled again afterwards and Gabor magnitude was used for representation. Continuation of detection of the emotions on faces, the paper utilizes the Support Vector Machine (SVM) with straight and Function of radial portions for classification of facial emotions. The outcome was later contrasted with the outcomes got from Adaboost, however SVM was discovered to be quicker in preparing as opposed to Adaboost. Nonetheless, the overall execution of Adaboost was generally quicker than Simple Machine Vector (SVM). The literature likewise talks about mix of SVM (Simple Machine Vector) and Adaboost, called AdaSVM's.

The objective of the SVM is, to make the choice limit. Hyperplane is that boundary.

SVM picksthe limit vectors, that help in making the hyperplane. Support Vector Machine Algorithm is named so as it works on extreme vectors. SVM falls under the category of algorithms that are supervised machine learning algorithm, that gives examination of information to regression and characterization.

The [5] provides a strategy to automatically recognize facial images. This particular framework uses a two-dimensional Gabor wavelet representation to measure the characterization. Three sets of paintings were tested, including gender, emotion, and race as class names. Dataset contains 193 picture nine female Japanese models and their images with expressed emotions. Another dataset utilized is a picture set with 59 female and 51 male expressers.

Another work that was based on Convolutional Neural Network was carried out through efforts of et al. [6] that utilized model named as Visual Geometry Group, create and build upon Convolutional Neural Network (CNN), trained again utilizing Japanese Female Facial Expression database (JAFFE) and Cohn Kanade (CK+) database so that it foreseen the facial emotion . For obtaining the results, from an info video, et al. utilized channel based on Haar-Cascade and display faces on the screen. Thereafter analysis of appearance was done as per the layers that are five in number, associated layers that are 3 in number and they are subdued, and a classifier named as softmax. Then a creation of a forecast is done by marking facial expressions utilizing any of the 6 emotions. The outcome delivered came to over 90% exactness level for the data sources.

The use of Action Units in MLP (Multilayer Perceptron) and kNN (k-Nearest Neighbor) also helps in the perception of facial emotions. As explored in [7], the utilization of AU (six AU units) shaped with the assistance of Microsoft Kinect 3D for face demonstrating giving rise to detectable emotions dependent on the AUs' appropriations. There were two different ways performed in [7] to perceive expressions: dependent on subject - for every client one by one and free from the subjects for every candidate at the same time. The data base made use of was marked in dual disseminations: "Random" distribution was the first one and "natural" distribution was the second. Both 3-NN and MLP created

great outcomes for both subject-reliant and subject-autonomous methods of perceiving emotions, and for both

dataset appropriations, for "random" dataset the accuracy was 90% and for "natural" dataset accuracy was 70%.

[24] In case the image used as input is grayed out, the skin tone recognition algorithm will be very inaccurate. For improving accuracy while background removal is taking place a circle-by-circle filter is also being used by the CNN. The filtering method or function uses the Hough conversion value to detect each circle. The Hough transformation (Figure B) has always been utilized as the second CNN input function in order to remove the background for uniformity maintenance, without worrying about the image type being used.

4. APPROACHES

Facial Emotion Recognition basically involves two key approaches which includes explicit classifier approach and extraction. There are two key approaches one of them using explicit classifier and the other key approach works by making categorization dependent on extracted facial highlights.

A) Facial emotion detection based on Conventional Approach

In Conventional Facial Emotion detection approaches, three significant strides are used for the Facial Expression Recognition as shown in Figure C: (1) Detection of face and its components, (2) Extraction of features, and (3) expression. Initial, a picture having a face is to be recognized in the input picture, and landmark (like nose and eyes) are identified using facial area. Subsequently, the segments faces are extracted with various temporal and spatial features. Finally, the Facial Expression classifiers that already kept ready, for example, a support vector machine (SVM), AdaBoost, and irregular woods, after utilizing the extracted features generate the Results.

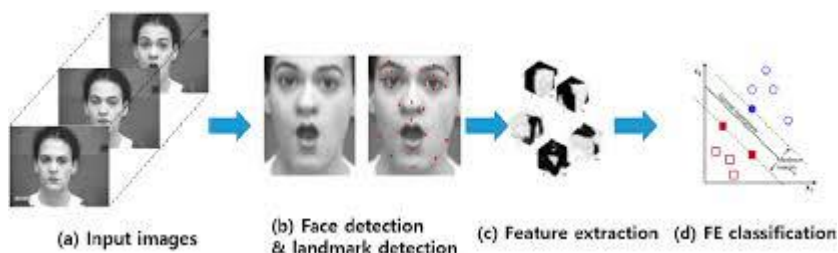


Figure C.[33] Steps involved in facial emotion detection

Using the input pictures (a) the face area and landmarks on the face are recognized (b) from the face parts and landmarks temporal as well as spatial features are extricated (c) and emotion on the face is resolved dependent any one from facial classifications utilizing already prepared pattern classifiers face pictures are taken from (CK+).

The main characteristic of this approach is recognizing the face area extraction of geometric features, facial highlights, or a mix of both on the input face.

Ghimire and Lee [15] utilized two sorts of geometric highlights dependent on the position and point of 52 facial landmark points. For the classifier, following strategies came to be introduced, either utilizing AdaBoost (multi-class) with examining two temporal sequences for similarity which may differ due to speed, or utilizing a Support Vector Machine on the advanced highlight vectors.

The global areas of face [16] or distinctive face areas are liable for extraction of appearance highlights [17,18]. To act as an illustration for global face region, a local binary fold was used by Happy et al. [16] for example (LBP) histogram having feature vector from different sizes of blocks from a region that is global, and facial emotions were characterized utilizing a principal component analysis (PCA).

Then et al. [19] focused on area explicit visible traits from isolating complete region of the face in the form of regions that are space explicit regions and are local. Significant local regions are resolved utilizing an incremental search approach, which brings about a decrease in dimensions of the features and an accuracy improvement.

In case of hybrid features, a few methodologies [20,19] have consolidated geometrical and appearance highlights to supplement the shortcomings of the two methodologies and give far superior outcomes in specific cases.

Sujono and Gunawan [34] made use of the Kinect motion sensor to distinguish face regions dependent on active appearance model (AAM) and information about the depth to find emotion of the identified face.

The Active Appearance Model, as requires a mix of measurable shape and surface models to frame a joined appearance model. This consolidated appearance model is then prepared with a bunch of model pictures. Subsequent to preparing the model, new pictures can be deciphered utilizing the Active Appearance Search Algorithm. The Algorithm permits us to discover the parameters of the model, which create a manufactured picture as close as conceivable to a specific objective picture. The operation performed by AAM includes fitting the shape as well as surface model in another picture having a face, as there are number of variety for shape

and surface contrasted with preparation result.

Classifiers are marked by the Conventional approaches and features by specialists. For extraction of features, some notable features that are handcrafted, for example, HoG, LBP, distance are utilized and the classifiers which are pre-trained, for example, Random Forest, SVM, and AdaBoost, are likewise utilized for Facial Emotion detection.

Generally lower Computation power and memory is required by the Conventional approaches as compared to deep learning Approach.

B) Facial emotion recognition Approach based on Deep Learning

Facial Emotion Recognition approaches based on Deep learning exceptionally diminish the reliance on face-material science oriented framework and other strategies that are planned from before by empowering a method of learning that is from "start-to-end" learning to happen in the line straightforwardly using the information pictures [21].

In approach based on utilizing CNN, the picture used as input with the help of convolution layers having filters is convolved to create an map of features which is then joined to completely

associated links, and the facial emotions are perceived like a part of specific category dependent on the softmax algorithm's output.

Deep learning with CNNs consistently requires enormous number of preparing pictures to acquire great classification results. So prior to preparing the CNN model, we need to augment the dataset with different changes for generate different little changes in appearances and stances.

It is a sort of Feed forward neural organization architecture. It has Collection of little neurons in different layers that cycle the information picture in divisions called as the receptive fields. The yield of these collections is lined so that there is a covering of the input areas that gives near perfect portrayal of the first information picture. The cycle is carried out for every one of the layers.

The principle benefit of CNN is that the counter of parameters is less when contrasted with other networks having similar number of hidden units.

The system of Convolutional Neural Network (CNN) depend approach, as appeared in figure D :

(A) Convolution layer filters help is convolving the input image.

(B) From the result of the convolution, an object map is created, and the layer with the largest aggregation reduces the

spatial resolution of the specified object map.

(C) Convolutional Neural Network (CNN) applies a completely connected neural network layer .

(D) Facial emotions are detected according to the softmax algorithm.

Deep learning techniques to perform facial emotion

classification also incorporate CNN hybrid known as CNN-LSTM based (CNN-Long Short-Term Memory) strategy.

LSTM is an exceptional kind of RNN (Recurrent Neural Network) that has a chain-like construction in spite of the modules that repeat sharing an alternate design.

A Recurrent Neural Network (RNN) is a type of neural network in which the results of the previous step are treated as a contribution to current progress.

The RNN has a "memory" that recalls all the data for the specified content. Use similar parameters for each contribution to perform similar tasks and provide yields for all sources or covered layers. This reduces the complexity of the parameters, unlike other neural networks.

Three distinctive online media datasets are utilized to try the proposed model and it is seen that proposed RNN model accomplish enhanced classification as well as detection of 95% which is obviously superior to conventional neural networks [34].

CNN can't reflect variations that change with time in facial segments. This disadvantage is solved by the hybrid strategy, CNN-LSTM. The LSTM model itself is direct in tuning with different models, and it underpins both fixed-and variable length data sources and outputs.

In ongoing many years, Algorithms and techniques of deep learning implied and made use of for enhancement in sector computer vision, such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), have advanced. These approaches are based on in-depth learning and are used for classification, trait extraction, and detection of emotion.

5. DATASET

The database helps build facial emotion recognition systems that can produce results that are even more contrasting with related works. Scientists working in the field of recognizing facial emotions have various databases. Most databases are based on 2D still images. There are some basic emotions that are categorized by databases namely (happiness, disgust, fear, sadness, surprise, and anger) additionally the neutral expression. Some databases for recognizing facial emotions

are control-based, while others are in uncontrolled or wild-based conditions. In addition, several information-based subjects for recognizing facial emotions have been approached to represent the emotions of a particular reference, while others attempted to animate unconstrained and real facial emotions. Some of the major dataset used for facial emotion recognition are as follows:

A)(CK) The Extended Cohn–Kanade information base [8] (CK+)The E:

A collection of 593 picture arrangements of presented and non-presented emotions are present in it. The 123 candidates were between the ages of 18 and 50, 69% were women, 81% were European Americans, 13% were African Americans, and 6% were diverse gatherings. The photos are digitized at a resolution of 640 x 490 or 640 x 480 and are usually gray. Each arrangement is based on a frontal perspective and a 30 degree perspective, starting with an expression that rises from neutral to the peak (final frame or sequences' last frame). Mostly there are eight emotions with which each sequence is marked: neutrality, anger, happiness, sadness, surprise, fear, disgust and contempt.

B) Facial Expression Recognition database 2013 [10] :

Created with Google's image search API to search for photos of people that coordinate a bunch of 184 emotions related to terms such as "happiness" , "madness" and so on. These terms, combined with words identified by age, gender, and nationality, resulted in a grayscale image of 35,887 with a resolution of 48 x 48 planned for six major emotions, in addition to neutral Emotions.

C) JAFFE:

The Japanese Female Facial Expression database [9]: This dataset has a collection of 213 images of six fundamental feelings, in addition to the neutral emotion presented by 10 Japanese female models. 60 Japanese subjects have labelled each of these of images.

D) Karolinska Directed Emotional Faces database [13]:

Includes a set of 4900 photographs depicting the emotions of the human face. This set includes 70 consisting of half men and half women, showing six basic emotions and including neutral expressions. Every emotion is seen from five distinct angles and was captured in two meetings.

E) Emotion Recognition in the Wild database [11]: It contain two sub-data sets which are Acted Facial Expression in the Wild (AFEW) and Static Facial Expression in the Wild (SFEW). SFEW holds static pictures and AFEW holds

recordings (image sequence including audio). This information base is based on six basic emotions, in addition to neutral emotions, with an image size of 128 x 128.

F) MMI information dataset [12]:

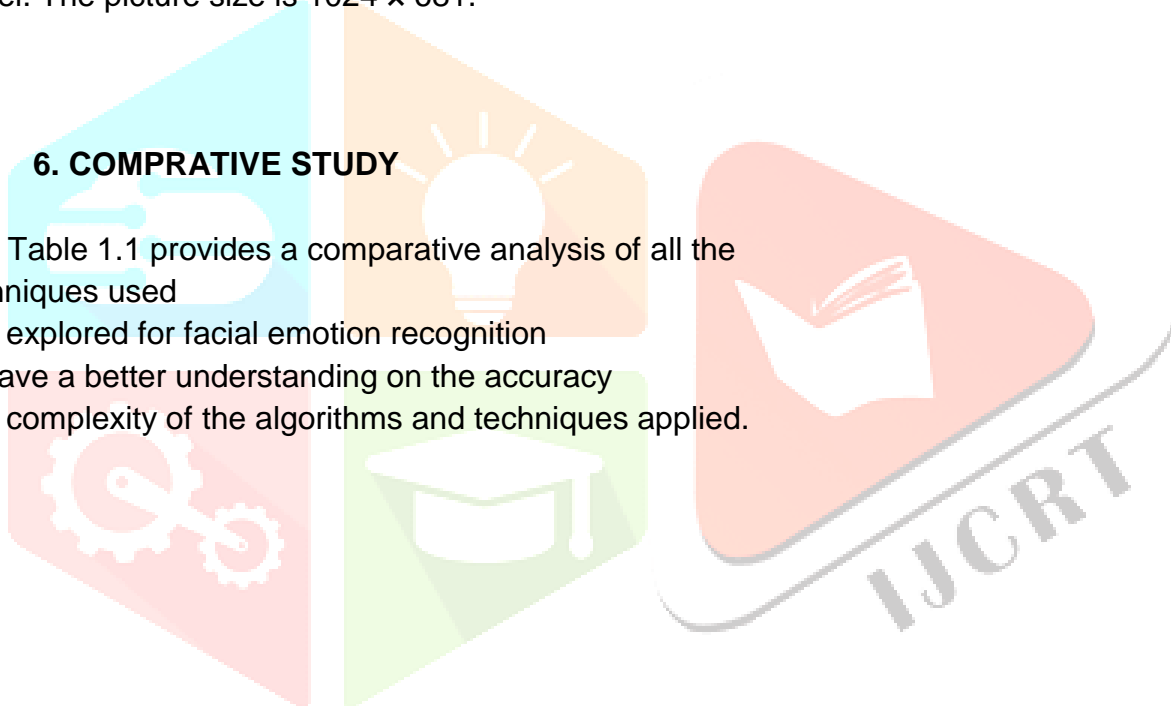
The MMI contains over 2900 recordings and high resolution still images from 75 subjects. It is fully clarified about the presence of AUs in the video, and each frame indicates whether the AU is in the neutral, early, peak, or offset phase. The dataset is based on six emotions: happiness, disgust, surprise, anger, sadness and fear.

G) Radboud Faces Database [14]:

RaFD has a set of 67 model photos showing eight enthusiastic expressions: happiness, surprise, disgust, anger, contempt, sadness, fear and neutrality; adding up to 120 pictures for each model. The picture size is 1024 x 681.

6. COMPRATIVE STUDY

The Table 1.1 provides a comparative analysis of all the techniques used and explored for facial emotion recognition to have a better understanding on the accuracy and complexity of the algorithms and techniques applied.



S.N O	Years	Approaches	Emotions Analyzed	Dataset	Feayures (Models)	FER Classifier
1.	[22] 2017	Conventional FER	Happiness, Anger, Disgust, Sadness, Surprise, Fear and Neutral	JAFEE	Face Localization - Viola Jones Face Detection Feature Extraction - ZernikeMoment s LBP, DCT	SVM KNN Random Forest
2.	[23] 2015	Deep Learning	Happiness, Anger, Disgust, Sadness, Surprise, Fear and Neutral	candid image facial expression (CIFE) dataset	Viola face detector to detect faces from the candid datasets. For Data Augmentation, five image appearance filters and six affine transform matrices are used	CNN Based Approach Input layer - 1 Hidden Layer - 3 Output Layer - 1
3.	[24] 2020	CNN	Anger, Sad, Happy, Fear, and Surprised	Caltech faces (CF), CMU and NIST datasets	Skin tone detection Algorithm and circles-in- circle filter is applied to extract human body parts from the image or for Background Removal.	CNN (divided into 2 levels : Background removal CNN and face feature extraction CNN)

4.	[25] 2018	ROI based Conventional FER	Happiness, Anger, Disgust, Sadness, Surprise, Fear and Neutral	JAFFE, CK+, RaFD	Preprocessing - Viola Jones Face Detection Method with resizing on grayscale images. Image Segmentation - Right eye, left eye, nose and mouth are four segmented facial parts. Feature Extraction - using a fusion of HOG and LBP features.	ANN as the classifier
5.	[26] 2017	Deep Learning based FER	Happiness, Anger, Disgust, Sadness, Surprise, Fear and Neutral	Collected their own dataset by experimenting on 6 subjects aged 26-50.	Six Action Units (AU) are produced by Kinect device derived	3-NN (nearest neighbor classifier) and MLP (2-layer neural network classifier)
6.	[27] 2011	ROI based Conventional FER	Happiness, Anger, Sadness, and Neutral	JAFFE	Preprocessing - facial feature acquisition and face normalization on grayscale images. Using FACS, the regions of the face (eyebrows, both mouth and eyes) were cropped from image. Feature Extraction - Pattern tracking Algorithm	Optical Flow Based Analysis to detect emotions

7.	[35] 2014	AAM based Conventional Approach	Happiness, Anger, Disgust, Sadness, Surprise, Fear and Neutral	JAFFE and Yale database	Active Appearance Model (AAM) is used for facial regions extraction. Facial features are extracted using Gabor Wavelet transformation.	SVM
8.	[36] 2018	Conventional Approach with Neural Network as a Classifier	Happiness, Anger, Disgust, Sadness, Surprise, Fear	JAFFE database	A Haar Cascades method is used to detect face, as the basis for the extraction of eyes and mouth. The detection of filters and edges is performed using the Sobel edge detection method (SEDM), followed by the extraction of the features.	Neural Network
9.	[37] 2020	CNN	Happiness, Anger, Disgust, Sadness, Surprise, Fear	CK+,JAFFE, ISED, MMI, MUG	Viola face detector to detect faces from the datasets. CNN Feature Extraction	SVM (used with LibLinear function)

10.	[38] 2003	FaceExpr ession Recognition via Linear Program ming	Neutral, Happy, Sad, Surprise, Anger, Disgust, and Fear	JAFFE	Features are selected using Concave Minimization (FSV).	Gabor wavelet to detect expressions
-----	-----------	--	---	-------	---	---

7. Conclusion

Ten papers have been mentioned in the comparison table, stating the algorithms and tools used in these papers for performing emotion detection by having Support Vector Machine, Random Forest and other classifiers based on neural networks and optical flow based analysis.

Emotions detection with two 4-layer CNN networks (FERC) is distinctive, as it focuses on background removal and face expression detection separately. While it reduces complexity and the tuning time, but misclassified disgust and neutral mood as being the only FERC network with keyframe extraction. FER with hybrid CNN-LSTM (RNN) outmatch previous CNN approaches by providing temporal variations but requires large dataset and heavy computing capacity. Action units(AU) with MLP and k-NN gives a sequential but time costly approach, and minor variation could lead to accuracy reduction.

In recent times, effectiveness of emotion detection has improved by the support of algorithms based on deep-learning. It has faced challenges of deviance, lighting and orientation problems but various studies on its future application shall continue with tuning deep learning methods to achieve significant results as well as lower computational complexity.

REFERENCES

- [1] Mehrabian A Nonverbal communication. Routledge, London, 2017.
- [2] In: Esposito A, Bourbakis NG, Avouris N, Hatzilygeroudis I (eds) Verbal and nonverbal features of human–human and human–machine interaction. Springer, Berlin, pp 1–20.
- [3] M. S. Bartlett, G. Littlewort, I. Fasel and J. R. Movellan, "real time face detection and facial expression recognition: development and applications to human computer interaction," Computer Vision and Pattern Recognition Workshop, vol. 5, July 2003.
- [4] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001, Kauai, HI, USA, 2001, pp. I-I, doi: 10.1109/CVPR.2001.990517.
- [5] Lyons, Michael J., Julien Budynek, and Shigeru Akamatsu. "Automatic classification of single facial images," IEEE Transactions on Pattern Analysis & Machine Intelligence.
- [6] D. Duncan, G. Shine and C. English, "facial emotion recognition in real time," 2016.
- [7] P. Tarnowski, M. Kołodziej, A. Majkowski and R. J. Rak, "Emotion recognition using facial expressions," Procedia Computer Science, vol. 108C, pp. 1175–1184, 12-14 June 2017.
- [8] Lucey, P.; Cohn, J.F.; Kanade, T.; Saragih, J.; Ambadar, Z.; Matthews, I. The extended cohn-kanade dataset (ck+): 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, San Francisco, CA, USA, 13–18 June 2010; pp. 94–101, doi:10.1109/CVPRW.2010.5543262. [9] Lyons, M.J.; Akamatsu, S.; Kamachi, M.; Gyoba, J.; Budynek, J. The Japanese female facial expression (JAFFE) database. In Proceedings of the Third International Conference on Automatic Face And Gesture Recognition, Nara, Japan, 14–16 April 1998; pp. 14–16, doi:10.5281/zenodo.3451524.
- [10] Goodfellow, I.J.; Erhan, D.; Carrier, P.L.; Courville, A.; Mirza, M.; Hamner, B.; Cukierski, W.; Tang, Y.; Thaler, D.; Lee, D.H.; et al. Challenges in representation learning: A report on three machine learning contests. In International Conference on Neural Information Processing; Springer: Berlin, Germany, 2013; pp. 117–124, doi:10.1007/978-3-642-42051-1_16.
- [11] Dhall, A.; Ramana Murthy, O.; Goecke, R.; Joshi, J.; Gedeon, T. Video and image based emotion recognition challenges in the wild: Emotiw 2015. In Proceedings of the 2015 ACM on International Conference On Multimodal Interaction, Seattle, WA, USA, 9–13 November 2015; ACM: New York, NY, USA, 2015; pp. 423–426, doi:10.1145/2818346.2829994.
- [12] Pantic, M.; Valstar, M.; Rademaker, R.; Maat, L. Web-based database for facial expression analysis. In Proceedings of the 2005 IEEE International Conference on Multimedia and Expo, Amsterdam, Netherlands, 6 July 2005; pp. 5–pp, doi:10.1109/ICME.2005.1521424.
- [13] Calvo, M.G.; Lundqvist, D. Facial expressions of emotion (KDEF): Identification under different display-duration conditions. Behav. Res. Methods 2008, 40, 109–115, doi:10.3758/BRM.40.1.109.

- [14] 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.* 2010, 24, 1377–1388, doi:10.1080/02699930903485076.
- [15] Ghimire, D.; Lee, J. Geometric feature-based facial expression recognition in image sequences using multi-class AdaBoost and support vector machines. *Sensors* 2013, 13, 7714–7734. [CrossRef] [PubMed].
- [16] Happy, S.L.; George, A.; Routray, A. A real time facial expression classification system using local binary patterns. In *Proceedings of the 4th International Conference on Intelligent Human Computer Interaction*, Kharagpur, India, 27–29 December 2012; pp. 1–5.
- [17] Siddiqi, M.H.; Ali, R.; Khan, A.M.; Park, Y.T.; Lee, S. Human facial expression recognition using stepwise linear discriminant analysis and hidden conditional random fields. *IEEE Trans. Image Proc.* 2015, 24, 1386–1398. [CrossRef] [PubMed]
- [18] Khan, R.A.; Meyer, A.; Konik, H.; Bouakaz, S. Framework for reliable, real-time facial expression recognition for low resolution images. *Pattern Recognit. Lett.* 2013, 34, 1159–1168. [CrossRef]
- [19] Ghimire, D.; Jeong, S.; Lee, J.; Park, S.H. Facial expression recognition based on local region specific features and support vector machines. *Multimed. Tools Appl.* 2017, 76, 7803–7821. [CrossRef].
- [20] Benitez-Quiroz, C.F.; Srinivasan, R.; Martinez, A.M. EmotioNet: An accurate, real-time algorithm for the automatic annotation of a million facial expressions in the wild. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, NV, USA, 26 June–1 July 2016; pp. 5562–5570.
- [21] Walecki, R., Rudovic, O., Pavlovic, V., Schuller, B. and Pantic, M., Deep structured learning for facial expression intensity estimation. *Image Vis. Comput.* 2017, 259, pp.143-154.
- [22] Jayalekshmi J, Mathew T. Facial expression recognition and emotion classification system for sentiment analysis. In *International Conference on Networks & Advances in Computational Technologies (NetACT)*, 20 July 2017 (pp. 1-8). IEEE.
- [23] Li W, Li M, Su Z, Zhu Z. A deep-learning approach to facial expression recognition with candid images. In *14th IAPR International Conference on Machine Vision Applications (MVA)*, 18 May 2015 (pp. 279-282). IEEE.
- [24] Mehendale N. Facial emotion recognition using convolutional neural networks (FERC). *SN Applied Sciences*, Mar 2020, 2(3), 1-8.
- [25] Islam B, Mahmud F, Hossain A, Goala PB, Mia MS. A facial region segmentation based approach to recognize human emotion using fusion of HOG & LBP features and artificial neural network. In *4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEICT)* 2018 Sep 13 (pp. 642-646). IEEE.
- [26] Tarnowski P, Kolodziej M, Majkowski A, Rak RJ. Emotion recognition using facial expressions. In *ICCS* 12-14 June 2017 (pp. 1175-1184).

- [27] Singh G, Singh B. Feature based method for human facial emotion detection using optical flow based analysis. An International Journal of Engineering Sciences. 2011, 4, 363-72.
- [28] Bishop, C.M. Pattern Recognition and Machine Learning; Springer: New York, NY, USA, 2006.
- [29] LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 436, doi:10.1038/nature14539.
- [30] Chao, Wei-Lun. "Face Recognition". GICE, National Taiwan University(2007).

