

Facial Emotion Recognition: A Survey

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Abstract: This paper describes different techniques in Facial Emotion Recognition. Face is a complex three-dimensional visual model and developing a computational solution for face recognition is a complicated task. Face recognition provides a challenging problem and as such has acquired a terrific deal of interest over the previous few years due to its applications in diverse domains. The step one in face recognition is face detection. Face detection used with face recognition strategies have a huge variety of applications. One of which is Emotion Detection. In Face detection we will be discussing viola-jones algorithm, multitask cascaded convolutional neural network (CNN) and R-CNN. Then further in face recognition we have four best holistic (Linear) approaches, viz Eigenfaces, Fisherfaces, Marginfaces, Laplacianfaces etc. further in final stage (Emotion detection) we have methods based on CNN and Histogram of oriented gradients (HOG) such as Alexnet CNN, Affdex CNN and HOG-ESRs Algorithm. Also we Image datasets such as CK+, JAFFE, FER2013 etc.

Keywords: Face detection, Face Recognition, Emotion detection, FER, Deep learning, Survey

1. Introduction

Facial expression is one amongst the foremost powerful, natural and established alerts for persons to convey their emotional states and intention.

Given image or still or video or sequence images of a scene, verify one person in the scene using a stored dataset of facial images. available facial information such as hair, age, gender, facial expression and speech can be used in enhancing the search recognition of one.

The solution of the problem needs segmentation of faces (face detection), feature extraction/removal from facial area or verification problems. The input into the system is an anonymous face and the system reports a limited id from a database of known people.

FER is a process in which the algorithm detects the type of emotion that the user has. These emotions can be Happy, sad, normal, etc. There are different types of algorithms to recognize the emotion of a user. There are 10 different methods to recognize which type of emotion it is. It either can be recognized by movements of hands or by the displacements of eyebrows. Emotion plays a very vital role in psychological aspects. Effective emotion recognition techniques will be very useful in Human Computer

Interaction and Affective computing. Emotion recognition can be applied in many areas. Emotion detection will help to improve product and services by monitoring customer behavior. In the psychological aspect emotions play a vital role so this technique helps to handle such cases.

2. Face Detection

Face detection is an object detection technique in the computer vision domain. This technology is used to find and identify human faces based on digital image or video input. It requires a number of mathematical algorithms, pattern recognition, and image processing to achieve the desired result. The various steps in the algorithm include looking for an area of the face, then performing additional tests to confirm a human face. After that algorithms are trained on large data sets to ensure high precision.

However, there are difficulties in Face detection due to some issues related to pose, expression, position and orientation, skin color and pixel values, the presence of facial hair, varying lighting conditions and different image resolutions.

Number of deep learning methods have been developed as possible solutions to the above problems.

2.1 Methods of Face detection

Knowledge-based, feature-based, template matching or appearance-based are some of the types of face detection methods.

Feature-based algorithms have been used widely from many years.

2.1.1 The Viola-Jones Algorithm

The most successful example of a Face detection algorithm is the cascade classifier. It was first presented by Paul Viola and Michael Jones. It was described in their 2001 paper, [1] "Rapid Object Detection using Boosted Cascade of Simple Features". This technique is still in use and has been very successful. They have raised the framework for real-time face detection by presenting a novel image known as an integral image and creating a boosted cascade of weak Haar-like feature classifiers.

This algorithm defines a box and searches the face inside that box. In small steps, the number of boxes detecting Haar-like

features and data for all those boxes combined, helps the algorithm to detect where the face is.

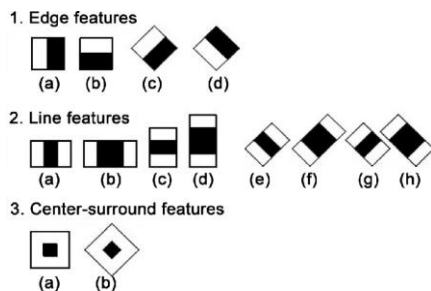


Fig. 1 Haar-like Features for Viola-Jones algorithm

Although the Viola-Jones framework is still very much successful and very commonly used in face-to-face applications for real-time applications, it has its limitations. For example, it may not work if the face is covered with a mask or scarf, or if there is no proper alignment, the algorithm may fail to detect it. Other algorithms-like [2]convolutional neural networks (R-CNN), have been developed to overcome these problems.

2.1.2 Deep Learning Methods

These techniques are centered on how a computer will automatically learn the pattern of the target object. The main process will focus on the Convolutional Neural Network (CNN) and the Object Proposal Mechanism.

Multi-Task Cascaded Convolutional Neural Network:

One of the most widely used deep learning methods is called the “Multi-Task Cascaded Convolutional Neural Network”, with 3 stages of CNN.

This approach was proposed by Kaipeng Zhang et al. in their paper ‘Joint Face Detection and Alignment using Multi-task Cascaded Convolutional Networks’ [3].

They proposed a new framework with three stages of facial recognition and simultaneous marking. In the first phase, it will raise a few windows for immediate appointment via shallow CNN. After that, the second network will clear the windows to reject a large number of stainless windows via sophisticated CNN and lastly, it uses the more powerful CNN to refine the results and output facial landmarks positions.

This technique achieves higher accuracy over the other techniques on the Fddb and WIDER FACE benchmark for face detection.

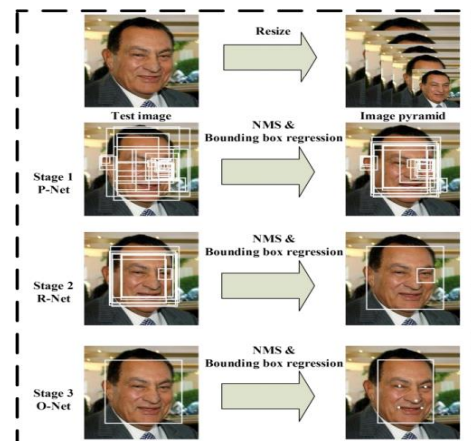


Fig. 2 Three-stage multi-task deep convolutional network

R-CNN for object detection:

In recent years researchers have applied faster R-CNN ,which is one of the state-of-art methods for generic object detection and has achieved promising results.

The original paper “Rich feature hierarchies for accurate object detection and semantic segmentation” [2] describes one of the first phases of CNN's use in 'R-CNN' that had the highest detection performance than other popular methods at the time.

Fast R-CNN for object detection:

Fast R-CNN for object detection was presented by Ross Girshick in his paper "Fast R-CNN" in 2015. This paper suggested a fast region-based approach [4]. Fast R-CNN builds on past work to effectively differentiate object proposals using deep convolutional networks. Compared to previous work, Fast R-CNN [4] uses many new methods to improve training speed and testing while also increasing the accuracy of detection.

Faster R-CNN for Object detection:

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun in their paper “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks” [5], proposed a discovery pipeline that uses RPN as a regional algorithm, and Fast R-CNN as a detector network.

Faster R-CNN [5] takes less computation time than both R-CNN [2] and Fast R-CNN [4], as it uses another convolutional network (RPN) to produce regional proposals.

The Faster R-CNN [5] has achieved impressive results on various object detection benchmarks.

Faster R-CNN for Face detection:

This paper published by Huaizu Jiang and Erik Learned-Miller [6] reports higher accuracy results on two Fddb and IJB-A

benchmarks when Faster R-CNN is trained on a large scale of WIDER facial data.

3. Face Recognition

Face recognition deals with Computer Vision technique, a discipline of AI and uses methods of image processing and Machine learning and Deep learning. When a Face is detected by a face detection algorithm it is then recognized / identified by Face Recognition System. Its output is whether the face is known or unknown. FR (Face Recognition) techniques can be divided into three categories :1) Local Approaches 2) Holistic Approaches 3) Hybrid Approaches. The most promising studies in the face recognition field are state of the art face detection techniques, approaches, viz. Marginface, Eigenface, Fisherface, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Elastic Bunch Graph Matching, Gabor Wavelets, Hidden Markov Models and 3D morphable Model. [10]

Various applications of FR:

- Person Recognition/Identification
- Human Computer Interaction (HCI)
- Security and Surveillance Camera Systems

Linear Transformation (Holistic) Approaches

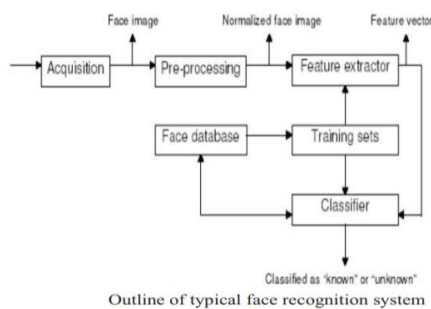


Fig. 3 Outline of Face recognition system

3.1 Eigenfaces

A set of eigenfaces will be generated by activity, a mathematical operation referred to as principal element analysis (PCA) on an outsized set of picture portraits of different human faces. This technique was developed by Sirovich and Kirby (1987). Informally, eigenfaces may be thought-about a collection of "standardized face ingredients", derived from applied math (statistics) analysis of the many images of human faces.

The tests conducted on numerous subjects in different environments shows that this approach has limitations over

the variations in light source, size and head orientation, nevertheless this methodology showed excellent classifications of faces(>85% success rate). a loud (noisy) image or partly occluded face would cause recognition low performance.[11]

3.2 Fisherfaces

In 1997, Belhumeur introduced the fisherface method for face recognition. When Eigenfaces were created with Linear Discriminant Analysis (LDA), New sets of vectors were formed, known as "Fisher Faces". Fisher faces exceeded the results, but still have some drawbacks. [12]

3.3 Laplacianfaces

This technique uses the output of the Eigenface algorithm as a source dataset. The goal of the LaplacianFace approach is to search out the transformation that preserves the native information in contrast to PCA that protects the structure of the image space. In other words, Eigen faces that are created with Locality Preserving Projections (LPP), are laplacianfaces. It was developed by Xiaofei He et al.(2005). It creates a face subspace which explicitly considers the face manifold structure. it has Better discriminating power than PCA. It reduces the dimension of the image space. [13]

3.4 Marginfaces

Marginface is a technique that uses the famous Average Neighborhood Margin Maximization (ANMM) algorithm. It was developed by Fei Wang(2009). The images are mapped into a face topological space (subspace) for analysis. completely different from PCA and LDA that effectively see solely the global euclidean structure of face space, ANMM aims at discriminating face pictures of various people supported by local information. Moreover, for every face image, it pulls the neighboring images of identical person towards it as close to as potential, whereas at the same time pushing the neighboring pictures of different people away from it as far as possible.[14]

3.5 Comparison

Table 1 Average and extreme false rejection and false acceptance rates [15]

	Eigen	Fisher	Laplacian	Laplacian+LDA	Margin (4,10)	Euclidean
FAR (%)	8.03	1.28	8.03	1.17	12.25	0.49
FRR (%)	14.22	30.30	14.22	28.53	14.34	19.32
max FAR	46.07	11.24	46.07	13.05	78.83	8.52
min FAR	0	0	0	0	0	0
max FRR	91.43	92.54	91.43	92.54	92.42	92.42
min FRR	0	0	0	1.52	0	0

From results we can say four well-known techniques of linear transformations within the context of the face verification task are precise with apx. 92% accuracy. [15]

4. Emotion Detection

Emotion recognition has application in varied fields like drugs (rehabilitation, therapy, counseling, etc.), e-learning, diversion, feeling observance, marketing, law. Totally different algorithms for feeling recognition embrace feature extraction and classification supported physiological signals, facial expressions, body movements. Nowadays, deep learning may be a technique that takes place in several computer vision connected applications and studies, whereas it's place within the following is totally on content based mostly image retrieval, there's still area for improvement by using it in numerous computer vision applications.

4.1 Methods Of Facial Emotion detection

So we classified methods of Facial Emotion Detection Techniques in 2 major types i.e Using Convolutional Neural Network (CNN) and Using Histogram Oriented Gradients(HOG).In this study, we aimed to understand CNN

Fig. 4 different Face Detection Methods

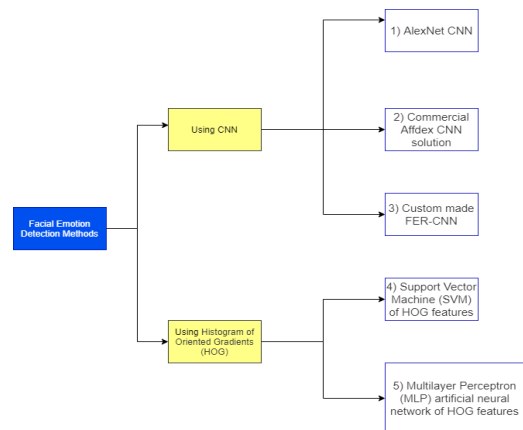
and HOG. Based methods in order to find the most optimistic and affordable method for Facial Emotion Detection. Further, we've got classified these two major sorts into their subtypes that essentially area unit the ways that area unit used wide for Facial feeling Detection on completely different occasions. We have compared 3 deep-learning approaches supported convolutional neural networks (CNN) and 2 standard approaches for classification of bar chart of directed Gradients (HOG) features: 1) AlexNet CNN, 2) industrial

Affdex CNN answer, 3) custom created FER-CNN, 4) Support Vector Machine (SVM) of HOG options, 5) Multilayer Perceptron (MLP) artificial neural network of HOG options.

4.1.1 Using CNN

AlexNet CNN

In recent years, facial emotion recognition (FER) has become a prevailing analysis topic because it is often applied in numerous areas. The present FER approaches embody handcrafted feature-based ways (HCF) and deep learning ways (DL). HCF ways trust however sensible the manual feature extractor will perform. The manually extracted options are also exposed to bias because it depends on the researcher's previous information of the domain. In distinction, DL methods, particularly Convolutional Neural Network (CNN), are sensible at activity image classification. The downfall of deciliter ways is that they need in depth knowledge to coach and perform recognition with efficiency. Hence, we have a tendency to propose a deep learning technique supporting transfer



learning of pre-trained AlexNet design for FER. We have a tendency to perform full model fine standardization on the Alexnet, that was antecedently trained on the Imagenet dataset, victimization feeling datasets. The projected model is trained and tested on 2 widely used face expression datasets, particularly extended Cohn-Kanade (CK+) dataset and FER dataset. The projected framework outperforms the present progressive ways in facial feeling recognition by achieving the accuracy of ninety nine.44% and 70.52% for the CK+ dataset and also the FER dataset.

Commercial Affdex CNN

Affdex CNN solution is a commercial solution. In the commercial space, Affectiva is a company that develops emotion measurement technology and offers it as a service for other companies to use in their products. Their core product is the AFFDEX algorithm, that is used in Affectiva's AFFDEX SDK, which is available for purchase on their website. It is mainly meant for market research, but it is also used in

other environments, such as the automotive industry to monitor emotions and reactions of a driver.

Also, AFFDEX has a high accuracy in detecting "key emotions", more precisely in the "high 90th percentile".[16]

As the AFFDEX SDK is a commercial solution, it is not easily accessible and has a price point of 25000 USD [17] (visited on Aug. 31, 2019). Therefore, this SDK is not the ideal solution for this research project and other solutions must be considered.

Custom Made FER-CNN

Custom made FER CNN solutions are the solutions that are based on FER(Facial Emotion Recognition) Datasets. These solutions are basically the methods which are used in models which are trained using the FER Datasets. Facial Expression Detection subsystem uses FER2013 [23] dataset which is an open source dataset consisting of 48x48 pixel grayscale images. This dataset has 35,887 images, with 7 emotions labeled as (1) happy, (2) neutral, (3) angry, (4) sad, (5) surprise, (6) disgust, (7) fear. In this dataset 32,298 images are used for training and the remaining 3,589 are used for testing.

The training dataset is a csv file consisting of an image in pixels (where each pixel varies from 0 - 255) along with a label indicating the emotion of the person in the image. The first 32,298 images are used to train the model. The remaining 3587 images are used for testing. The confusion matrix is found as shown in Table.

The trained model was used to test against 3,589 images for emotion classification in real-time and its results are shown in Paper.[22]

Table 2 the confusion matrix for various emotions

Target Class	Predicted class							Accuracy (%)
	Angry	Disgust	Fear	Happy	Sad	Surprise	Neutral	
Angry	0.58	0.01	0.11	0.03	0.14	0.02	0.11	58
Disgust	0.24	0.64	0.04	0.04	0.01	0.02	0.01	64
Fear	0.13	0.01	0.42	0.05	0.18	0.12	0.09	42

Happy	0.02	0.00	0.02	0.87	0.03	0.02	0.04	87
Sad	0.11	0.01	0.09	0.05	0.51	0.01	0.22	21
Surprise	0.02	0.00	0.13	0.06	0.02	0.74	0.03	74
Neutral	0.04	0.01	0.05	0.06	0.13	0.02	0.69	69

In Table 1, the confusion matrix for various emotions have been shown. The matrix shows the comparison of actual values with the predicted values for each emotion. The matrix shows that angry and sad are confused with a probability of 0.14. Similarly surprise and fear are also confused with a probability of 0.13. The diagonal values give us the accuracy of predicting various emotions. The highest accuracy is that of happiness with an accuracy of 87%. The least accurately detected emotion is fear with an accuracy of 42%.

Overall Accuracy=Number of correct predictions/Total number of predictions

$$= \frac{286+35+223+766+300+309+4313589}{100}$$

$$= 65.48\%$$

HOG 4.1.2 Using HOG

HOG is a descriptor that is used in detection of objects. It counts occurrences of gradient orientations in confined portions of an image. It is also useful to understand the changes in facial muscles by method of edge analysis.

HOG feature implementation process :

HOG with SVM classifier :

Fig. 5 Steps in HOG with SVM

1. In a 2014 paper entitled "Facial Expression Recognition based on the Facial Components Detection and HOG Features" they suggested an effective approach to facial emotion recognition problems. They have proposed a plan that includes three activities. The first task was to find the face and get the facial features. The second function used HOG to encode those parts. The final task was to train the SVM Classifier. The proposed method was tested on the JAFFE database and the extended Cohn-Kanade database. The average classification rate on the two datasets reached 94.3% and 88.7%, respectively.[24]

2. Similar method was proposed in a 2019 paper titled "Robust face recognition system using HOG features and SVM classifier" They used 500 images of 10 persons of age ranging from 20-30 years. Images were captured in different lighting conditions. For training, 50 images of every person were collected and testing was performed on 2 different images of each person and the accuracy of this experiment came around 92%.[25]

HOG-ESRs algorithm :

Another efficient method is proposed in a 2021 paper titled "HOG-ESRs Face Emotion Recognition Algorithm Based on HOG Feature and ESRs Method". They have combined HOG features with ensembles with shared representations (ESRs) methods. Combining ESRs with HOG has improved the accuracy and robustness of the algorithm. The results of the experiments on the FER2013 dataset showed that the new algorithm can efficiently extract features and decrease the residual generalization error. The accuracy of HOG-ESRs method on CK+, JAFFE and FER2013 datasets on an average was around 88.3%, 87.9% and 89.3% respectively.[26]

5. Image Datasets

Dataset plays an important role in FER systems, having sufficient labeled trained/untrained data that include several variations of the populations and environments is very important for the design of emotion recognition systems.

There are many publicly available datasets that contain basic expressions/emotions and that are widely utilized in many reviewed papers for machine learning, deep learning algorithms evaluation.

5.1 CK+

The Extended CohnKanade (CK +) dataset is a widely used laboratory controlled dataset to test FER systems. CK + contains 593 video sequences from 123 subjects (different people). Sequences vary in length from 10 to 60 frames and show a change from a neutral facial expression to a high (peak) expression. Among these videos, 327 sequences from 118 people are labeled with seven basic labels (anger, contempt, disgust, fear, joy, sadness and surprise). [27]

5.2 JAFFE

JAFFE (Japanese Female Facial Expression) database which is a laboratory controlled database containing 213 samples of various expressions from 10 Japanese females. Each person has 3-4 pictures with each of the six faces (anger, disgust, fear, joy, sadness and surprise) and one image with a neutral (normal) expression. [28]

5.3 FER2013

This database is automatically collected by the Google Image Search API. All images are enlarged/reduced to 48*48 pixels after cutting negatively labeled frames and cropping unnecessary areas. FER2013 contains 28709 training pictures, 3589 confirmation pictures and 3589 test portraits with seven labels (anger, disgust, fear, joy, sadness, surprise and neutrality).[29]

6. Conclusions

Face detection methods have evolved from time to time. The Viola-Jones algorithm is one the most popular face detection algorithms with high accuracy. Number of deep learning approaches are developed to overcome its problems and increase the accuracy of face detection algorithm. Faster R-CNN approach is we found in our study to be the most accurate algorithm with state-of-art results.

We can say that four well-known techniques of linear transformations in the holistic face recognition system are almost 92% accurate. With fisherface giving more accurate results in most cases.

After analyzing many techniques of Facial emotion detection we came to a conclusion that the AlexNet CNN solution is the best way to do facial emotion detection compared to others on the basis of accuracy and pricing. After studying various techniques using Histogram of Oriented Gradients with different classifiers and combination of HOG with other methods, HOG-ESRs algorithm provides greater accuracy with increased robustness than previous available methods.

Among all datasets CK+ gives the best result in many cases.

References:

- [1] 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, 2001, pp. I-I, doi: 10.1109/CVPR.2001.990517.
- [2] R. Girshick, J. Donahue, T. Darrell and J. Malik, "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation," 2014 IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 580-587, doi: 10.1109/CVPR.2014.81.
- [3] K. Zhang, Z. Zhang, Z. Li and Y. Qiao, "Joint Face Detection and Alignment Using Multitask Cascaded Convolutional Networks," in IEEE Signal Processing Letters, vol. 23, no. 10, pp. 1499-1503, Oct. 2016, doi: 10.1109/LSP.2016.2603342.

- [4] R. Girshick, "Fast R-CNN," 2015 IEEE International Conference on Computer Vision (ICCV), 2015, pp. 1440-1448, doi: 10.1109/ICCV.2015.169.
- [5] S. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 1 June 2017, doi: 10.1109/TPAMI.2016.2577031.
- [6] H. Jiang and E. Learned-Miller, "Face Detection with the Faster R-CNN," 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017), 2017, pp. 650-657, doi: 10.1109/FG.2017.82.
- [7] Pandya, Jigar M. , Devang Rathod, and Jigna J. Jadav. "A Survey of Face Recognition approach." International Journal of Engineering Research and Applications (IJERA) 3. 1 (2013): 632-635.
- [8] G. M. Zafaruddin and H. S. Fadewar, "Face recognition: A holistic approach review," 2014 International Conference on Contemporary Computing and Informatics (IC3I), 2014, pp. 175-178, doi: 10.1109/IC3I.2014.7019610.
- [9] Sasan Karamizadeh, Shahidan M. Abdullah and Mazdak Zamani. An Overview of Holistic Face Recognition. International Journal of Research in Computer and Communication Technology, Vol 2, Issue 9, September-2013
- [10] Kortli Y, Jridi M, Falou AA, Atri M. Face Recognition Systems: A Survey. Sensors (Basel). 2020 Jan 7;20(2):342. doi: 10.3390/s20020342. PMID: 31936089; PMCID: PMC7013584.
- [11] M. A. Turk and A. P. Pentland, "Face recognition using eigenfaces," Proceedings. 1991 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1991, pp. 586-591, doi: 10.1109/CVPR.1991.139758.
- [12] Mustamin Anggo1, La Arapu. (2018) Face Recognition Using Fisherface Method. IOP Conf. Series: Journal of Physics: Conf. Series 1028 (2018) 012119, <https://doi.org/10.1088/1742-6596/1028/1/012119>
- [13] He, Xiaofei & Yan, Shuicheng & Hu, Yuxiao & Niyogi, Partha. (2005). Face Recognition Using Laplacian Faces. IEEE transactions on pattern analysis and machine intelligence. 27. 328-40. 10.1109/TPAMI.2005.55.
- [14] Fei Wang, Xin Wang, Daoqiang Zhang, Changshui Zhang, Tao Lib. marginFace: A novel face recognition method by average neighborhood margin maximization. Pattern Recognition. 2009 Nov 1;42(11):2863-75
- [15] Smiatacz, Maciej. (2013). Eigenfaces, Fisherfaces, Laplacianfaces, Marginfaces – How to Face the Face Verification Task. Advances in Intelligent Systems and Computing. 226. 10.1007/978-3-319-00969-8_18.
- [16] Affectiva.(2019). "DeterminingAccuracy," [Online]. Available: <https://developer.affectiva.com/determiningaccuracy/> (visited on Sep. 23, 2019).
- [17] Affectiva. (2019). "Pricing – Affectiva Developer Portal," [Online]. Available: <https://developer.affectiva.com/pricing/> (visited on Aug. 31, 2019).
- [18] Marc Franzen , Michael Stephan Gresser , Tobias Müller Prof. Dr. Sebastian Mauser :Developing emotion recognition for video conference software to support people with autism, 2020
- [19] Vedat Tümen , Ömer Faruk Söylemez , Burhan Ergen : Facial emotion recognition on a dataset using CNN, IEEE Nov 2017.
- [20] Aneta Kartali , Miloš Roglić , Marko Barjaktarović , Milica Đurić-Jovičić , Milica M. Janković : Real-time Algorithms for Facial Emotion Recognition: A Comparison of Different Approaches, IEEE 2018.
- [21] Sarmela A-P Raja Sekaran , Chin Poo Lee , Kian Ming Lim : Facial Emotion Recognition Using Transfer Learning of AlexNet, IEEE 2021.
- [22] Supreet U Sugur, Sai Prasad K, Prajwal Kulkarni, Shreyas Deshpande :Emotion Recognition using Convolution Neural Network , 2019.
- [23] Goodfellow I.J.etal. (2013) Challenges in Representation Learning: A Report on Three Machine Learning Contests. In: Lee M., Hirose A., Hou ZG., Kil R.M. (eds) Neural Information Processing. ICONIP 2013. vol 8228. Springer, Berlin, Heidelberg
- [24] Junkai Chen, Zenghai Chen, Zheru Chi, and Hong Fu : Facial Expression Recognition Based on Facial Components Detection and HOG Features, International Workshops on Electrical and Computer Engineering, 2014.
- [25] Amrendra Pratap Singh, Ankit Kumar : Robust face recognition system using HOG features and SVM classifier, IJISA, 2019.
- [26] Yuanchang Zhong, Lili Sun, Chenhao Ge and Huilian Fan : HOG-ESRs Face Emotion Recognition Algorithm Based on HOG Feature and ESRs Method, MDPI , 2021.
- [27] P. Lucey, J. F. Cohn, T. Kanade, J. Saragih, Z. Ambadar, and I. Matthews, "The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression," in Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on. IEEE, 2010, pp. 94–101.

[28] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, "Coding facial expressions with gabor wavelets," in Automatic Face and Gesture Recognition, 1998. Proceedings. Third IEEE International Conference on. IEEE, 1998, pp. 200–205

[29] I. J. Goodfellow, D. Erhan, P. L. Carrier, A. Courville, M. Mirza, B. Hamner, W. Cukierski, Y. Tang, D. Thaler, D.-H. Lee et al., "Challenges in representation learning: A report on three machine learning contests," in International Conference on Neural Information Processing. Springer, 2013, pp. 117–124.