Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

CROSS-CULTURAL FACIAL EXPRESSION RECOGNITON USING GRADIENT FEATURES AND SUPPORT VECTOR MACHINE

TAIBA MUSTAFA
M.Phil Scholar, Department of Computer Science, University of Okara, Okara Pakistan.
Email: tayybamustafa2k22@gmail.com

GHULAM ALI
Assistant Professor, Faculty of Computing, Department of Software Engineering, University of Okara, Okara Pakistan. Email: ghulamali@uo.edu.pk

ARSLAN AKRAM
Ph.D Scholar, Department of Computer Science, the Superior University Lahore, Lahore, Pakistan. Email: aaadoula11@gmail.com , phcs-f21-014@superior.edu.pk

AALIA TARIQ
MS / M.Phil Computer Science, Department of Computer Science, the Superior University Lahore, Lahore, Pakistan. Email: aalia.se@gmail.com

MUHAMMAD USMAN TARIQ
M.Phil Scholar, Department of Computer Science, the University of Lahore, Lahore, Pakistan.
Email: tariqusman263@gmail.com

MUHAMMAD SALMAN ALI
M.Phil Scholar, Department of Computer Science, the University of Lahore, Lahore, Pakistan.
Email: msalmanali0683@gmail.com

Abstract

The purpose of the study is to develop an efficient method to recognize facial expressions more efficiently, especially for different cultures. Humans interact verbally and non-verbally, but facial expressions play a key role in determining verbal communication also. This lot of information through nonverbal communication is not considered in the previous human-computer interaction. A system is needed, which can detect and understand the intents and emotions as stated by social and cultural pointers. In this paper, we have purposed a method to classify face images among six types of expressions. The method consists of three phases; in the first phase, we applied viola jones to crop only the face from the whole image and generate new images. Then we extracted gradient features using a HOG histogram. Lastly, we have classified image features using SVM and produced promising results. The proposed method shows remarkable results among other state-of-the-art methods. It provides 99.97% accuracy on combined cross-cultural databases.

Keywords: FER, multicultural database, neural networks, nonverbal communication, facial expression classification

1. INTRODUCTION

Facial expressions have been known as the "general language of feeling," yet people from different societies look glad, angry, or sad facial expressions in new manners, as

ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

shown by modern research supplied by the “American Psychological Association”. A psychological portrayal of a facial appearance is the picture we find in our 'inner being the point at which we consider what a dreadful or glad face resembles. Interaction is a basic need for people. Numerous logical research indicated that the greater part of human correspondence is through nonverbal communication.

The examination found that the Chinese depend on the eyes more to speak to outward appearances, while Western people depended on the eyebrows and mouth. Those social qualifications could prompt missed prompts or confusing signals about feelings during culturally diverse interchanges, the investigation detailed. Emotion recognition from confronting images has attracted wide tending in a broad chain of Human-Computer Interaction (HCI) uses such as robotics, educational fields, biometric systems, and health informatics. Giving computers the content to understand human users' states is key for spontaneous human-computer interaction within these applications [23].

Articulation acknowledgment is an errand that people perform every day and easily, however, it is not yet effortlessly performed by PCs, regardless of late techniques that have given correctness bigger than 95% in certain conditions. The calculation of facial terms is not a simple task for machine learning techniques, as people can show the manner in, which they portray different expressions. Still image frames of the only individual can vary for one facial expression in sense of light, background, and posture.

There are many hindrances in determining (FER) because of the variety of facial expressions among different cultures and deviation even for the same individual. Still, we humans may get into errors [2]. Then again, FER by computers is exceptionally important in several applications, for instance, human beings conduct understanding and human-PC between faces [3]. Facial appearances are of two kinds; unconstrained and presented. The present examination demonstrated that these two kinds of articulations are distinctive in numerous viewpoints [44]. The components, for example, lighting, present, head position, social varieties and so on make unconstrained articulations increasingly troublesome and testing to perceive. The target of the investigation is to build up a framework that is sufficiently strong for such varieties [2]. Among the biometric systems, the Face Recognition system is the one that can bring spontaneous things which means that it can operate without any contact with the subject. Despite its speediness and acceptance amongst people, it has still been disadvantaged in accuracy if related to other types of physiological forms. In this research, three pre-processing techniques will be applied to the face recognition system to get better accuracy [43]. Moreover, these three techniques will be applied separately and combined with different feature extraction parameters [39]. There are many explanations for current improved concerns in facial recognition; most people are concerned with security, the requirement for identification in the current situation in a digital world, facial expression examination, and modeling methods in data organization in software and computer entertainment. Facial recognition, including main components such as detection of face, tracing, arrangement and extraction of features, and tackling issues of erection of a face recognition system [38]. Face detection of the face is major to all facial analysis techniques, including face position, alignment, illumination factors, gender recognition, and glass-no glass. The focus of detection techniques is detecting facial or non-facial regions. It may be an easy task for a human to detect faces, but it may be difficult for computers to identify 100% accurately with all limitations of light, background, poses, positions, age factor, wrinkles, etc. [24].

Presented or impulsive expressions: Face expressions can be extensively separated into 2 classifications, presented appearance dataset and natural face appearance datasets. The posed outward appearances are frequently gotten by training on-screen characters to play out a particular facial appearance, and spontaneous outward appearance is regularly caught while having the subject watch a video. SVM helps in the classification of facial expressions [45]. It uses geometric and algebraic operations for extraction of high-dimension features to isolate input data images into a high-dimension featured space using a selected non-linear kernel function, and a learning algorithm shaped for its help. A specific radial-basis function was useful as the kernel in this paper. Facial hairs, glasses, or any disability may affect the correct facial expression recognition; coping with these will be a challenge for future work. Geometrical-based extraction of features considers the nose, mouth, eyebrows, and other face constituents, and in the case of look-based feature extraction exact area of the face is required [42]. The main segment in facial expression recognition is face detection, which is used to identify whether there are any faces in the image or not and if there exist, return the position and the size of each face. While face identification is a minor for human eye detection, it is a challenge for computers because of deviations in scale, position, alignment, posture, facial appearance, illumination, and many exterior features (like glasses, facial hair, and makeup.) [21].Now a study has been recognized by various safety providers such as palm biometrics, fingerprint services, and different biometrics. Face biometrics are much safe because of their different features, which provide benefits over other biometric applications that as fingerprint and palm identification [31].

The facial expressions are firm signals of larger communication. Oral connectedness implementation act between frail animals via eye contact, motion, facial expressions, embody communication, and paralanguage. Eye occurrence is the big point of communication that provides the motley of ideas. Eye happening controls the effort, and discussions and creates a statement with others. Tackling expressions let the grin, sad, feel, revolt, surprise, and awe. A grin on the anthropoid surface shows pleasure and shows the eye with a filiform work. The sad demo is hypoesthesia of looseness, which may normally say as travel-tilted eyebrows and grimace. The angriness of hominid play is affinal to forbidding and uncomfortable conditions. The manifestation of choler is verbalized with enfolded eyebrows, and slim and extended eyelids. The sicken expressions are uttered with deplume medico eyebrows and crinkled smell [24].

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

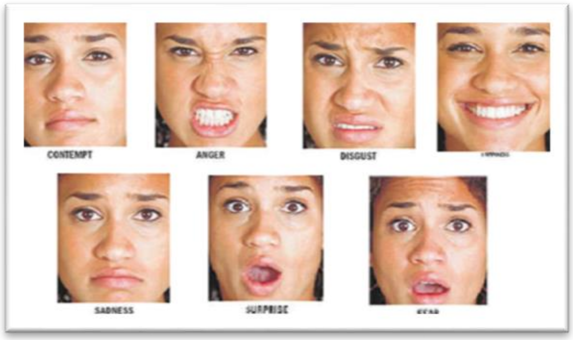


Figure 1: Different facial expressions

Facial expression recognition is very easy for humans but in the case of computers it's a difficult task to develop a reliable and accurate system is much more challenging. But one advantage is that people have different faces that are unique so it's an advantage to determine each person's identity. Although people can likewise appear to be identical, however, no two individuals are equivalent. Then again, from the point of view of facial appearance acknowledgment, calculations should be powerful and complex enough to comprehend the face data. Some face surface properties are known (they have two eyes, a nose, a mouth, and so forth.), and the structure and surface of a specific face should be learned. Facial appearances are mostly not clear and separated. Facial appearance acknowledgment, which incorporates facial picture examination, is talked about in unstructured or uncontrolled conditions (realistic world). In a perfect world, we might want to gather unconstrained information in genuine conditions. Shockingly, most openly accessible information doesn't consider in such a reasonable setting, however, shows facial pictures taken in research facilities and workplaces where lighting is controlled, and individuals are continually looking legitimately into the camera (Zeng et al. 2009). Albeit a few endeavors have been made to build naturalistic databases yet they despite everything have numerous impediments alongside publicly available issues.

The usage of cross-cultural databases of facial appearance is a difficult and complex task because in every culture there are different meanings of facial expressions that are difficult to recognize. Construction of a cross-cultural database is an important task, as there is no such database that is capable of dealing with such variations. We will try to construct a database that can cope with such problems.

2. LITERATURE REVIEW

Convolution neural network along with a special preprocessing technique was used, using public databases (BU-3DFE, CK, and JAFFE). A study shows that there are no such databases that can cover facial expressions with deep architecture [1]. Proposed an incremental model that can adjust for different environments. A dynamically weighted majority voting (DWMV) was suggested for generalization for ensemble systems for real-life scenarios. Generative Adversarial Networks, Convolution neural networks, Deep Auto encoder (DAE), Recurrent Neural Networks (RNN), and Deep belief networks, were used for feature learning. For classification, CNN was used that regulate the error by adding a loss layer to the end of the network [4].

A pattern averaging technique used for dimension reduction improves system speed. PAT takes an average of the matrix and gives a result by reducing matrix dimensions, after that classifier was applied. SVM classifier was more efficient than previous classifiers and has an accuracy of approx. 90.17% on JAFFE, 93.34% on Cohn Kanade, and 96.16% on MMI datasets. Two types of features that were geometry-based and Gabor wavelet extracted from face images and architecture developed reveals that Gabor wavelet transformation was more efficient than geometric-based positions [3].

The Paper uses an Eigenvector along with the Euclidean distance technique for facial expression recognition. Neural networks then classify and train data. Only 30 images were used for 6 expressions Anger, sad, disgust, surprise, happy. MLP shows better results compared to the decision tree and SVM. It uses backpropagation to train the network [6]. There were several techniques used for preprocessing the images but ROI was found to be more useful. Its accuracy is 99%. The database used for recognition was mostly JAFFE and CK for comparison of performance. For feature extraction, GF was suitable as it was simpler and less complex than other was. For classification, SVM was found best by comparison as it has the highest accuracy [2].

Posed facial appearance images, the technique of grid tracking and distortion for maximum geometric deformation of the facial area, and the use of a Support Vector Machine to classify and have the best results and has good performance recognition that was up to 99.7% and probably the best on Cohn Kanade database. Practicality, real-time, and accuracy were the different dimensions used for comparison [8]. The area of interest eyes nose lips was extracted through a template matching technique and the distance between the eyes and mouth was measured to detect whether a face was smiling or not. PCA algorithm was used to match sub-regions against sub-patterns. Classification was done using k-nearest neighbor [9]. We learn how machine-learning methods, e. g convolution neural networks, can progress the Facial expression recognition correctness in biometric applications. In our analysis, we have tried to locate a productive arrangement equipped for improving acknowledgment precision. It was found that this type of answer can be found using (CNNs).

Having described our procedure, it was found that the suggested method increases the results to 91. 2% on the FER 2013 information that includes original face images associated with seven face appearance classes [10]. Analyzing the confusion matrices, CAM effects, and classification accuracy based on three databases (RAF database, FER +and ExpW data), we can number out overall approaches for different expressive expressions. The area around the mouth shows more information about facial feelings, particularly happiness disgust, and normal. The surprise emotion was more readable through the eyes [11].

A survey on different techniques for facial expression detection, extraction, and classifier was made to detect the accuracy and performance with several emotions [12]. Model parameter initialization CNN with activation function, initialization of model parameters copes with the problem of overfitting in neural networks and overcomes the problem of bad recognition due to improper parameter initialization. CNN was used for the collection of images and LSTM for training. It associates BU-3DFE, CK, FER2013, JAFFE, and Oulu-CASIA facial expression databases [13]. Relative study of diverse techniques for extraction and detection Gabor function with Support vector machine classification has an accuracy of 99% and classifies facial expressions like sad, angry, fearful, happy, and neutral [14]. A huge amount of memory and processing were obligatory to process an image. A more appropriate substitute for this problem was the geometric features. The facial landmark detection was deployed for feature extraction and "CNN" for Classification purposes [15]. "Western" and "Eastern" face emotions. Built on trial outcomes, it was decided that like mental findings, the planned "FER system" offers a set of advantages, whereas "WSN" facial expression recognition was easiest to classify than "ASN" [45]. Additionally, measurable and non-measurable study shows, fear and hate were culturally specific, whereas other expressions were known by the diverse environment. "LFC" and "Facial Fourier Descriptors" were used for feature extraction and SVM for categorizing [17]. Preprocessing was done to sense the exact region of interest so that extraction of the face was completed easily.

Using the dataset then use CNN for the training of that dataset. Train network with epoch's size and size of the batch was 100. An accuracy rate of 70% percent was attained. After that when we improved the epochs to 200 accuracies increased to 72% and with an epoch size of 300 accuracy rate was 78% [18]. Firstly, the proposed model concerns the extraction of locally aligned facial patches. The face landmarks were used to confine and represent the main areas of the face (eyebrow, mouth nose, eyes, and jawline). Landmark detector for facial expression of Kazemi et al., 2014. In this technique, a fully differential technique based on a cascade of decision-boosted forests to lapse the location of landmarks from a sparse set of pixel strengths was performed [46]. Aliment was performed concerning the position of the eyes. Specific features were learned at every patch using different sub-networks and the concatenate layer sum up all sub-networks together [19]. Generally, work done in order of articulations pick classes of seven articulations that were similarly simple to work with, however, can just recognize a confined number of outward appearances and cannot determine the degree of articulation. Strategies were many reasons while considering the issues existing in true circumstances, similar to posing changes, brightening with losing precision [8].

A survey on different FER procedures was examined. The assessment of different FER techniques depends on the absolute of articulations unsurprising and the calculation's multifaceted nature. The return on initial capital investment method gives a precision of 99%. Gabor Filter gives great exactness between 82.5 t0 99% yet the SVM classifier gives the most noteworthy precision pace of 99%. JAFFE and CK information base was by all accounts more proficient data sets in performance [20].

The paper clarifies various strategies that were examined and thought about. From hypothetical investigation and correlation and zeroing in on the principal restrictions, the HAAR-like element extraction face identification approach ends up being an excellent methodology for face location. Highlight-based, mathematical base and HAAR-like

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

highlights were analyzed. Highlight bases have low execution time and were more exact, mathematical based were anything but difficult to actualize while HAAR based have more improved element extraction part [21]. Viola-Jones, neural networks SVM and “Successive Mean Quantization Transform (SMQT) Features” and “Sparse Network of Winnows (SNOW) Classifier Method” were analyzed dependent on exactness and review boundaries.

It was discovered that viola jones ends up being the best face identifier among other thoughts. The best was viola jones for face detection [22]. Discussing Speediness and consistency for face detection from an image and calculates the total of white and black rectangles and the calculated ratio and only use the best features, unlike previous algorithms. Such features were well for recognizing black and tilted faces [23]. Features in the image may be damaged due to light intensity, noisiness, and obstruction. Boundaries of features can deteriorate, or shadows of an image may cause strong edges while shadows may cause many algorithms inadequate in the case of a feature-based approach, but it’s easy to implement.

Using the Geometric based approach, it’s difficult to implement and dimensions were usually reduced to save computation [24] A new approach to facial expressions recognition was discussed called DSST, which was primarily based on shearlet transforms and normalized mutual information feature selection. Firstly, all the images were preprocessed, and then apply “Discrete Separable Shearlet Transform”, and all transformation coefficients were obtained. Thirdly improved standardized data including choice was applied to discover the best highlights. At that point, highlights were diminished utilizing Linear Discriminant Analysis and finally, SVM was utilized to order includes for acknowledgment. The exact pace of the examined calculation was 96.63%, [25].

They talked strategy that applies Contrast Limited Adaptive Histogram Equalization and Fast Fourier Transform methods to reward the awful light impacts. At that point combined paired example code was created for every pixel. With two pieces for every area and producing 16-cycle codes for every pixel, it consolidates nearby highlights to improve the viability of face acknowledgment. MBPC descriptor captures varieties along adequate edges and recognizable framework round eyes foreheads, mouth, eyes, swellings, and wrinkle lines of the face [47]. The results of gave strategy were broken down into different choices of Local Binary Pattern and LGC-based procedures for both drafted and comprehensive pictures. For experimentation, the Static Face Expression in the Wild dataset was picked. MBPC gives preferred execution over different strategies with 67.2% and 96.5% exactness for division-based and comprehensive methodology separately.

A comprehensive strategy has many preferred outcomes over a division-based method [26]. Another procedure utilizing a Histogram of Oriented Gradient highlights was removed both for the challenging picture and for the preparation pictures and arranged to utilize a Support Vector Machine. This procedure was dissected with Eigen's face acknowledgment strategy and thought about. The examined method and Principal Component Analysis were tried on eight datasets. At the point when the consequences of the proposed procedure were contrasted and Eigenfaces acknowledgment then it was discovered to be empowering. An upgrade of 8.75% in facial acknowledgment contrasting and Principal Component Analysis calculation. ORL information base was utilized for preparing reasons. Three assessment boundaries to be specific CMC, EPC and ROC were thought of. The boundaries show that the proposed calculation beats the PCA calculation [27]. The nearby slope ternary example was proposed in this paper and effective increment in identifying light varieties variety and clamor. Pre-handling was improved in this method and Scharr angle administrator was utilized. Dimensionality decrease was finished utilizing head part examination.

This strategy minded CK+ information base and JAFEE and end up being more exact and productive than past ones [28]. Ripplet transform was utilized for include extraction as it was acceptable in edge identification and surface portrayal. At that point, LDA and PCA were utilized to extricate highlights for more precision and conservativeness. Outspread Basis Function alongside Least square variation SVM was utilized. JAFFE and CK+ were utilized as datasets [29]. Analyzing the basic strategies of steady learning on fluctuated, static, and non-static datasets. It gives a brisk review concerning the principal credits of the distinctive arrangement of considered methods. SVMs give commonly the greatest precision at cost of the most intricate one. LASVM diminishes the preparation time and performs for bigger informational collections contrasting and ISVM.ORF execution was more regrettable however its preparation and execution time was significantly less.

ILVQ nearly offers a decent option contrasted with SVM's. SGD and NB were acceptable decisions for enormous-scope learning. NB and tree-based techniques were anything but difficult to apply. SVM and ILVQ request delicate settings [30]. The practical effects of the three techniques on different datasets were better but the best accuracy of 98% was attained using Viola jones. Viola-Jones with FEI Dataset was accurate when experimental results were detected among all three databases. For front face recognition, the Viola-Jones technique was much more accurate among all techniques and attained improved results on three databases [31]. A similar examination of two element extraction techniques for face acknowledgment LDA and PCA on various boundaries of outward appearance, light varieties, and individuals wearing non-glass or glass for front face pictures. Utilizing Yale's information base LDA performs effectively, Recognition pace of 74.47 % was accomplished by preparing a set of 68 pictures, and 123 pictures were perceived out of 165 pictures. Facial Recognition recurrence can be improved that incorporating the full front faces utilizing LDA and PCA. The face acknowledgment ratio can be enhanced with a mixture of preprocessing strategies for PCA and LDA. PCA and LDA joined with different strategies LBP, DCT, DWT, and so forth can expand the face acknowledgment rate [32]. Histogram-put together nearby descriptors utilized concerning Facial Expression Recognition (FER) for fixed pictures and give capable audit and investigation. To start with, we portray the principal steps in encrypting parallel examples in a neighborhood fix, that were compulsory in each histogram-based nearby descriptor. All out, 27 nearby descriptors were applied on 4 information bases, utilizing similar situations. The quality of the specific nearby descriptors was checked under various

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

circumstances, for example, changing picture goals and several sub-regions, and classifiers. As indicated by the complete investigation it shows that the top neighborhood descriptors for Facial Expression Recognition, by checking the full length, computational expense, and the classification exactness all at the same time, was LPQ [33].

A new face-trimming procedure was utilized alongside CNN to eliminate pointless locales. To normalize the facial picture, histogram balance, Z-score standardization, and down inspecting were useful. To improve dataset size during the instructional meeting, even flipping and irregular turns were performed. Extended preparing datasets were utilized to prepare the CNN, and the best Convolution Neural Network model was spared. While the testing stage, standardized testing pictures (without development) were sent to the CNN model from the preparation stage for an estimate. The forehead of the picture was edited to improve productivity and sign open cv.CK+ and JAFEE information bases were utilized. On JAFEE information base outcomes were 98.12% [34]. A new descriptor called Local gradient Neighborhood was proposed, it comprises two main things feature extraction and recognition using mapped intervals. The goal was to have a high recognition but low expense. The relation of gray levels of the neighboring pixels was considered in the Local Gradient Code (LGC). The center pixels and neighboring pixels' relation were checked in LBP. The paper proposed a method that combines LBP and LGC qualities to form a Local Gradient Neighborhood. It unites the relation of gray levels of the neighboring pixels and center pixels with neighboring pixels. Using SVM and KNN as classifiers. Results show that SVM outperforms KNN. The proposed method with KNN achieves an accuracy of 72.38% with the JAFEE dataset [35].

The technique combines a boost decision tree with NN. Decision trees were trained to extract local binary features. With limited resources, this model helps boost speed and accuracy rate and makes it best for limited resources environments. Using Shallow neural networks' joint classification contributes to the correct classification of difficult expressions [36].

The faster R-Convolution Neural Network was used. Features were automatically separated by network using training datasets, unlike the traditional feature extraction techniques. Experiments using such techniques give a better rate of accuracy. Chinese Linguistic Data Consortium (CLDC) was used, comprising cross-cultural expressive aural and videotape datasets. The value of mAP was 0.82. Using a trainable convolution network implicit feature were extracted. Maximum pooling for facial dimension reduction and Classifiers like Softmax and regression layers were used [37]. Classical facial expression algorithms were inadequate as they fail to represent faces when there was high variation in light. Artificial Neural Networks were good at recognizing faces with little occlusion, but their disadvantage was that it requires a large number of training dataset images. Different biometric applications support Gabor Wavelet; the disadvantage was high dimensionality in features. The approach was unsuitable for real-time applications. Face descriptor-based approaches were discriminative and vigorous for light variations and deviations in expressions. They deal with compact, easy extraction and were extremely high discriminative descriptors. The disadvantage of 3-D-based face recognition was that it was computationally expensive and not suitable for real-time situations [38]. The accuracy of recognition was enhanced by preprocessing techniques but time was still a big challenge. An Enhanced Face Recognition System was proposed that uses the LBPH technique. In experiments LBPH techniques were changing with preprocessing techniques to achieve a high rate of accuracy for different databases. 98.5% rate was achieved but time was still a hurdle as it keeps on increasing with the increase in images in the database [39]. The analysis was built on gesture, activity, and facial expression recognition, as they were vital for expression recognition. These 3 fields were then divided into standing computing methods. HAAR feature was a good substitute for expression recognition. In facial expression recognition, LBP was the most standard choice. The explicit benefits of the analysis are: it offers a good analysis of computational methods for the gesture, activity, and facial expression recognition. This also comprises both kinds of approaches, which comprise particular human, and also several human actions. It gives a transitory report of standard databases deployed for activity, gestures, and face expression estimation [40].

3. METHODOLOGY

In this section proposed method is described. Fig 2 shows the basic steps involved in Facial expression recognition are preprocessing, feature learning /extraction, and classification.

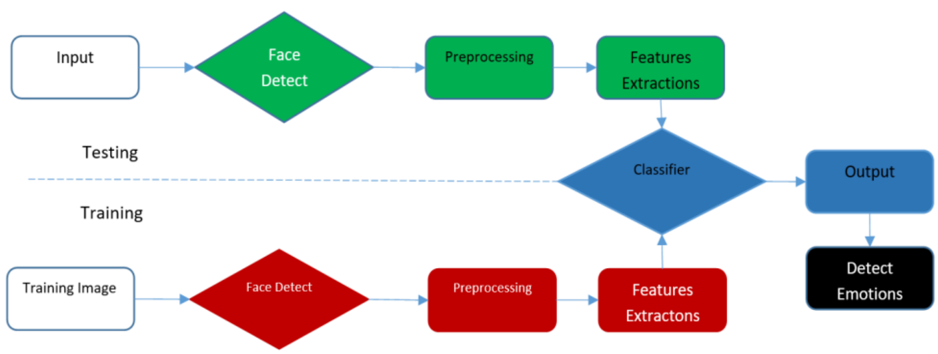


Figure 2: Proposed FER approach

3.1 Pre-processing

It is necessary before training a neural network that irrelevant data such as light, head postures, etc. It is necessary to normalize the information conveyed by facial expressions. Pre-processing involves various steps i.e, adjustment of light, contrast, removal of noise, clarity in an image, scaling, cropping, etc.

3.2 Face Detection

Face recognition is a trivial task. Some previous work done like viola john's 2001 and Rowley 1998. But for changing environment and complex conditions it's a bit difficult. Detection techniques may be knowledge-based, templates based, appearance-based, and feature-based. The knowledge-based technique involves knowledge of human being and face detected according to knowledge about appearance.in Template based technique some templates in the database are matched to detect. Appearance-based techniques involve training of network to match the desired one. For face detection, we used the Viola-Jones face detection algorithm.

3.2.1 "Viola Jones" Face Detection Technique

This face detection method is the only structure that is built on entity detection, which offers a degree of the best accuracy in, real-time and is presented in the year 2001 by "Paul Viola & Michael Jones". Viola-Jones face detection algorithm was implemented in 'MATLAB' using a vision method called Cascade Object Detector [41]. The Viola-Jones algorithm consists of three procedures for the detection of facial regions:

1. HAAR-like features estimated using the internal image for the feature extraction are "rectangular" type.
2. "Ada boost "is a machine learning algorithm used for face area detection. Word "boosted" defines classifiers that are multifaceted in nature at every stage, that are composed of simple classifiers consuming any 4 boosting techniques.
3. "Cascade-classifier" employed for combining most features proficiently. Word "cascade" in the classifier defines numerous filters on the subsequent classifier.

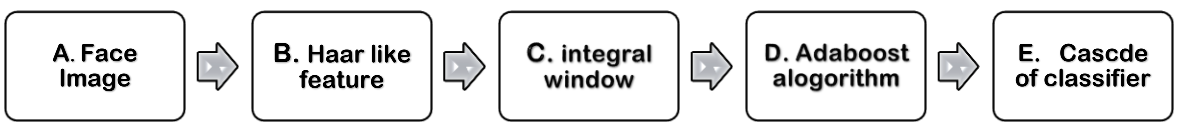


Figure 3: Basic Flow Diagram of Viola-Jones Algorithm

A. "Viola Jones" Upper Body Detection

Chest area portions can be distinguished utilizing the viola jones technique for still pictures based on object detection structure that contains the model for recognition of close and front chest area region. Viola jones's model has been utilized to distinguish the part of the chest area of humans and gives face object identification. Chest area identifying part of the model distinguishes chest area locale, that comprises of the head just as shoulder region in blend with the face. Every one of these specifics of head and shoulder territory has been modified utilizing HAAR highlights and item location. Consequently, an object in the head and face zone utilizes extra kinds of highlights, viola jones's model is more incredible against posture and picture changes, for instance turning the head or flickering eyes with an edge. Identifying chest area territory utilizing the arrangement model there are 3 things:

1. Produce a detector object and its characteristics.
2. Sample image that is given as an input is read and it identifies the upper body area.
3. Shows the detected/identified higher body area in the bounded box.

B. "Viola-Jones" Face objects Identification algorithm

At first face identification in pictures was a confounding undertaking. Since lighting varieties, act, and various components it has numerous varieties. Even though later it was executed in ongoing specialized items e.g., a camera to recognize a facial entity anyplace on the off chance that exchange camera with a district of the box. The face object recognition calculation here is made out of varieties like helping, acting, and rotational faces on it. It can be recognized by receiving various window classifiers using Viola Jones's calculation.

C. Eye Identification Algorithm

The area of the eye is more obscure compared with different pieces of face, along these lines discovering districts of the eye are fixated on the division of a little zone of the picture that is indicated as a hazier region. The focus part of the eye locale is more obscure compared with another region fixated on this technique the region of the eyebrow has been eliminated. Certain eye territory is finished by methods for histogram investigation strategy, the locale of the eye shows two pinnacle focuses while the zone of eyebrows speaks to just one pinnacle. The two primary pivots have the course of action, which is the last limitation here, subsequently, the two eye locales identify with the same line.

D. Iris & Pupil Identification

Iris in the eye is valuable in biometric acknowledgment since it has numerous properties for acknowledgment. The pupil is a focused part of the eye and more obscure zone pixels in our eye are hovered by the iris. Light enters through the understudy and afterward, it goes through the focal point and in the end, it is engaged to the retina. There might be some data loss close by a student as edges of understudy is not generally a roundabout region and there can be a little mix-up in the discovery of this limit. If the head/eye is additionally turned, at that point there happens some trouble in a division of the iris region.

E. "Viola-Jones" Nose Identification Algorithm

The nose has various attributes to identify it without any problem:

a) Dark White Dark Pixels:

At the point when a picture is taken as info, and it is converged with such dim white and dull pixel focuses then the area of nostrils is perceived. This identification depends on 2 zones of gaps on the button, which means dim pixels and emphasis region of nose marks white pixels.

b) Relationship and comparable locale on both sides:

The nostrils have a district of dark territories on right and left areas of the nose that is fundamentally similar. Such qualities are reflected as a similitude record on each margin of area.

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

F. Mouth Identification Viola-Jones algorithm

A weak classifier can arrange mouth identification calculation in which recognizable proof and extraction of highlights from mouth territory depend on a standard choice stump, which devours the highlights of "HAAR" to encrypt the subtleties of an area of the mouth. Trial outcomes indicate that the zone of mouth can be seen dependent on the spot of the nose, lips, and eyes, which we can recognize, by utilization of these calculations. The such application might be utilized in an extensive scope of highlights and is operational, for the convoluted foundation dependent on mouth discover.

3.2.2 HAAR Features

The whole picture deteriorates in littler windows or rectangular shape areas of size M x M. Every window exclusively included is registered. Generally, 3 kinds of highlights are locked in for face-recognizable proof that is, two rectangular highlights, three rectangular highlights, and four rectangular highlights.

Two square shape highlights are the contrast between the entireties of pixel focuses inside the two-rectangular districts. These square shapes are neighboring and have comparative size, and shape and are adjoining to one another on a level plane or vertically. Three rectangular element figure entirety of pixel focuses inside 2 external rectangular districts and is deducted from the whole of pixels in the middle square shape. In conclusion, a four rectangular component computes the distinction between inclining sets of the square shape, as appeared in Fig. 3. Additionally called "powerless classifiers". The three-square shape include appeared on the face in Fig. 4.

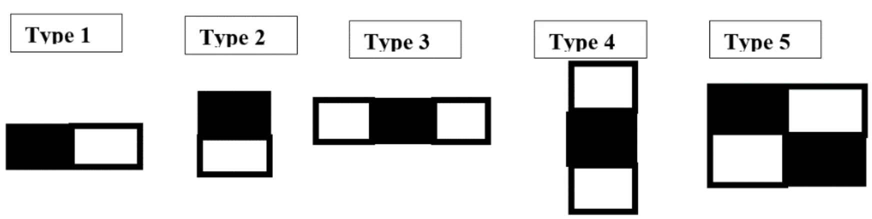


Figure 4: HAAR feature of detected faces

3.2.3 Integral Image Formation

Features of HAAR type are determined effectively utilizing an in-middle portrayal for picture - indispensable picture. The essential picture at area 1 in Fig. 5 is the total of pixels in area an; at area 2 it is an aggregate of pixels in locale A+B; at area 3, it is the whole of the pixels in district C+A; and at area 4, it is total of the pixels in the area A+B+C+D.

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

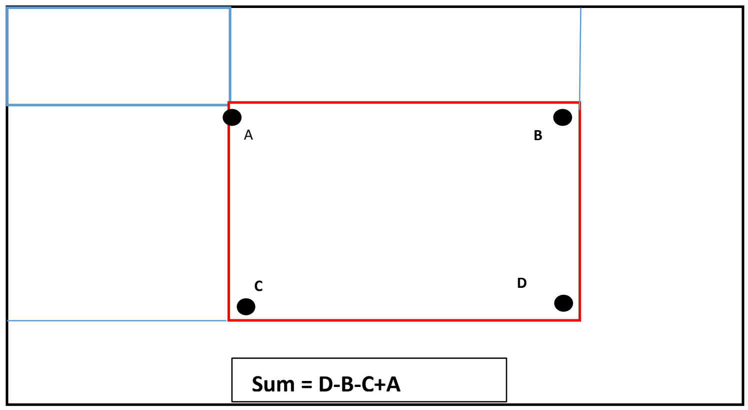


Figure 5: Integral window

3.3 Features Classification using the "Adaboost" algorithm

The number of HAAR features determined for each window is excessively enormous enough (approx: 180,000). Generally, these highlights are rehashed. To lessen excess, ADA-boost calculation is utilized.

The ADA-boost calculation is getting the hang of collection work that is utilized to kill rehashed features and change the huge arrangement of features in a packed one. This is a classifier that is made by a weighted blend out of the weak classifiers. Each element of the window is a frail classifier.

The ADA-boost calculation might be seen as a component choice calculation since it chooses the best highlights from every single accessible element. Chosen features are which are more important for face portrayal. This calculation diminishes a huge number of highlights to two or three hundred highlights.

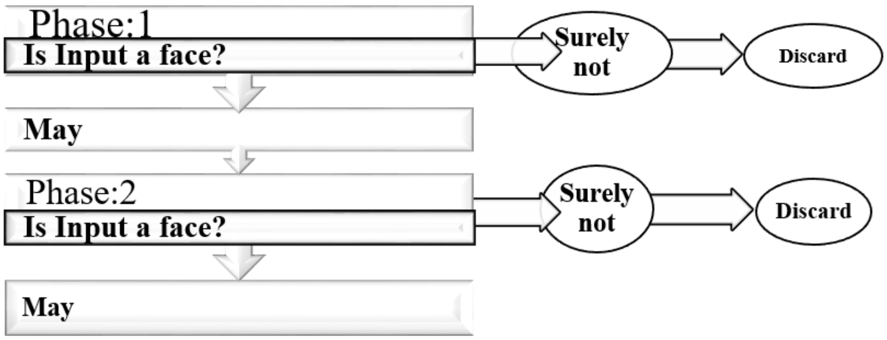
3.4 Cascading

Choosing the best of the features in every window, presently choose the windows that contain faces. By normal, just 0.01% of the windows in the picture are affirmative that is they have faces. Discovering positive windows at first recognized appearances to disregard many fell stages.

Each stage diminishes the number of bogus positives, which are areas that are wrongly distinguished as appearances. A high number of stages in falling shows that higher will exactness however the calculation time additionally increments so there is a conflict in both.

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

Figure 6: Detecting face windows



Now in FER is the extraction of the feature. Here positive or interesting features are extracted for further pre-processing. It is the most important part of the FER technique. Feature extraction is a procedure by which dimensions are reduced by an original set of collected raw materials is condensed to some further adaptable sets for further processing. A characteristic of such large data sets is that a large number of variables need many computing resources for processing. Feature extraction is used to pool up variables into features, and efficiently decrease the number of records that must be handled, though precisely and entirely relating real data set.

3.5 Classification:

The last phase of Facial expression acknowledgment is characterization, here various classifiers arrange the articulations like outrage, glad, nauseate, miserable, shock, and unbiased. Classification is a significant advance, as the right grouping by classifier will prompt great preparation of the information that outcomes in high exactness. Backing vector machines are connected arrangements of regulated learning strategies utilized for grouping and relapse methods. SVMs are identified with a group of general straight classifiers. Then again, the Support Vector Machine is a relapse and arrangement method. Backing Vector machines can be all around characterized as a strategy that utilizes speculation unique plane of a straight capacity in higher dimensional component space, it is prepared to utilize taking in calculation from enhancement hypothesis 'those utilizations learning predisposition resultant of factual learning hypothesis. SVM is celebrated when utilizing pixel maps as information; it produces higher exactness contrasted with refined neural organizations with extended highlights close by composing acknowledgment. Utilized in different applications, similar to hand composing requests face acknowledgment, etc., especially in design grouping and relapse-focused applications. The nuts and bolts of Support Vector Machines have been set up by Vapnik, and a device of relapse expectation uses AI hypothesis to build forecast exactness however consequently staying away from over fit to information. Backing Vector machines might be characterized as frameworks that utilize speculative space of direct capacities in high dimensional element space, preparing finished with learning calculation utilizing advancement hypothesis that executes taking in predisposition coming about because of measurable learning hypothesis.

ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

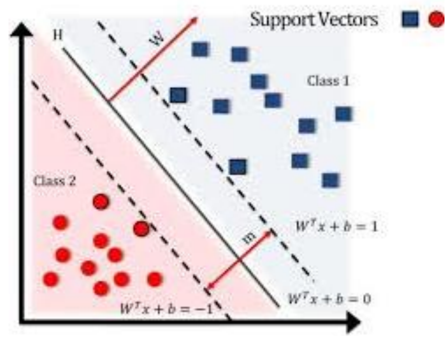


Figure 7: Classification using SVM

Machine learning procedures accept I /p information through a training stage, create a model of I /p and o /p, and hypothesis function which may be deployed to forecast future data. Assume a set of labelled training examples: S = ((x1, y1, …. , (xl , yl)), yi∈ {−1, 1}. The learning systems normally try to catch a decision function like H (x) =sgn(w · x)+ b). This produces a label that belongs to {−1, 1} for a beforehand unobserved example x. SVM's built on things grown from arithmetic learning theory, founded by Vapnik, despite similarities with natural learning systems. Such outcomes show the interpretation accomplishment of a learned function on coming hidden facts based on the difficulty of the class of functions it is chosen from despite the complexity of the function itself. Restricting this class difficulty, theoretic assures on simplification performance can be done.

4. RESULTS AND DISCUSSION

4.1 Datasets

In this section experiment results for our proposed technique using 3 datasets are shown. Firstly, JAFFE is used for experimentation. This information dataset comprises the 7 essential articulations which were presented by 10 Japanese female models. 213 images are total in this dataset, angry images are 30, disgust 29 images, fear images are 32, happy images are 31, contain 30 neutral, 31 sad images, and 30 are of surprise. Separately every model gave roughly three pictures to every apparent expression. Each picture was spared in grayscale with a goal of 256 × 256.

This dataset contains eight articulations that incorporate seven essential articulations in addition to one scorn that was posed by over 200 individuals running from 18 to 50 years old. It by and large comprised of European-American and African American people. The pictures were taken in periods where the underlying edge was nonpartisan, which at that time progressed into the articulation that was wanted toward the end outline (the pinnacle outline). Such pictures were spared, few in grayscale and few in shading, in 640 × 490 or 640 × 480 pixels. The dataset contains neutral 123 images and images with certain expressions 327. The expressive image pictures consist of angry images in 45, contempt in 18 pictures, images that are disgust 59, 25 images fearful, 69 images in happy, 28

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

images with sad expressions, and surprise in 83 images. The contempt expression images are excluded in this work.

The third dataset used is KDEF, The Karolinska Directed Emotional Faces (KDEF) is a set of 4900 images of human facial expressions. A total of 70 individuals is displaying seven dissimilar emotions. Each expression is viewed from 5 different angles but only frontal images of 70 individuals were included in the dataset. So the total number of images is 980.

4.2 Results of Datasets

4.2.1 JAFFE

Experiments done using the JAFFE dataset produces good results having an accuracy of 95.30%. Evaluating different parameters like AUC, the accuracy of 7 classes individually, and Precision, Specificity, Sensitivity, F1 Score and Accuracy shows very good results. All classes' identification rate is above 95%. Results for the JAFFE dataset for all seven classes are shown in the table

Table 1: Evaluation results for JAFFE dataset

SVM ACC using JAFFE dataset = 95.30 %					
Expression	**Precision**	**Specifcity**	**Sensitivty**	**F1 score**	**Accuracy**
Anger	0.97	0.99	1.00	0.98	1.00
Contempt	0.91	0.98	1.00	0.95	0.99
Disgust	0.96	0.99	0.93	0.95	0.99
Fear	0.97	0.99	1.00	0.98	1.00
Happy	0.94	0.99	0.97	0.95	0.99
Sadness	0.94	0.99	0.97	0.95	0.99
Surprise	0.96	0.99	0.87	0.91	0.98

4.2.2 CK +

Experiments done using the CK+ dataset produces very good results having an accuracy of 99.70%. That is considered almost 100%. Evaluating different parameters like AUC, the accuracy of 7 classes individually, and TPR, FPR, TNR, and TFR shows excellent results. All classes' identification rate is above 97%. Results for the CK+ dataset for all seven classes are shown in the table.

Table 2: Evaluation results for CK+ dataset

SVM ACC using CK+ dataset = 99.70 %					
Expression	**Precision**	**Specifcity**	**Sensitivty**	**F1 score**	**Accuracy**
Anger	1.00	1.00	1.00	1.00	1.00
Contempt	1.00	1.00	1.00	1.00	1.00
Disgust	1.00	1.00	1.00	1.00	1.00
Fear	1.00	1.00	0.97	0.99	1.00
Happy	1.00	1.00	1.00	1.00	1.00
Sadness	1.00	1.00	0.99	0.99	1.00

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

Surprise	0.99	1.00	1.00	1.00	1.00

4.2.3 KDEF

Experiments done using KDEF dataset produces very good results having an accuracy of 99.70%. That is considered almost 100%. Evaluating different parameters like AUC, the accuracy of 7 classes individually, and TPR, FPR, TNR, and TFR shows excellent results. All classes' identification rate is above 97%. Results for the KDEF dataset for all seven classes are shown in the table.

Table 3: Evaluation results for KDEF dataset

SVM ACC using KDEF dataset = 92.30 %					
Expression	**Precision**	**Specifcity**	**Sensitivty**	**F1 score**	**Accuracy**
Anger	0.97	1.00	0.91	0.94	0.98
Contempt	0.94	0.99	0.94	0.94	0.98
Disgust	0.79	0.96	0.86	0.82	0.95
Fear	0.99	1.00	0.96	0.97	0.99
Happy	0.92	0.99	0.86	0.89	0.97
Sadness	0.90	0.98	0.93	0.92	0.98
Surprise	0.93	0.99	0.98	0.95	0.99

4.2.4 Combined

Table 4: Evaluation results for all combined datasets

SVM ACC using Combined dataset = 90.04%					
Expression	**Precision**	**Specifcity**	**Sensitivty**	**F1 score**	**Accuracy**
Anger	0.96	0.99	0.90	0.93	0.98
Contempt	0.94	0.99	0.89	0.91	0.98
Disgust	0.82	0.96	0.85	0.84	0.94
Fear	0.98	1.00	0.90	0.94	0.99
Happy	0.86	0.98	0.89	0.88	0.97
Sadness	0.89	0.99	0.87	0.88	0.97
Surprise	0.89	0.97	0.97	0.93	0.97

5. CONCLUSION AND FUTURE WORK

In this report, machine-learning algorithms are used to increase the overall efficiency of face detection and recognition system. To check the accuracy of the technique we used traditional databases like JAFFE, CK+, and KDEF and then combine all these datasets to check the overall cross-cultural accuracy of the proposed technique. Firstly, viola jones is used for face detection; this algorithm is efficient for up-frontal faces and gives high accuracy. Then the feature of the detected face is extracted using the Histogram of Gradient (HOG) descriptor. These features are reduced using PCA and then passed to the SVM classifier for evaluation. This method gives high accuracy of 99.7% using CK+, using JAFFE accuracy calculated is 95.30%, KDEF 92.30% accurate classes were classified and combining CK+ and JAFFE features gives 98.5% accuracy while if all three datasets are combined for cross-cultural emotions that accuracy is approximately 90%.

ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

This shows that our proposed technique gives good results if used for cross-cultural databases. In the future, all this work can be experimented with different techniques and other than frontal faces.

REFERENCES

1) Lopes, A.T., et al., Facial expression recognition with convolutional neural networks: coping with few data and the training sample order. 2017. **61**: p. 610-628.

2) Revina, I.M., W.S.J.J.o.K.S.U.-C. Emmanuel, and I. Sciences, A survey on human facial expression recognition techniques. 2018.

3) Banerjee, T., et al., Automatic Facial Expression Recognition Using Geometrical Features, in Emerging Technology in Modelling and Graphics. 2020, Springer. p. 519-531.

4) Gopalan, N., S.J.I.I. Bellamkonda, Graphics, and S. Processing, Pattern averaging technique forfacial expression recognition using support vector machines. 2018.**9**: p. 27-33.

5) Zhang, Z. Comarison Between Geometry-Based and Gabor-Wavelets-Based Facial ExpressionRecognition Using Multi-Layer Perceptron. In 3rd IEEE Int. Conf. Automatic Face and Gesture Recognition, 1998. 1998.

6) Tripathi, A., S. Pandey, and H. Jangir, Efficient facial expression recognition system based ongeometric features using neural network, in Information and Communication Technology for Sustainable Development. 2018, Springer. p. 181-190.

7) Takalkar, M., et al., A survey: facial micro-expression recognition. 2018. **77**(15): p. 19301-19325.

8) Chen, Y., et al. A Comparison of Methods of Facial Expression Recognition. In 2018 WRCSymposium on Advanced Robotics and Automation (WRC SARA). 2018. IEEE.

9) Benitez-Garcia, G., et al., Multicultural facial expression recognition based on differences ofwestern-caucasian and east-asian facial expressions of emotions. 2018.**101**(5): p. 1317-1324.

10) Ghaffar, F.J.a.p.a., Facial Emotions Recognition using Convolutional Neural Net. 2020.

11) Mane, V. and S. Shinde, An Integrated Copy-Move Forensic Method for Tamper Detection andLocalization of Duplicated Regions.

12) Li, S. and W.J.a.p.a. Deng, Deep facial expression recognition: A survey. 2018.

13) Christou, N. and N. Kanojiya. Human facial expression recognition with convolution neural networks. In Third International Congress on Information and Communication Technology. 2019. Springer.

14) Djerghri, A., A.R. Hazourli, and A.J.a.p.a. Othmani, Deep Multi-Facial patches AggregationNetwork for Expression Classification from Face Images. 2019.

15) Ghosh, S. and S.K.J.m. Bandyopadhyay, A Method for Face Recognition from Facial Expression. 2015. **5**: p. 9.

16) Goh, K.M., et al., Micro-expression recognition: an updated review of current trends, challenges and solutions. 2020.**36**(3): p. 445-468.

17) Gopalan, N., S. Bellamkonda, and V.S. Chaitanya. Facial Expression Recognition Using GeometricLandmark Points and Convolutional Neural Networks. in 2018 International Conference on Inventive Research in Computing Applications (ICIRCA). 2018. IEEE.

18) Lian, Z., et al., Expression Analysis Based on Face Regions in Read-world Conditions. 2020. **17**(1): p. 96-107.

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

19) Hazourli, Ahmed Rachid, et al. Deep Multi-Facial Patches Aggregation Network for Facial Expression Recognition. arXiv preprint arXiv:2002.09298 (2020).

20) Revina, I. Michael, and WR Sam Emmanuel. A survey on human face expression recognition techniques. Journal of King Saud University-Computer and Information Sciences (2018).

21) Chauhan, Mayank, and MukeshSakle. Study & analysis of different face detection techniques. International Journal of Computer Science and Information Technologies 5.2 (2014): 1615-1618.

22) Dang, Kirti, and Shanu Sharma. Review and comparison of face detection algorithms. 2017 7th International Conference on Cloud Computing, Data Science & Engineering-Confluence. IEEE, 2017.

23) Vikram, K., and S. Padmavathi. Facial parts detection using Viola Jones algorithm. 2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS). IEEE, 2017.

24) Kumar, Ashu, Amandeep Kaur, and Munish Kumar. Face detection techniques: a review. Artificial Intelligence Review 52.2 (2019): 927-948.

25) Lu, Yang, Shigang Wang, and Wenting Zhao. Facial expression recognition based on discrete separable shearlet transform and feature selection. Algorithms 12.1 (2019): 11.

26) Munir, Asim, et al. Illumination invariant facial expression recognition using selected merged binary patterns for real world images. Optik 158 (2018): 1016-1025.

27) Dadi, Harihara Santosh, and GK Mohan Pillutla. Improved face recognition rate using HOG features and SVM classifier. IOSR Journal of Electronics and Communication Engineering 11.04 (2016): 34-44.

28) Holder, Ross P., and Jules R. Tapamo. Improved gradient local ternary patterns for facial expression recognition.EURASIP Journal on Image and VideoProcessing 2017.1 (2017): 42.

29) Kar, Nikunja Bihari, et al. Face expression recognition system based on ripplet transform type II and least square SVM. Multimedia Tools and Applications 78.4 (2019): 4789-4812.

30) Losing, Viktor, Barbara Hammer, and HeikoWersing. Incremental on-line learning: A review and comparison of state of the art algorithms. Neurocomputing 275 (2018): 1261-1274.

31) Srikrishnaswetha, Kone, Sandeep Kumar, and Prashant Johri. Comparision Study on Various Face Detection Techniques. 2018 4th International Conference on Computing Communication and Automation (ICCCA). IEEE, 2018.

32) Vyas, Riddhi A., and S. M. Shah. Comparision of PCA and LDA techniques for face recognition feature based extraction with accuracy enhancement. International Research Journal of Engineering and Technology (IRJET) 4.6 (2017): 3332-3336.

33) Turan, Cigdem, and Kin-Man Lam. Histogram-based local descriptors for facial expression recognition (FER): A comprehensive study. Journal of visual communication and image representation 55 (2018): 331-341.

34) Li, Kuan, et al. Facial expression recognition with convolutional neural networks via a new face cropping and rotation strategy. The Visual Computer 36.2 (2020): 391-404.

35) AYECHE, Farid, Adel ALTI, and Abdallah BOUKERRAM. Improved Face and Facial Expression Recognition Based on a Novel Local Gradient Neighborhood. Journal of Digital Information Management 18.1 (2020): 33.

36) Gogić, Ivan, et al. Fast facial expression recognition using local binary features and shallow neural networks. The Visual Computer (2018): 1-16.

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 01-2023
DOI 10.17605/OSF.IO/XWZTK

37) Li, Jiaxing, et al. Facial expression recognition with faster R-CNN. Procedia Computer Science 107 (2017): 135-140.

38) Wójcik, Waldemar, Konrad Gromaszek, and Muhtar Junisbekov. Face recognition: Issues, methods and alternative applications. Face Recognition-Semisupervised Classification, Subspace Projection and Evaluation Methods (2016).

39) Muhammad, RaafatSalih, and Mohammed IssamYounis. The Limitation of Pre-processing Techniques to Enhance the Face Recognition System Based on LBP. Iraqi Journal of Science 58.1B (2017): 355-363.

40) Nigam, Swati, Rajiv Singh, and A. K. Misra. A Review of Computational Approaches for Human Behavior Detection. Archives of Computational Methods in Engineering 26.4 (2019): 831-863.

41) Iqbal, M. J., Bajwa, U. I., Gilanie, G., Iftikhar, M. A., & Anwar, M. W. (2022). Automatic brain tumor segmentation from magnetic resonance images using superpixel-based approach. Multimedia Tools and Applications, 1-19.

42) CNKIONLINE and... SOBIA YAQOOB et al, “A NOVEL METHOD FOR IMAGE BASED BREAST CANCER CLASSIFICATION,” Dec. 2022, doi: 10.17605/OSF.IO/JZFRM.

43) CNKIONLINE and. ARSLAN AKRAM et al, “A ROBUST AND SCALE INVARIANT METHOD FOR IMAGE FORGERY CLASSIFICATION USING EDGE WEIGHTED LOCAL TEXTURE FEATURES,” Dec. 2022, doi: 10.17605/OSF.IO/MVWDU.

44) CNKIONLINE and. MUHAMMAD SALMAN ALI et al., “CHEST X-RAY BASED PNEUMONIA CLASSIFICATION USING VGG-19,” Jan. 2023, doi: 10.17605/OSF.IO/M2FPD.

45) Akram, S. Ramzan, A. Rasool, A. Jaffar, U. Furqan, and W. Javed, “Image splicing detection using discriminative robust local binary pattern and support vector machine,” WJE, vol. 19, no. 4, pp. 459–466, Jun. 2022, doi: 10.1108/WJE-09-2020-0456.

46) CNKIONLINE and. MUHAMMAD USMAN TARIQ et al, “REAL TIME AGE AND GENDER CLASSIFICATION USING VGG19,” Dec. 2022, doi: 10.17605/OSF.IO/BKJWH.

47) Asis Jamal, Sarah Javed, Arslan Akram, and Shahzaib Jamal, “Recovery Method for Disasters of Network Servers by Using POX controller in Software defined Networks.,” Research Journal Of Computer Science And Information Technology, vol. 3, no. 4, pp. 45–52, Dec. 2019, doi: 10.54692/lgurjcsit.2019.030492.