A Review of Human Emotion Recognition

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Abstract:

A research has been introduced to add on Human Computer Interaction (HCI) over the decades. Emotions are due to any activity in brain and identified through face, as face has maximum sense organs. Facial expression is an important medium for human communication and it can be applied in many real time applications. Between Verbal and Non-Verbal form of communication facial expression is a non-verbal communication. It express human thinking, feelings and his or her current mental situation. This paper aims to introduce the literature review of facial emotion recognition by extracting emotional features using various transforms or with the help of fiducial points on facial image along with various classifiers. It includes introduction of facial emotion recognition system, a comparative study of facial expression recognition techniques. The comparison with the state-of-the-art performance on the CK+, JAFFE database, FER 2013, self-generated subjects and its percentage accuracy.

Keywords: Facial emotion recognition, Gabor filter, Support Vector Machine, face detection, Convolution Neural Network.

1.Introduction

Emotion plays an important role in human life. Emotional aspect is a big impact on social interaction and communication understanding which also helps to recognize the behavioral manner. Humans express emotions in day to day interactions. Interpersonal communication includes not only language which can be spoken, but also non-verbal ways as hand, body gestures and tone of the voice, which are used to express feeling and react through facial expression. Understanding and knowing how to react to people's expression will enriches the interaction [1]. Facial expression for emotion detection has always been an easy task for humans, but achieving the same task with a computer algorithm is quite challenging. Facial emotion expression is an important part of human body in daily life. As human can shows number of emotions everyday depending upon the mental and emotional state of a human being. Universally seven types of facial emotions are considered which shows the internal feelings and emotional states of a person in different expressions like happy, sad, surprise, anger, disgusted faces as shown in Table 1 [2] Facial emotions can be captured by its muscles movement with features of eyebrows, mouth, nose and eyes, cheek, chin. When no expression on face considered as neutral. With the recent advancement in computer vision and machine learning, it is possible to detect emotions from facial images [3].

Table1. Universal Emotion Identification

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

Facial expression recognition (FER) is one of the most active research topics due to its wide range of applications in the human-computer interaction field. [4,5]. Facial emotional recognition is essentially pattern recognition and involves finding regularities in the set of data being analyzed. Using these regularities, faces, as well as emotions, can be recognized. Various techniques are followed to carry out the tasks which are widely fall into two classes, method of parameterization, and the method of recognition [6]. It is argued to achieve effective human-computer intelligent interaction, there is a need for the computer to interact naturally with the user, similar to the way humans interacts. Humans interact with each other mostly through speech, but also through body gestures to emphasize a certain part of speech and display of emotions. Emotions are displayed by visual, vocal and other physiological means. There is more and more evidence appearing that the emotional skills are part of intelligence [7]. If we want to achieve more effective human-computer interaction, recognizing the emotional state of the human from his or her face could prove to be an invaluable tool [4]. Facial emotion analysis is one of the most important tasks in affective computing, human-computer interaction, computer vision. [8]. The power spectrum density (PSD) features of EEG were extracted by time-frequency analysis, and then EEG features were selected for regression [9].

2.Related Work:

Since, human emotion recognition plays an important role in the interpersonal relationship, automatic recognition of emotions has been an active research topic from early eras, hence there are several advances made in this field. Between Verbal and Non-Verbal form of communication facial expression is form of non-verbal communication but it plays pivotal role. It express human perspective or feeling and his or her mental situation. Extensive efforts have been made over the past two decades in academia, industry, and government to discover more robust methods of assessing truthfulness, deception, and credibility to enhance Human Computer Interaction (HCI). Efforts have been made to catch human expressions of anyone hence human facial activity is considered. Emotions are due to any activity in brain and it is known through face, as face has maximum sense organs. Interpersonal communication between a human being and a computer can be increased rapidly by combining the pros of both human and machine. Ashwini Ann Varghese et al [1] described the advances made in this field and the various approaches used for recognition of emotions and proposed real time implementation of emotion recognition system. Dhwani Mehta et al [6] detected the emotions by facial expressions and compared results of emotion recognition by the Microsoft HoloLens (MHL) and a regular webcam. The algorithm consists of a combination of steps involved in a machine learning based approach and geometric-based approach for face detection and emotion recognition along with classification. Hatice Gunes et al [10] explored mechanisms for human recognition using modalities like voice and face display. This exploration has led to the identification of the main mechanisms, including the important role played in the recognition process by the dynamics of modalities. Constrained by the human physiology, the temporal evolution of a modality appears to be well approximated by a sequence of temporal segments called onset, apex, and offset. The method automatically detect temporal segments or phases, explores whether the detection of the temporal phases can effectively support recognition of affective states, and recognized affective states based on phase synchronization/alignment. Monika Dubey et al [2] introduced needs and applications of facial expression recognition. Bo-Lin Jian et al [11] constructed an emotion-specific activation maps to establish infrared thermal facial image sequences as an alternative approach to the determination of the correlation between emotional triggers and changes in facial temperature. During the testing process, data stored in the International Affective Picture System (IAPS) were used to create emotional clips that triggered three different types of emotion in the subjects, and their infrared thermal facial image sequences were simultaneously recorded. The test results showed that the problem of analyzing frame temperature had been resolved. The emotion-specific facial activation maps provide visualized results that facilitate the observation and understanding of information. The method improved data visualization, facilitating subsequent analysis of the correlation between emotions and facial temperature. Zachary Witkower et al [12] proved that bodily expressions of the emotions are reliably recognized by members of an isolated small-scale traditional society. The Mayangna of Nicaragua found that recognition rates for sadness and anger bodily expressions were high, and recognition rates for a fear bodily expression were lower but still signifcantly greater than chance, given that the Mayangna are unlikely to have learned these bodily expressions through cross-cultural transmission, their ability to recognize these displays provides strong evidence for the universality of each expression. Maha Shadaydeh et al [13] measured a better understanding of unintentional behavior cues about socio-emotional cognitive processes which is concerned with the analysis of the direction of emotional influence in dyadic dialogues based on facial expressions only.

Automatic perception of facial expressions with scaling differences, pose variations and occlusions would greatly enhance natural human robot interaction. Li Zhanget al [14] proposed unsupervised automatic facial point detection integrated with regression-based intensity estimation for facial Action Units (AUs) and emotion clustering. The facial point detector is able to detect 54 facial points in images of faces with occlusions, pose variations and scaling differences using Gabor filtering, Binary Robust Invariant Scalable Keypoints (BRISK), an Iterative Closest Point (ICP) algorithm and fuzzy c-means (FCM) clustering. Ligang Zhang et al [15] proposed an approach to solve this limitation using salient distance features, which are obtained by extracting patch-based 3D Gabor features. Correct cognition rate (CRR) on the Japanese Female Facial Expression (JAFFE) database and is among the top performers on the Cohn-Kanade (CK) database. The results indicates that patch-based Gabor features show a better performance over point-based Gabor features in terms of extracting regional features, keeping the position information, achieving a better recognition performance, and requiring a less number. The approach can be potentially applied into many applications, such as patient state detection, driver fatigue monitoring and intelligent tutoring system. Boughida Adil et al [3] proposed facial expression recognition approach based on the use of Gabor filter features. The extracted regions are the components of the face most involved in the expression of emotions and selected the best features with Principal Component Analysis (PCA). The Support Vector Machine (SVM) classifier is used for the classification of basic facial expressions. The recognition rates were found to be of 95.11% for JAFFE and 92.19% for CK+ datasets. The limitation of the work is the parameters of Gabor and SVM are chosen manually. It has been possible to search for the best values of these parameters with the generic algorithm, but the process will take enough time. Deriving an effective facial representation from original face images is a vital step for successful facial expression recognition. Caifeng Shanet et al [16] evaluated facial representation based on statistical local features, Local Binary Patterns (LBP), for person-independent facial expression recognition. Extensive experiments illustrate that LBP features are effective and efficient for facial expression recognition. Further formulated Boosted-LBP to extract the most discriminant LBP features, and the best recognition performance is obtained by using SVM classifiers with Boosted-LBP features. Yelin Kim et al [17] focused on facial emotion recognition in a domain of speakers produce emotional facial expressions while speaking. The main challenge of this domain is the presence of modulations due to both emotion and speech. They investigated the joint effects of emotion and speech on facial movement and it is critical to employ proper temporal segmentation and to leverage knowledge of spoken content to improve classification performance. Tong Zhang et al [18] proposed Scale Invariant Feature Transform (SIFT) features corresponding to a set of landmark points of each facial image are firstly extracted from each facial image. Then, a feature matrix consisting of the extracted SIFT feature vectors is used as input data and sent to a well-designed Deep Neural Network (DNN) model for learning optimal discriminative features for expression classification. In this paper, a DNN-driven feature learning method is used to deal with the multi-view Facial Emotion Recognition (FER) problem by borrowing the visual mechanism of facial expression recognition. Panagiotis C. et al [19] presented the mirror neuron system concept to efficiently foster emotion induction by the process of imitation. Higher order crossings (HOC) analysis was employed for the feature extraction scheme and a robust classification method, namely HOC-Emotion Classifier (HOC-EC), was implemented testing four different classifiers [quadratic discriminant analysis (QDA), k-nearest neighbor(k-NN), Mahalanobis distance and SVMs, in order to accomplish efficient emotion recognition. It facilitated the integration of HOC-EC in human machine interfaces, such as pervasive healthcare systems, enhancing the affective character and providing information about the user's emotional status. Usman Tariq et al [20] addressed both subject-dependent and subject-independent emotion recognition in this paper. The features consisting of hierarchical Gaussianization, Scale-Invariant Feature Transform (SIFT), and some coarse motion features have been used. The classification task has been divided into person-specific and person-independent emotion recognitions using face recognition with either manual labels or automatic algorithms. They achieved 100% performance for the person-specific, 66% performance for the person-independent, and 80% performance for overall results, in terms of classification rate, for emotion recognition with manual identification of subjects. Yimin Yang et al [21] proposed a hierarchical network structure with sub-network nodes to discriminate positive, neutral and negative human emotions. Each sub-network node embedded in the network that are formed by hundreds of hidden nodes, could be functional as an independent hidden layer for feature representation. The top layer of the hierarchical network, like the mammal cortex in the brain, combine such features generated from subnetwork nodes, but simultaneously, recast these features into a mapping space so that the network can be performed to produce cognition.

Automatic facial expression recognition is a sub-area of face analysis research that is based heavily on methods of computer vision, machine learning, and image processing. Chao Li et al [22] explored automatic recognition of facial expressions using 3D range images. The paper outlines the development of an algorithm designed to distinguish between neutral and smiling faces and summarizes its experimental verification with a database containing 30 subjects who posed for both (neutral and smiling) expressions. As a comparison with 2D facial expression recognition, a PCA algorithm was used to exact features from 2D images and used for expression recognition. Results show that 3D facial expression recognition outperforms 2D ones. This pursues the recognition of "absolute facial expressions" which means that the recognition is being attempted without prior knowledge about the neutral facial expression of a subject. The psychological background of emotion recognition from the micro-expressions problem, Anna D. Sergeeva et al [23] described the modern viewpoint that considers the main preliminary steps or task of searching for the areas of a face and eyes in the facial image. The Viola – Jones algorithm based on the color intensity estimation is suitable for color images and faster for the small images and also be applied to grayscale images and faster for images of a higher resolution. Experiments approved that considered algorithm provide sufficient results for the tasks of determining the face and eyes areas in the image and intended to investigate the whole pipeline to detect and recognize the human micro-expressions, thereby to develop the more precise emotion recognition methods. As one of the most comprehensive and objective ways to describe facial expressions Brais Martinez et al [7] used Facial Action Coding System (FACS) which provides a comprehensive survey of research into machine analysis of facial actions. All components of such systems are reviewed through pre-processing, feature extraction and machine coding of facial actions. Qi-rong Mao et al [24] captured the deformation of the 3D mesh during facial expression and combined the features of AUs and Feature Point Positions (FPPs) tracked by Kinect. Real-time emotion recognition approached is based on both 2D and 3D facial expression features captured by Kinect sensors. To A fusion algorithm based on Improved Emotional Profiles (IEPs) and maximum confidence is proposed to recognize emotions with these real-time facial expression features. C. Mumenthaler et al [25] investigated the influence of socio-affective inferential mechanisms on the recognition of social emotions. They used synthesized facial expressions that are investigated by the influence of socio-affective inferential mechanisms on the recognition of social emotions. The dynamics of the facial expressions and the head/gaze movements of the two avatars were manipulated in order to create an interaction in which the two avatars shared eye gaze only in the social interaction condition. Shangfei Wang et al [26] proposed a dynamic model using Efficient Learning and inference algorithm an Interval Temporal Restricted Boltzmann Machine (IT-RBM) that is able to capture both universal spatial patterns and complicated temporal patterns in facial behavior for facial expression analysis. Facial expression as a multifarious activity composed of sequential or overlapping primitive facial events. Experiments on posed and spontaneous expression distinction and expression recognition demonstrate IT-RBM achieves superior performance compared to state-of-the art research due to its ability to incorporate these facial behavior patterns.

Combining global and local features is an essential solution to improve discriminative performances in facial expression recognition tasks. The limitations of existing methods are that they cannot extract crucial local features and ignore the complementary effects of local and global features. To address these problems Haifeng Zhang et al [27] proposed a Weakly Supervised Local-Global Attention Network (WS-LGAN), which uses the attention mechanism to deal with part location and feature fusion problems. Similar hybrid feature descriptor-based method is proposed by Tehmina Kalsum et al [28] to recognise human emotions from their facial expressions. A combination of Spatial Bag of Features (SBoFs) with Spatial Scale-Invariant Feature Transform (SBoF-SSIFT), and SBoFs with spatial speeded up robust transform are utilised to improve the ability to recognise facial expressions. For classification of emotions, k-NN and SVMs with linear, polynomial, and radial basis function kernels are applied. SBoF-SSIFT with SVM resulted in a recognition accuracy of 98.5% on CK+ and 98.3% on JAFFE data set. Images are resized through selective pre-processing, thereby retaining only the information of interest and reducing computation time. These methods are highly robust and powerful for emotion recognition.

Ye Tian et al [29] proposed Secondary Information aware Facial Expression Network (SIFE-Net) to explore the latent components without auxiliary labeling, and a novel dynamic weighting strategy to teach the SIFE-Net. They developed a dynamic weighting training strategy that can progressively add in secondary information during network training, enabling the target net to learn from an appropriate portion of primary and secondary information at every step.

Many researchers have used Artificial Neural Networks (ANN) an effective way to make use of both spatial and temporal dependencies of the input signals to machine for automatic emotion recognition. Kavita Kushwah et al [30] recognized the human emotions using the system that depends upon the human face, as we know face also reflects the human brain activities or emotions. The ANN has been used for better results. The paper comparisons of existing Human Emotion Recognition (HER) System has been made with new one. Pedro M. Ferreira et al [5] proposed end-to-end neural network architecture along with a well-designed loss function based on the strong prior knowledge that facial expressions are the result of the motions of some facial muscles and components. The loss function is defined to regularize the entire learning process, so that the neural network is able to explicitly learn expression-specific features. The facial-parts component aims to regress a relevance map, representing the most important facial regions for the expression recognition Tong Zhang et al [31] proposed two-layer Recurrent Neural Network (RNN) model provides an effective way to make use of both spatial and temporal dependencies of the input signals for emotion recognition. The network which contains only Temporal Recurrent Neural Network (TRNN) achieves the accuracy of 85.20% with the deviation of 9.13%, while the network containing only Spatial Recurrent Neural Network (SRNN) achieves a little higher accuracy of 85.88% but with a higher deviation of 9.98%. Spatial Temporal Recurrent Neural Network (STRNN) achieves the accuracy of 89.50% which is about 4% higher than SRNN or TRNN with a lower deviation. Kaustubh Kulkarni et al [32] suggested behavior would be easier to distinguish when captured in high resolution at an increased frame rate. The overall the problem of recognized whether facial movements are expressions of authentic emotions or not can be addressed by learning Spatio-Temporal representations of the data. They proposed a method that aggregates features along fiducial trajectories in a deeply learning space. Initially, current state of the art Convolution Neural network (CNN), such as Visual Geometric Group-Face(VGG-Face), do not work at the required spatial resolution to detect minute changes in facial muscle movements, which are required to differentiate and distinguish between unfelt Facial Emotional Expressions (FEEs). Finally, alternative temporal analysis strategies could be considered to analyse SASE-FE at high fps, which may include variants of Recurrent Neural Nets or 3D-CNNs approaches. Hadjer Boubenna et al [33] proposed Generic Algorithm (GA) based on Linear Discriminant Analysis (LDA) classifier and hinge loss to evaluate and select the relevant features. The method efficiently decreased the features size and improved the classification accuracy within a reasonable time. The approach has outperformed Principal Component Analysis (PCA)-based feature selection approach and other existing algorithms, and compared method to VGG-face CNN in terms of accuracy, training time and features size. Though the method based on evolutionary algorithm optimization has been trained on a small dataset, it outperforms other well-known dimensionality reduction approaches. Luis Lopes Chamino et al [34] exploited in facial recognition applications, to detect facial expression variations, pose variations and presentation attacks, a facial analysis system can benefit not only of images from the visible spectral band but also of infrared images. It can be concluded that the most used methods for facial recognition and the ones that achieved best results are based on neural networks. In fact, 36% of the most relevant papers use neural networks as a multispectral facial recognition method. Paweł Tarnowski et al [35] presented the results of recognition of emotional states based on facial expressions. Coefficients describing elements of facial expressions, registered for six subjects, were used as features. The features have been calculated for 3D face model. The classification of features was performed using k-NN classifier and Multilayer Perceptrons Neural Network (MLPNN). In the carried out experiments, for 7 emotional states were achieved a very good classification accuracy of emotions as 96% for random division of data and satisfactory classification accuracy of 73%, for "natural" division of data. Sabrina Begaj et al [36] studied the challenges of Emotion Recognition Datasets and also try different parameters and architectures of the CNNs in order to detect the seven emotions in human faces. Ming Li et al [37] expressed different subjects on a specific expression in different ways due to inter-subject variabilities and proposed an identity and emotion joint learning approach with deep CNNs to enhance the performance of FER tasks. Experimental results show that the proposed approach achieves 99.31% and 84.29% accuracy on the CK+ and the FER+ database, respectively, which outperforms the residual network baseline as well as many other state-of-the-art methods. Duncan Dan et al [38] implemented an application wherein an emerging one of six expressions is superimposed over a user's face in real time using custom trained VGGs network with a face-detector provided by OpenCV. Each pair of images indicates a pair of images. The emotion detected by the CNN is indicated by the type of emoji superimposed over the subject's face. A particularly difficult aspect of real-time recognition is deciding how to classify transition frames from neutral to fully formed expressions of emotion. Ninad Mehendale [39] proposed a technique called Facial Emotion Recognition using convolutional neural networks (FERC). FERC differs from generally followed strategies with single-level CNN, hence improving the accuracy. A novel background removal procedure applied, before the generation of Expressional Vector (EV), avoids dealing with multiple problems that may occur (for example distance from the camera). FERC was extensively tested with more than 750K images using extended CK, Caltech faces, CMU and NIST datasets. The main advantage of the FERC algorithm is that it works with different orientations (less than 30°) due to the unique 24 digit long EV feature matrix. The background removal added a great advantage in accurately determining the emotions. FERC could be the starting step, for many of the emotion-based applications such as lie detector and also mood-based learning for students, etc. Chen Jia et al [40] proposed a recognition method based on CNN ensembles. The model is composed of three sub-networks, and uses the SVM classifier to integrate the output of the three networks to get the final result. The recognition accuracy of the model's expression on the FER2013 dataset reached 71.27%. The results show that the method has high test accuracy and short prediction time, and can realize real-time, high-performance facial recognition. Said et al [41] proposed CNN to solve the emotion recognition task. The proposed CNN was built to be sensitive to faces in images to analyze facial expressions and then recognizing emotions. A Face-Sensitive CNN (FS-CNN) for human emotion recognition, used to detect faces on large scale images then analyzing face landmarks to predict expressions for emotion recognition. The FS-CNN is composed form two stages, patch cropping, and convolutional neural networks. The proposed FS-CNN was trained and evaluated on the UMD Faces dataset. High performance was achieved with a mean average precision of about 95%. Madupu et al [42] proposed an automatic facial emotion classification system using the CNN with the features extracted from the Speeded Up Robust Features (SURF). 91% accuracy is achieved with the proposed model which supports tracking human emotion with facial expressions. Abdullah Talha Kabakus [43] is proposed on CNN architecture known as PyFER. The accuracy of PyFER was calculated to be as high as 96.3% on a de-facto standard dataset, namely, CK+, and all facial expressions, except for happiness, were correctly detected by PyFER, 16.67% of the images that actually represented the facial expression happiness were misdetected as the facial expression fear. Akash Saravanan et al [44] classified images of human faces into one of seven basic emotions. A number of different models were experimented with, including decision trees and neural networks before arriving at a final CNN model. The model consists of six convolutional layers, two max pooling layers and two fully connected layers. Upon tuning of the various hyperparameters, this model achieved a final accuracy of 0.60. The ability of the model to make predictions in effectively real-time, indicates that real world uses of facial emotion recognition is barred only by the relative inaccuracies of the model itself. A MultiTask Convolutional Neural Network (MTCNN) has been employed to accurately detect the boundaries of the face, with minimum residual margins. Ali Ghofrani et al [45] proposed model outperforms the state-of-the-art on FER 2013 dataset which has been provided by Kaggle. The algorithm integrates two different CNN based modules. An MTCNN, is used for correctly cropping the face boundary, a ShuffleNet V2 is exploited to recognize the emotions using the optimum depth which could be used in realtime. Gerard Pons et al [46] presented to improve the assembling of the committee by introducing supervised learning on the ensemble computation. Trained a CNN on the posterior-class probabilities resulting from the individual members allowing to capture non-linear dependencies among committee members, and to learn this combination from data. The validation shows an accuracy 5% higher with respect to previous state-of-the art results based on averaging classifiers, and 4% to the majority voting rule.

Deep convolutional neural networks (DCNNs) have achieved outstanding results in facial expression recognition (FER). Hui Ma et al [47] proposed a novel lightweight attention DCNN (LA-Net) for robust FER, which uses squeeze-and-excitation (SE) modules and the network slimming strategy. The LA-Net model can achieve 95.52%, 87.00% and 100% test accuracy on KDEF, RAF-DB and FERG-DB FER datasets respectively. The experimental results show that the method achieves better or comparable results than state-of-the-art FER methods and significantly reduces the computational cost and the number of parameters, with better generalization capability and robustness. Hyeon-Jung Lee et al [48] introduced positive and negative emotion recognition methods using facial images and the development on app. The deep-learning technology is used to generate models with emotion-based facial expressions to recognized emotions. They recognized seven emotions and also classified the calculated emotion-recognition scores into positive, negative and neutral emotions and implemented an app which provides the user with seven emotions scored and positive and negative emotions. When applied those recognition methods into apps, application performance rate was 50.7% in seven emotions and in positive and negative was 72.3%. Wentao Hua et al [49] considered Human emotions recognition

(HERO) for realizing the intelligent Internet of Things. The deep recognition algorithm based on the ensemble deep learning model. The algorithm consists of three sub-networks with different depths. Each sub-network is comprised of CNN and trained independently. The three sub-networks are assembled together to constitute the whole model. The experiment is based on the Kaggle facial expression recognition challenge database (FER2013), JAFFE and AffectNet database. The experimental results show that the algorithm achieves a test accuracy of 71.91%, 96.44%, and 62.11% better than other competitors, and increases the test accuracy by approximately 2–3% than unique sub-networks. Machine learning algorithms and especially deep neural network can learn complex features and classify complex patterns. Zadeh et al [50] presented a deep learning based framework for human emotion detection. The framework uses the Gabor filters for feature extraction and then the DCNN. By applying Gabor filter, the system learning became faster and the accuracy has improved. This is because the Gabor filter actually extracts the image sub feature and gives the neural network. By doing this, the CNN receives a number of sub feature and takes one step further in extracting the emotions from the faces. Kaviya P et al [8] proposed the human group facial sentiment recognition system using a deep learning approach. The framework uses the Haar filter to detect and extract face features. Then the CNN is developed to recognize facial expressions and classify them into five basic emotion states. The experimental results prove that the CNN can learn facial expression characteristics and the test accuracy of the model becomes 65% for FER-2013 and 60% for custom datasets. Hsiuao-Ying Chen et al [51] proposed a hybrid-boost learning algorithm for multi-pose face detection and facial expression recognition as well as three decision rules which generates higher detection rate and lower false alarm rate. This system detects human face in different scales, various poses, different expressions, partial-occlusion, and defocus. Major contribution is proposing the weak hybrid classifiers selection based on the Harr-like (local) features and Gabor (global) features. The experimental results show that the system has better performance than the others using Harr-like feature or Gabor feature. J. J. Wong et al [52] Described a structural approach to recognize the human facial features for emotion recognition and proposed to extract facial expression features vectors as Localized Gabor Features (LGF) and then transform these feature vectors into FacE Emotion Tree Structures (FEETS) representation. A structural connectionist architecture based on a probabilistic approach to adaptive processing of data structures is presented. The probabilistic based recursive neural network is developed to train and recognize human emotions by generalizing the FEETS representation.

An improved DCNN is proposed by Garima Verma et al [53] to predict emotions by analysing facial expressions contained in an image. The model developed consists of one CNN to analyse the primary emotion of the image as being happy or sad and a second CNN to predict the secondary emotion of the image. A dropout rate of 0.2 was applied to obtain maximum accuracy. The FER2013 and JAFFE datasets were used to evaluate the performance of the model, for which accuracies of 97.07% and 94.12% were obtained. Jiacheng Liao et al [54] presented a model called the Deep Facial Spatiotemporal Network (DFSTN) for engagement prediction. The model contains two modules: the pretrained SE-ResNet-50 (SENet), which is used for extracting facial spatial features, and the Long Short Term Memory (LSTM) Network with Global Attention (GALN), which is employed to generate an attentional hidden state. The paper evaluated the methods on the Dataset for

Affective States in EEnvironments (DAiSEE) and obtain an accuracy of 58.84% in four-class classification and a Mean Square Error (MSE) of 0.0422. Marios Kyperountas et al [55] presented and evaluated a facial expression classification (FEC) method. The salient-feature-and-reliable-classifier selection (SFRCS) algorithm produces high-quality features and implements a classification scheme, where results from the most reliable classifiers are integrated in order to produce the classification decision. To properly integrate the two class classification results and produce the FEC decision, a computationally efficient and fast classification scheme is developed. The JAFFE and the MMI databases are used to evaluate the performance of the proposed SFRCS methodology. Classification rates of 96.71% and 93.61% are achieved under the leave-one-sample-out evaluation strategy, and 85.92% under the leave-one-subject-out evaluation strategy.

Jan Jaracz et al [56] evidenced that facial emotion recognition is disturbed in schizophrenic patient's and is associate with other neurocognitive deficits. Some evidence suggests that affect recognition is an important aspect of psychosocial functioning of patients with schizophrenia. Schizophrenic patients performed worse on emotion recognition test than control group. Dysfunction of prefrontal cortex may negatively influence the recognition of emotions. Lize C. Jiskoot et al [57] developed to overcome shortcomings of static emotion recognition paradigms, by identifying more subtle deficits in emotion recognition across different intensity levels. Also investigated an emotion recognition deficits across the frontotemporal (FTD) and Alzheimer's Dementia (AD) spectrum. This highlights the importance of incorporating dynamic emotion recognition paradigms such as the ERT into the standard neuropsychological assessment for early differential diagnosis in dementia and as potential clinical endpoints in upcoming therapeutic trials for FTD and AD. Tanya Keshari et al [58] studied Plethora to analyze human emotions using facial expressions, EEG signals and speech etc. They presented a bimodal emotion recognition system constructed on face expressions and upper body gestures. Psychological research findings advocate that humans depend on the collective visual conduits of face and body to comprehend human emotional behavior. Hongli Zhang [59] proposed an expression-EEG interaction multi-modal emotion recognition method using a deep automatic encoder. The recognition rate of discrete emotion state type and the average emotion recognition rate have been improved in which the average emotion recognition rate is 85.71%. Overall, the emotion recognition ability has been greatly improved. Laura Piho et al [60] suggested, that using only the signal section which best describes emotions improves the classification of emotions. This is achieved by iteratively comparing different-length EEG signals at different time locations using the mutual information between the reduced signal and emotion labels as criterion. Emotion recognition using brain wave signals involves using high dimensional electroencephalogram (EEG) data. Aya Hassouneh et al [61] classified physically disabled people (deaf, dumb, and bedridden) and Autism children's emotional expressions based on facial landmarks and electroencephalograph (EEG) signals using a CNN and LSTM classifiers by developing an algorithm for real-time emotion recognition using virtual markers through an optical flow algorithm that works effectively in uneven lightning and subject head rotation, different backgrounds, and various skin tones. The paper achieved a maximum recognition rate of 99.81% using CNN for emotion detection using facial landmarks. However, the maximum recognition rate achieved using the LSTM classifier is 87.25% for emotion detection using EEG signals. Chunmei Qing et at [62] proposed a coefficients-based method based on machine learning using EEG signals. This method not only outperformed the benchmark algorithms in terms of accuracy but also interpret the progress of emoton activation. The algorithm extracts features from EEG signals and classifies emotions using machine learning techniques, in which different parts of a trial are used to train the proposed model and assess its impact on emotion recognition results. Dahua Li et al [9] presented a decision level fusion framework for detecting emotions continuously by fusing the EEG and facial expressions. Three types of movie clips (positive, negative, and neutral) were utilized to elicit specific emotions of subjects, the EEG and facial expression signals were recorded simultaneously. The results have shown that the proposed method achieved continuous emotion recognition, and it yields 0.625±0.029 of concordance correlation coefficient (CCC). Peiyang Li et al [63] proposed to combine brain network topology and power spectral activation patterns based on EEG data for emotion recognition. The method not only captures the local activities responding to emotion, but also mines the interactions among the related brain areas. The reduced electrodes by selecting the crucial channels and combining the compensative features derived from EEG signal can improve the performance and robustness of emotion recognition.

Loic Kessous [64] constructed a scenario of people pronouncing a sentence in where they interacted with an agent using speech. Ten people pronounced a sentence corresponding to a command while making 8 different emotional expressions. Gender was equally represented, with speakers of several different native languages including French, German, Greek and Italian. Facial expression, gesture and acoustic analysis of speech were used to extract features relevant to emotion. Fusing the multimodal data resulted in a large increase in the recognition rates in comparison to the unimodal systems. The results show that the best pairing is 'gesture-speech'. Using all three modalities resulted in a 3.3% classification improvement over the best bimodal results. Zheng Lian et al [65] proposed a multimodal learning framework for conversational emotion recognition, called conversational transformer network (CTNet) to overcome limitations in modeling the intra-modal and cross-modal interactions. Experimental results on the IEMOCAP and MELD datasets demonstrate the effectiveness of the proposed method. The method shows an absolute 2.1~6.2% performance improvement on weighted average F1 over state-of-the-art strategies. The paper proved that capturing the long-term contextual dependency improves the performance of conversational emotion recognition. Hiranmayi Ranganathan et al [66] presented the emoFBVP database of multimodal recordings of actors enacting various expressions of emotions. The database consists of audio and video sequences of actors displaying three different intensities of expressions of 23 different emotions along with facial feature tracking, skeletal tracking and the corresponding physiological data. Next described four deep belief network (DBN) models and showed that these models generate robust multimodal features for emotion classification in an unsupervised manner. Linqin Cai et al [67] recognized a multimodal emotion model based on speech and facial expression is proposed a method that combines speech and facial expression features from CNN and LSTM to learn speech emotion features. Simultaneously, multiple small-scale kernel convolution block was designed to extract facial expression features. At last Used DNNs to fuse speech and facial expression features. Ciprian Adrian et al [68] introduced emotional body gestures for showing general aspect gender differences and culture dependence. They have briefly introduced important pre-processing concepts like person detection and body pose estimation and detailed a large variety of methods which recognizes emotion from body gestures grouped along important concepts such as representations learning and emotion recognition methods. A live video stream connected to a face detector and feeds images to the neural network. An overall training accuracy of 90.7% and test accuracy of 57.1% is achieved. For dynamic expression recognition two key issues presented by Mengyi Liu et al [69] temporal alignment and semantics-aware dynamic representation, must be taken into account that solves both problems via manifold modeling of videos based on a novel midlevel representation. Aitor Azcarate et al [4] presented a system for recognizing emotions through facial expressions displayed in live video streams and video sequences which is based on the Piecewise B´ezier Volume Deformation tracker and has been extended with a Haar face detector to initially locate the human face automatically. The experiments with Naive Bayes and the Tree-Augmented-Naive Bayes (TAN) classifiers in person-dependent and person-independent tests on the Cohn-Kanade database obtained good classification results for facial expression recognition. The classifier shows a strange behavior when readapting the mask after it loses it, due a continuous classification of the deformations. This should be transparent to the user, using the face detector to localize the position and the scale of the face and sequentially apply another algorithm to adjust those markers to the current face. 3D videos of a face contained more information in terms of the facial dynamics which are very critical for expression recognition. Hayat et al [70] presents a fully automatic framework which exploits the dynamics of textured 3D videos for recognition of six discrete facial expressions. An efficient graph-based spectral clustering algorithm is used to separately cluster these points for every expression class. The proposed framework is also implemented in parallel on 2D videos and a score level fusion of 2D and 3D videos is performed for performance improvement of the system. SVM models are learnt on the Grassman followed by a voting based strategy for classification. The theory of RKHS has been explored to adapt the SVM classifier for the Grassmannian manifold. A new Grassmannian kernel function is also proposed. The performance of the system is tested on the largest publicly available 3D video database, BU4DFE.

3.Results and Discussions:

This section covers comparative analysis of the state-of-the-art research work under consideration. The parameters used for comparison are author's name, databases used, various emotions used, features extracted, methodology or classifiers used and percentage accuracy achieved. Table 2 summarizes the state-of-the-art research work using various transforms like Gabor, PCA, Haar features, LBP, boosted LBP, LGF, SBoF-SSIFT, ICA, Tandem facial expression etc. for feature extraction followed by different classifiers.

Table 2 State-of-the-art research work using various transforms for feature extraction.

Sr. No	Name of Author	Database	Emotions Used	Features Used	Methodology/ Classifier	Result and Accuracy
1.	Boughida Adil [3]	JAFFE, CK+	Happy, Neutral, Sadness,	Gabor, PCA	SVM	95.11%

			Surprise, Anger, Disgust			
2.	Ligang Zhang [14]	JAFFE, CK	Happy, Neutral, Sadness, Surprise, Anger, Disgust, Fear	Facial movement using patch based Gabor filter	Adaboost feature selector, SVM (Linear,Polynomial,RBF,Sigmoid),	92.93% 94.48%
3.	C. Shan [16]	JAFFE CK	Happiness, Angry, Surprise, Sadness, Disgust, Fear	Boosted-LBP	Local binary patterns,SVM, Adaboost LDA	81.0% 95.1%
4.	Tehmina Kalsum [28]	JAFFE CK+	Happy, Sad, Surprise, Disgust, Fear, Anger	Spatial Bag of Features (SBoFs) with Spatial Scale-Invariant Feature Transform (SBoF-SSIFT)	SVM Classifier k-NN Classifier	98.5% 98.3%
5.	Ye Tian [29]	JAFFE CK+ RAF	Happiness, Angry,Surprise, Sadness, Disgust, Fear, Neutral	hand-craft features LBP, HOG and Gabor	SVM Classifier	88.95% 91.98% 77.28%
6.	Boubenn [33]	Radboud Faces Database(RaFD)	Happiness, Angry, Surprise, Sadness, Disgust, Fear	Genetic algorithm with Linear discriminant classifier, Pyramid Histogram oriented gradient (PHOG)	Visual Geometry Group (VGG-face) CNN, LDA classifier	98.67%

7.	Dan Duncan [38]	JAFFE, CK+	Angry, Fear, Neutral, Happy, Sad, surprise	Haar cascades	VGG_S network CNN	90.9%
8.	Yahia said [41]	CelebA, UMD	Anger, Disgust, Fear, Happy, Sadness, Surprise, Neutral	Handcrafted feature extractor	FS-CNN	95%
9.	Hyeon-Jung Lee [48]	eNTERFACE+LAB DB	Happiness, Angry,Surprise, Sadness, Disgust, Fear, Neutral	Histogram orientented gradient(HOG)	DCNN	*51.2% *75.92%
10.	Milad zadeh [50]	JAFFE	Anger, Disgust, Grief, Fear, Happy, Surprise	Gabor	CNN	91%
11.	H. Y. Chen [51]	CK	Happy, Anger, Sad, Surprise, Fear, Disgust	Gabor, Haar features	Multi pose face detection method	93.1%
12.	J. J. Wong [52]	JAFFE CK	Happy, Neutral, Fear, Anger, Sad, Surprise, Disgust	Localised Gabor Features (LGF)	Navie Bayes SVM k-NN FEETS + PRNN	83.84% 95.87%
13.	Kaviya Arumugaprakash T [8]	FER-2013 Custom database	Happy, Sad, Anger, Surprise, Neutral	Haar features	CNN	65% 60%
14.	Zhang [15]	CK	Happiness, Angry,Surprise, Sadness	Gabor,Iterative closest points, Binary robust invariant	Support Vector Regression (SVR) based AU intensity	90.38%

				scalable keypoints		
15.	Dahua Li [9]	Movie clips	Emotion states- positive, negative and neutral	PCA, t-Distributed Stochastic Neighbor Embedding (t-SNE), ICA spatial filtering	Valence continuous detection	62.5%
16.	Li [22]	Self-generated dataset	Neutral, Smiling	PCA algorithm	LDA classifier, SVM	3D database- above 90% 2D database- above 80%

Bougida Adil et al [3] used Gabor and PCA features for SVM classifier over the emotions like happy, sad, neutral, surprise, anger and disgust. The accuracy achieved is 95.11% and databases used are JAFFE and CK+. Ligang Zhang et al [14] proposed that no more processing is conducted to imitate the results of real face detectors. Multiresolution Gabor images are attained by convolving eight scale, four-orientation Gabor filters with the scaled facial regions. To capture facial movement features, the matching area and matching scale are defined to increase the matching space, whereas the minimum rule is used to find the best matching feature in this space. For JAFFE and CK dataset by applying Gabor and CNN achieved the accuracy of 92.93% and 94.48%.The emotions used are happiness, angry, surprise, sadness, disgust and fear. C. Shan et al [16] formulate Boosted-LBP to extract the most discriminant LBP features, and the best recognition performance is obtained by using SVM classifiers with Boosted-LBP features. In the experiments observed that LBP features perform stably and robustly over a useful range of low resolutions of face images, and yield promising performance in compressed low-resolution video sequences captured in real-world environments with JAFFE and CK database achieved an accuracy of 81% and 95.1%. The emotions used are happiness, angry, surprise, sadness, disgust, fear and neutral. The method proposed by Tehmina Kalsum et al [28] differs from conventional methods that are used for simple object categorisation without using spatial information. Experiments have been performed on extended CK+ and JAFFE data sets. SBoF-SSIFT with SVM resulted in a recognition accuracy of 98.5% on CK+ and 98.3% on JAFFE data set. The emotions used are happiness, angry, surprise, sadness, disgust, fear and neutral. Ye Tian et al [29] used a dynamic weighting strategy to teach the SIFE-Net, that takes advantage of secondary expression information and has more rational feature distributions. From the experiments and analysis on CK+ dataset, JAFFE dataset and the RAF dataset achieved an accuracy of 91.98%, 88.95% and 77.28% respectively. The emotions used are happiness, angry, surprise, sadness, disgust, fear and neutral. Boubenna et al [33] applied an evolutionary algorithm in combination with linear discriminant analysis (LDA) to enhance the feature selection in a static image-based facial expressions system. The approach performs linear-based dimensionality reduction algorithms and other existing genetic-based feature selection algorithms and compared this approach with VGG-face CNN, the overall accuracy is 98.67% for VGG face. The emotions used are happiness, angry, surprise, sadness, disgust and fear. Dan Duncan et al [38] used connected layers of an existing convolutional neural network which was pretrained for human emotion classification. An overall training accuracy of 90.9% is achieved. The network subsequently classifies an arbitrary number of faces per image simultaneously in real time, wherein appropriate emojis are superimposed over the subjects' faces. The dataset used are JAFFE and CK+. Yahia Said et al [41] proposed a face-sensitive convolutional neural network (FS-CNN) for human emotion recognition. The emotions used are happiness, angry, surprise, sadness, disgust, fear and neutral. The proposed FS-CNN was trained and evaluated on the UMD Faces dataset. High performance was achieved with a mean average precision of about 95%. Hyeon-Jung et al [48] have used the Histogram oriented gradient (HOG) with DCNN. The accuracy achieved from experimental results is 51.2% for eNTERFACE dataset and 75.92% for LAB Database. The emotions used are happiness, angry, surprise, sadness, disgust, neutral and fear. Milad Zadeh et al [50] used Gabor feature for CNN and achieved an accuracy of 91% over JAFFE database. The emotions used are happy, sad, neutral, surprise, anger and disgust. H. Y. Chen et al [51] proposed a hybrid-boost learning algorithm for multi-pose face detection and facial expression recognition.The major contribution is proposing the weak hybrid classifiers selection based on the Harr-like (local) features and Gabor (global) features. The experimental results show that the face detection obtained an accuracy of 93.1% for CK database. J. J. Wong et al [52] used Localised Gabor feature over the happy, sad, neutral, surprise, anger, fear and disgust emotions. The Naïve Bayes, SVV, k-NN classifiers are used and results obtained is 83.84% for JAFFE database and 95.87% for CK database. Kaviya et al [8] proposed framework uses the Haar filter to detect and extract face features. Then the convolutional neural network (CNN) is developed to recognize facial expressions and classify them into five basic emotion states like happy, sad, anger, surprise and neutral. The proposed model achieves a accuracy of 65% for Facial Expression Recognition (FER)-2013 and 60% for custom datasets. L. Zhang et al [15] used Gabor, Binary robust invariant scalable key points for SVR based Action units. The accuracy achieved is 90.38% for CK database and the emotions used are happiness, angry, surprise and sadness. Dahua Li et al [9] presented a decision level fusion framework for detecting emotions continuously by fusing the Electroencephalography (EEG) and facial expressions. Three types of movie clips (positive, negative, and neutral) were utilized to elicit specific emotions of subjects, the EEG and facial expression signals were recorded simultaneously. The power spectrum density (PSD) features of EEG were extracted by time-frequency analysis, and then EEG features were selected for regression. Long short-term memory networks (LSTM) were utilized to accomplish the decision level fusion and captured temporal dynamics of emotions. Movie clips are used as a dataset with an accuracy of 62.5%. Chao Li et al [22] designed and developed an algorithm to distinguish between neutral and smiling faces. Summarizes its experimental verification with a database containing 30 subjects expressions. As a comparison with 2D farcical expression recognition, a PCA algorithm was used to exact features from 2D images. Results show that 3D facial expression recognition outperforms 2D ones with an accuracy of 90% with LDA and SVM.

Table 3 shows the comparative analysis of state-of-the-art research work based on fiducial points of facial image. The table summarizes the research papers who have used various features like movement of facial points, phased based Gabor, MLP neural network, k-NN classifier, frame based classifier, LDA, LSTM, DFSTN, SE-ResNet-50, SVM and CNN etc. for feature extraction.

Table 3 State-of-the-art research work based on fiducial points of facial image.

Sr. No	Name of Author	Database	Emotions Used	Features Used	Methodology/ Classifier	ult l Accuracy
1.	Aitor Azcarate [4]	CK	Happiness, Angry,Surprise, Sadness, Disgust, Afraid, Neutral	Marker points on facial features	Naïve Bayes, Tree Augmented naïve Bayes	Person dependent-93.2% Person independent-62.1%
2.	Hatice Gunes [10]	FABO	Anger, Disgust, Fear,Happiness and Sadness	Various points of face(eye, eyebrows, nose, mouth)	Frame based classifiers	82.65%
3.	Shangfei Wang [26]	DISFA+ SPOS	Anger, Disgust, Contempt, Fear, Happy, Sadness, Surprise	Movements of facial feature points	IT-RBM model	94.90%
4.	Kaustubh Kulkarni [32]	CK+ Oulu-CASIA	Happiness, Angry,Surprise, Sadness, Disgust, Fear	Appearance based, Geometric facial features	CNN	98.7%

5.	Pawel Tarnowski [35]	FACS-AU	Neutral, Joy, Angry,Surprise, Sadness, Disgust, Fear	Action unit coefficients	MLP Classifier and k-NN Classifier	96%
6..	Chen Jia [40]	FER2013	Anger, Disgust, Contempt, Fear, Happy, Sadness, Surprise	Facial emotions expression features	SVM, CNN	71.27%
7.	Akash Survanan [44]	Live testing module	Anger, Disgust, Contempt, Fear, Happy, Sadness, Surprise	Tandem facial expression feature, Adan optimizer	Decision tree, Feedforward NN, CNN	60.58%
8.	Aya Hassouneh [61]	EEG database(own developed dataset)	Happiness, Anger, Sadness, Fear, Disgust, Surprise	Face feature extraction	LSTM classifier, DCNN	99.8%
9.	Jiacheng Liao [54]	EmotiW-EP	Anger, Disgust, Fear, Sad, Happy, Surprise(any one emotion)	Facial spatial features, Long short term memory with Global attention	DFSTN, SE-ResNet-50	58.84%

Aitor Azcarate et al [4] used automated marker points on landmark facial features and detected the initial location of the human face automatically. They used this information to place the marker points near their landmark features by placing a scaled version of the landmark model of the face on the detected face location. A selection of features through a boosting algorithm with Naïve Bayes and Tree Augmented Naïve eyes with an accuracy of 93.2% for person dependent and 62.1% for person independent system. The emotions used are happiness, anger, surprise, sadness, disgust and fear with CK database. Hatice Gunes et al [10] used a combination of appearance (e.g., wrinkles) and geometric features (e.g., feature points) for face feature extraction. For face feature extraction, only the videos obtained from the face camera are used (self-generated dataset) and achieved 82.65% accuracy by Frame based classifier with the emotions like anger, disgust, fear, happiness and sadness. Shangfei Wang et al [26] shows that the movement of one facial muscle can activate, overlap, or follow the movement of another muscle. Because of the difficulty in measuring minute facial muscle motions, the movements of facial feature points are used to define primitive facial events. They have selected the primitive event pairs with the largest interval relation variance among the different expressions like anger, disgust, contempt, fear, happy, sadness and surprise. For each type of expression, an Interval Temporal Restricted Boltzmann Machine (IT-RBM) model is constructed using the selected events and interval relations with the accuracy of 94.90% over the DISFA and SPOS database. Kaustubh Kulkarni et al [32] presented the methodology used for recognising unfelt FEEs from video sequences considered learning a discriminative spatio-temporal representation to be central for this problem. They built features from sequences of varying length using a Fisher Vector encoding which we use to train a SVM for final classification with 98.7% of accuracy from appearance based and geometric facial features. The emotions used are happiness, anger, surprise, sadness, disgust and fear with CK+ and Oulu-CASIA datasets. Pawel Tarnowski et al [35] proposed spatial coordinates points which are stored in a form of a matrix. Changes in facial expressions resulting from the activity of specific muscles have been defined in the developed by FACS system (Facial Action Coding System) in the form of special coefficients - Action Units (AU). Kinect device provides six Action Units (AU) derived from the FACS system. The Action Units may be used to describe emotions either separately or in combinations. AU take values between −1 and +1 which provides 96% accuracy of emotion recognition using k-NN classifier with the emotions of neutral, joy and angry, surprise, sadness, disgust and fear. Chen Jio et al [40] proposed a facial expression recognition method based on convolutional neural network ensemble learning. The model is composed of three sub-networks, and uses the SVM classifier to integrate the output of the three networks to get the final result. The recognition accuracy of the model's expression on the FER2013 dataset reached 71.27%. The emotions used are anger, disgust, contempt, fear, happy, sadness and surprise with FER2013 dataset. The results show that the method has high test accuracy and short prediction time, and can realize real-time, high-performance facial recognition. Akash Survanan et al [44] used Tandem facial expression and Adan optimizer on decision tree and feed-forward NN and CNN. The dataset used is from live testing module with 60.58% accuracy. The emotions used are anger, disgust, happy, contempt, fear, sad and surprise. Aya Hassouneh et al [61] used face feature extraction using LSTM classifier and DCNN. The experimental results achieved 99.8% accuracy over EEG signal from own developed dataset on 30 subjects. The emotions used are happiness, anger, surprise, sadness, disgust and fear. Jiacheng Liao et al [54] presented a Deep Facial Spatiotemporal Network (DFSTN) model for engagement prediction. The model contains two modules: the pretrained SE-ResNet-50 (SENet), which is used for extracting facial spatial features, and the Long Short Term Memory (LSTM) Network with Global Attention (GALN), which is employed to generate an attentional hidden state. The DFSTN can capture facial spatial and temporal information. They have evaluated the methods on the Dataset for Affective States in E-Environments (DAiSEE) and obtain an accuracy of 58.84% in four-class classification over the emotions like anger, disgust, happy.

Table 4 dipicts comparative analysis of state-of-the-art research work using various artificial neural network classifiers. It summarizes the research work using various transforms like

Feature vector, Expressional vector, speeded up robust features, Low level edge feature, deep feature, feature map channels, silent features and reliable classifiers (SFRCS) etc. for feature extraction. The parameters used for comparison are author's name, databases used, emotions used, features extracted, methodology or classifiers used and percentage accuracy achieved.

Table 4 State-of-the-art research work using various artificial neural network classifiers.

Sr. No	Name of Author	Database	Emotions Used	Features Used	Methodology/ Classifier	Result And Accuracy
1.	Tong Zhang[31]	SEED CK+	Anger, Disgust, Contempt, Fear, Happy, Sadness, Surprise	Discriminative features, EEG features	DBN, STRNN	89.5% 95.4%
2.	Ram Kumar Madupu [42]	Ramdom 200 images	Sad, Smile, Anger, Surprise, Fear, Disgust, Confused	Speeded up robust features	CNN	91%
3.	Abdullah Talha [43]	CK+	Anger, Contempt, Disgust, Fear, Happy, Sad, Surprise	Low level edge feature, Deep feature	PyFER DCNN	96.3%
4.	Ali Ghofrani [45]	FER2013	Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral	Feature map channels	MTCNN, miniShuffle V2	71.19%
5.	Chunmei Qing [62]	DEAP SEED dataset	Anger, Disgust, Fear, Sad, Happy, Surprise	First and second order differential features	Decision tree, KNN and Random Forest	63.09% 75%
6.	Hayat [70]	BU4DFE	Anger, Disgust, Happiness, Fear, Sadness, Surprise	Feature vector	SVM	94.34%

7.	M. Kyperountas [55]	JAFFE	Happiness, Sadness, Anger, Fear, Surprise, Disgust, and Neutral expression.	Silent feature and reliable classifier (SFRCS)	Facial expression classification (FEC) method	85.92%
8.	Ninad Mehandale [39]	CK CMU NIST	Happy, Angry, Surprised	EV	FERCNN	85% 78% 96%

Tong Zhang et al [31] proposed a deep learning framework, called spatial–temporal recurrent neural network (STRNN), to integrate the feature learning from both spatial and temporal information of signal sources into a unified spatial–temporal dependency model. The discriminative features and EEG features are with DBN, Spatial temporal recurrent neural network. The datasets used are SEED and CK+ achieves experimental results of 89.5%, 95.4% respectively. Ram Kumar et al [42] proposed Convolution Neural Network (CNN) with the features extracted from the Speeded Up Robust Features (SURF). 91% accuracy is achieved with the proposed model which supports tracking human emotion with facial expressions with random images. The emotions used are anger, disgust, happiness, fear, sadness and surprise. Abdullah et al [43] introduced a convolutional neural network architecture, namely PyFER, is proposed to address the FER problem. According to the experimental results, the accuracy of PyFER was calculated to be as high as 96.3% on a CK+ and facial expressions used are anger, disgust, happiness, fear, sadness, contempt and surprise. Except for *h*appiness thay have correctly detected by PyFER. Ali Ghofrani et al [45] addressed the problem, which contains two different stages: 1. Face detection, 2. Emotion Recognition. For the first stage, an MTCNN (MultiTask Convolutional Neural Network) has been employed to accurately detect the boundaries of the face, with minimum residual margins. The second stage, leverages a ShuffleNet V2 architecture which can tradeoff between the accuracy and the speed of model running, based on the users' conditions. The experimental results clearly Shows that our proposed model outperforms the state-of-the-art on FER 2013 with an accuracy of 71.19%. The emotions used are anger, disgust, happiness, fear, sadness and surprise. Chunmei Qing et al [62] used Feature map channels with MTCNN, miniShuffle V2 classifiers. The dataset used is DEAP SEED dataset with an experimental results of 63% and 75% respectively. The emotions used are anger, disgust, happiness, fear, sadness and surprise. Hayat et al [70] presents a fully automatic framework which exploits the dynamics of textured 3D videos for recognition of six discrete facial expressions. Local video-patches of variable lengths are extracted from numerous locations of the training videos and represented as points on the Grassmannian manifold. The experimental results on the largest publicly available 3D video database, BU4DFE and achieves an accuracy of 94.34%. The emotions used are anger, disgust, happiness, fear, sadness, surprise. M. Kyperountas et al [55] used Silent features and reliable classifier (SFRCS) with Facial expression classification method with an accuracy of 85.92% on JAFFE dataset. The emotions used are anger, disgust, happiness, fear, sadness, neutral and surprise. Ninad Mehandale et al [39] proposed a FERC is based on two-part convolutional neural network (CNN): It was possible to correctly highlight the emotion with 96% accuracy, using a EV of length 24 values. The two-level CNN works in series, and the last layer of perceptron adjusts the weights and exponent values with each iteration. FERC was extensively tested with more than 750K images using extended CK expression, Caltech faces, CMU and NIST datasets with an accuracy of 85%, 78% and 96% respectively. The emotions used are happy, angry and surprised.

4.Concluding remarks:

The main objective of this paper is to study and analyze various techniques used in the emotion recognition system. The paper investigate the comparison of facial expression recognition using extracted features with the help of various transforms, facial movements, fiducial points as features along with various classifiers. The effectiveness of the state-of-the-art algorithms have been compared with reference to percentage recognition accuracy, performance based on feature extraction techniques and various classifiers used on various databases. From the study done in the specified papers various techniques and methodologies were identified, compared by the percentage accuracy achieved over different database. The comparison with the state-of-the-art performance confirms that the highest percentage accuracy on the JAFFE, CK+ databases is higher than other databases.

Funding and/or Conflicts of interests/Competing interests.:

- No funding by any agency.
- Authors declared that they have no non competing financial interest or personal relationships that could have appeared to influence the work reported in this manuscript

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