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FACIAL EXPRESSION RECOGNITION WITH LOCAL BINARY PATTERN IN MACHINE LEARNING: A REVIEW

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ABSTRACT

Automatically analyzing facial expressions is an intriguing and challenging problem which has significant applications in numerous fields, including data-driven animation and human–computer interaction. An essential step in successfully recognizing facial expressions is obtaining an accurate facial representation from original face image. For person-independent facial expression recognition, in this paper we have local feature- based facial representation and local binary patterns (LBP) techniques. On a number of databases, comprehensive analysis has been presented on various machine-learning techniques for facial recognition. LBP Feature extraction technique has been demonstrated to recognize facial expressions. Further, to extract the most discriminating local binary pattern features a boosted- LBP feature with support vector machine classifiers has been suggested which results in best face recognition performance accuracy. Additionally, we have described the investigations of low-resolution facial expression recognition with LBP feature extraction which is a crucial issue which have not received earlier consideration.

Keywords: Facial expression, Expression-specific local binary pattern, Class-regularized locality preserving projection, Dimensionality reduction, Feature extraction

INTRODUCTION

Facial expressions are most natural, effective, and immediateway for people to express their feelings and intentions. Automatic facial expression recognition has received a lot of attention in recent years due to its numerous applications Despite significant progress, it is still challenging torecognize facial expressions with high accuracy due to their subtlety, complexity, and variability [W.M, 2020]. An essential step in successfully recognizing facial expressions is obtaining an accurate facial representation from original face images. The extraction of facial features can be done in one of two ways: techniques that are based on how they look and how they look like. The FER technology has grown significantly asa result of recent technological advancements in biometrics analysis, machine learning, and pattern recognition, as well as the widespread use of cameras.

There are three stages to FER analysis: a) face recognition;

b) expression recognition; and c) expression classification in relation to an emotional state. Feeling location depends on the examination of facial milestone positions (for example end of nose, eyebrows). Changes in those positions are also looked at in videos to find contractions in a group of facial muscles. Facial expressions can be divided into basic emotions (such as anger, disgust, fear, joy, sadness, and surprise) or compound emotions (such as sadly sad, sadly disgusted, sadly afraid, sadly angry, and sadly surprised), depending on the algorithm. In other instances, facial expressions may be related to a person's mental or physical state (such as exhaustion). The images or videos that FER algorithms use as input come from a variety of sources, including surveillance cameras, cameras on social media andstreaming services, cameras placed close to advertising screens in retail establishments, cameras on personal devices,and so on. Biometric identification and FER can both be used in conjunction. Technology that analyzes a variety of sources, including voice, text, health data from sensors, and image-inferred blood flow patterns, can improve its accuracy. Recently, Valstar [K.A.2022], has demonstrated geometric feature- based methods which outperform appearance-based methods in action unit recognition. Geometric feature-based techniques, on the other hand, typically necessitate the detection and tracking of precise and dependable facial features, which can be difficult to accommodate. In appearance-based methods, picture channels like Gabor wavelets are applied to the entire faceor specific face districts to remove changes in how the face looks. The majority of appearance-based method studies have focused on using Gabor-wavelet representations because of their superior performance [Borgalli, 2022].

To extract coefficients for multiple scales and orientations, face images are convolved with a bank of Gabor channels. However, this process takes a lot of time and memory. The facial features can be thought of as a complicated, dynamic structure whose properties can change a lot over time. This isthe primary central point of social life and plays a significant role in identifying individuals. Consequently, facial expression re-organization is a vital component of biometrics and can be utilized for critical purposes such as credit card verification, system security, and criminal identification. When used as part of other security measures for access control, face recognition can also significantly increase security by reducing the need to remember passwords. The proposed system offers a novel method for determining a person's emotion.The most illustrative vectors are the Eigen vectors, which correspond to the highest Eigen values of the covariance matrix. In a facial expression recognition system, the most advanced principal component analysis (PCA) method is theEigen face approach. The faces are reduced to Eigen faces, a small set of essential characteristics, using this strategy. This

is thought to be one of the primary image dataset's most important components. The person's facial expression can be classified by comparing its position in the Eigen face space to that of a known individual after selecting a new image from the Eigen face subspace. For person- independent facial expression recognition, the author empirically investigates facial representation based on local binary pattern (LBP) features [K.A,2022].

LBP features have only recently been used to represent faces in facial image analysis, despite the fact that they were initially suggested for texture analysis. The LBP's adaptability to changes in illumination and computational simplicity are its most important characteristics. In order to use LBP features for facial expression recognition, the authors investigate a variety of machine learning strategies. In contrast to Gabor wavelets, our research demonstrates that LBP features quickly and effectively extract discriminative facial information from a single raw image scan. Using AdaBoost algorithm to learn the most discriminating LBP features, the author further develops boosted-LBP. The boosted-LBP features improve the classifiers' recognition capabilities. The author also looked into how well LBP features have worked with different databases. Given the high resolution of frontal faces, one of the current facial expression recognition techniques' limitations is that they attempt to recognize facial expressions from data collected in a highly controlled environment [J. Akriti, 2020].

However, input face images frequently lack resolution in real-world applications like smart meetings and visual surveillance. Clearly, expression recognition is much more difficult in real-world environments with low-resolution image. The first attempt at low-resolution facial expression recognition. The effects of various image resolutions on each automatic facial expression recognition step. In this work, the author investigates LBP characteristics for low-resolution facial expression recognition. Experiments on a variety of image resolutions show that LBP features perform consistently and robustly across a useful range of low- resolution face images. The impressive performance of truly packed video groups under real-world conditions demonstrated their promising applications

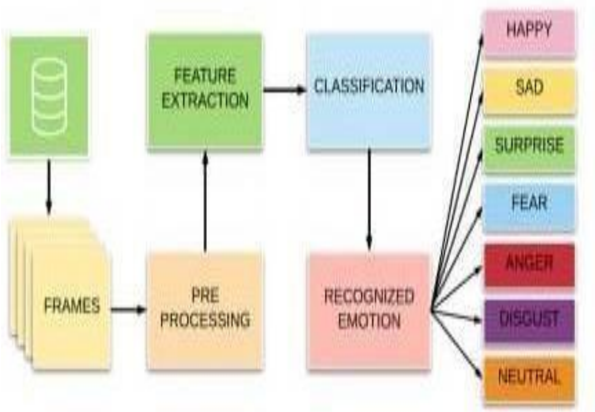

Fig. 1: Overview To Face Localzation

FACE LOCALISATION

The first step in a fully automatic facial feature extractor is to locate the face region and its boundaries. Several issues, some of which are outlined below, ought to be addressed by a comprehensive face localization system.

Pose: Face features like the eyes, nose, and mouth may partially disappear or become distorted due to the camera's relative position.

Occlusion: Facial features can be obscured by glasses, mustaches, and beards. Additionally, makeup can make the appearance of artificial regions on the face or conceal normal facial boundaries.

Expression: Facial features exhibit significant shape shifts under a variety of facial expressions. Some features may disappear entirely or only become visible, depending on the expression.

Prerequisites for Imaging: Changes in lighting and camera characteristics have a significant impact on the chrominance of face regions. If certain facial features are obscured or combined with shadows or shines, color information may be lost.

For locating faces in images, there are a few suggestions. A group of these calculations is suggested in [Lu, 2022] despite the fact that a thorough description of these calculations is impossible due to their extremely broad limits. Figure depicts the four primary categories of face localization techniques.

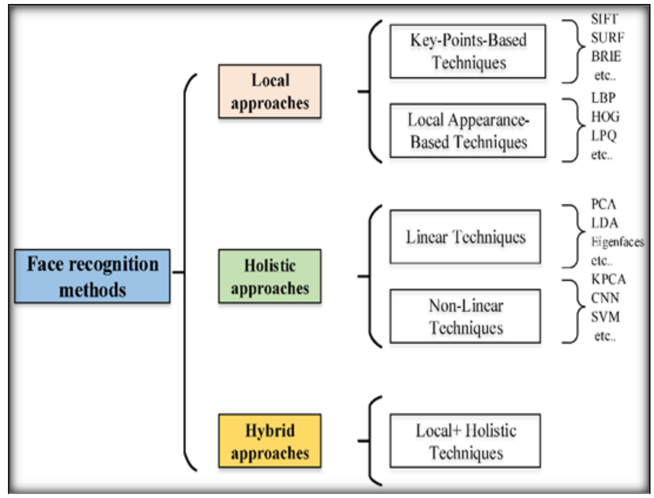

Fig.2: Categorization of Face Localization Techniques [W.M, 2020]

LITERATURE SURVEY

C.Dalviet [2021] investigated the idea that facial expressions serve as mirrors for human emotions and thoughts. It gives the viewer a lot of social cues, like where their attention is going, what they intend to do, why they are doing it, and how they feel. It is thought to be an effective method for communicating in silence. These expressions can be analyzed to provide a much deeper understanding of human behavior. In this paper, the authors provide an in- depth analysis of AI-based FER techniques, including

dataset feature extraction techniques, algorithms, and the most recent developments in facial expression identification applications.

Mellouk et al. [2020] described automatic emotion recognition AI-based FER has emerged as one of the most significant areas of research in recent years with numerous applications in dynamic analysis, pattern recognition, interpersonal interaction, mental health monitoring, and a variety of other fields. However, it lacks a comprehensive literature review that identifies aligned future directions and highlights previous accomplishments.

Khan et al. [2022] present a comprehensive overview of FER reputable studies that have been published in the past ten years. In order to improve computer predictions, the researchers have developed methods to interpret, code, and extract facial expressions. They compare the progress made by utilizing the proposed methods to the results that were achieved to demonstrate the progress, highlighting the contributions that were covered, the architecture, and the databases that were utilized.

R. A. Borgalli et al.[2022] have done FER work using a variety of methods, such as using both static images and dynamic sequences and number of sensors, machine learning, and a deep learning framework. The most recent findings demonstrate that convolutional neural network (CNN)-based deep learning systems are significantly more powerful than conventional FER approaches. Deep learning- based FER techniques that make use of deep networks enable automatic feature extraction rather than the need for manual feature extraction. On lab-controlled and wild facial expression static image datasets like KDEF, RAFD, RAF-DB, SFEW, and AMFED+, this paper focuses on training and testing various custom and standard CNN architectures. Y.Gaoetal. [2015] present a deep learning algorithm that simultaneously learns the characteristics of EEG signals and classes them according to their emotions. It sets itself apart from conventional approaches by applying deep learning to the raw signal without explicitly performing hand-crafted feature extraction. Because the EEG signal is subject-dependent, it is preferable to train the emotion model subject-by-subject because there are few epochs available foreach subject. A deep learning algorithm offers a pre-training strategy that is made possible by three layers of restricted Boltzmann machines (RBMs). Back-propagation makes it possible to fine-tune the network subject by subject and pre- train the deep network using epochs from all subjects. Our experiments show that the recognition accuracy of our proposed framework is superior to that of conventional algorithms.

Jaiswal et al.[2020] have presented the design of an artificial intelligence (AI) system that is capable of emotion detection through facial expressions. It outlines the three primary phases of emotion detection: This paper proposes a deep learning architecture for emotion classification, face detection, and feature extraction for emotion detection from images that is based on convolutional neural networks (CNN). Two datasets, the Japaness female facial emotion (JAFFE) and the Facial emotion recognition challenge (FERC-2013), are used to assess the effectiveness of the proposed method. For the FERC-2013 and JAFFE datasets, the proposed model achieves 70.14 and 98.65 percent accuracy, respectively.

Xi. Lu et al.[2022] set out to find out how the intelligent learning environment on the Internet can recognize emotions in speech and graphically visualize students' facial expressions. An improved convolution neural network-Bi-directional Long Short-Term Memory (CNN-BILSTM) algorithm is proposed following a comparison of its performance to that of a number of neural network algorithms related to deep learning. A simulation experiment is used to determine how useful this algorithm is. With an accuracy of 98.75%, the experiments showed that the CNN-BILSTM algorithm is at least 3.15 percent more accurate than other algorithms. In addition, the recognition rate is at least 90% higher and the recall is at least 7.13 percent higher than that of other algorithms.

Arora et al.[2022] improved the convolutional neural network method for identifying seven fundamental emotions and evaluated a variety of preprocessing methods to see how they affected the CNN's performance. Enhancement of facial features and expressions based on emotional recognition is the primary focus of this study. Computers can make more accurate predictions about a person's mental state and provide more modified responses by recognizing facial expressions that elicit human responses. As a consequence of this, they investigate the possibility of enhancing facial feature-based emotion detection using a deep learning approach based on convolutional neural networks (CNN). Consequently, the existing paper uses optimization to classify multiple facial reactions in a manner that is comparable to the FACS's seven emotions, despite the fact that our proposed paper identifies the same seven emotions as the FACS.

Gaddamet.al. [2022] study shown that either deep neural networks or convolutional neural networks. Using static images, they have proposed a ResNet50-based network to classify human facial emotions. When trained with the FER2013 dataset, the proposed model performed significantly better than other models.

Jain et al.[2021], have analyzed various types of modules that are combined in this approach to improve the model's operation are primarily the result of advancements in deep learning. The development of a neural network model that can classify human emotions into seven distinct categories is the primary focus of this work. Image data are used to train, validate, and test the model.

Lalitha et al.[2021]presented a deep learning model for facial expression recognition. The model was trained on the Facial Expression Recognition 2013 [FER2013] dataset, and the outcomes were analyzed. The proposed model had a training accuracy of 78% and a validation accuracy of 67%. The system can handle both real-time video and static images

The three input modes are image from the device, webcam image capture, and webcam video capture. There are three outcomes from the model: a voice output that stated the expression that was detected, an emotion that was linked to the expression, and an image of the expression that was detected.

A novel deep learning-based hand-over-face gesture-based emotion recognition method that incorporates a coding scheme with additional hand gestures is proposed by Naik et al.[2018]. They eliminate the requirement for manual feature extraction by employing a Convolutional Neural Network (CNN) to automatically extract additional class- specific features. They also employ a Recurrent Neural Network(RNN) to recursively learn the features and classify them into more complex emotion categories. Therefore, the approach that we propose identifies more advanced feelings like confidence, decision-making, fear, shame, and okay.

Emotions and human behavior will be identified using Deep Learning and Machine Learning in this paper.

According to S. K. Singh et al.[2022], idiomatic expressions, eye movement, and other body language techniques are crucial when attempting to connect machines and people. Because it describes a person's mental state and feelings, facial emotion is the most frequently used method among these options. Identifying the various emotions can sometimes be extremely challenging due to the numerous challenges associated with recognizing facial emotion expression and the lack of a specific template or framework for distinguishing between the various types of feelings. Emotional facial expressions are a big part of nonverbal communication because they show an individual's inner feelings. Deep learning, neural network algorithms, and machine learning methods are utilized in emotion recognition. This study will suggest a useful approach for recognizing anger, disgust, happiness, fear, sadness, calmness, and surprisingness using Convolutional Neural Networks (CNNs).

The work reported by Brintha et al.[2022] aims to help law enforcement conduct investigations and can also be used by robots to recognize human emotions. Over the past few years, drug smuggling has increased significantly at airports. To deal with these suspects, narcotics officers are employing the conventional strategy of searching for suspicious individuals, removing them from the scene, and continuing the investigation. In this work, a potential solution that is suggested is to install software on the CCTV camera. This keeps track of the person's facial expressions, which will beshared with the people needed to identify the suspect. This work helps robots and narcotics officers capture and identify a variety of emotions by providing a supportive mechanism. Utilizing a Convolutional Neural Network (CNN) algorithm and deep learning to recognize human facial expressions has been investigated [2021]. The system uses a labelled data set with approximately 32,298 images of various facial expressions for both training and testing. The pre-training phase includes a face detection subsystem with noise removal and feature extraction. The generated classification model used for prediction can identify seven facial action coding system (FACS) emotions. Our ongoing research demonstrates that it can accurately identify all seven fundamental human emotions without the use of optimization techniques.

A facial expression dataset from Kaggle web resources has been suggested by Sai et al.[2020]. The seven facial expressiontags in the dataset are happy, neutral, irate, afraid, sad, disgust, and surprised. In this system, emotion classification and gender classification are combined because it matters that software applications and social media and social networking websites include automatic gender recognition. Gender and facial expression recognition are investigated using this system's face detection with a Convolution Neural Network (CNN). The work's primary objective is to improve the detection of human movement for various legal purposes. Computer vision is used for customer service, user safety, user feedback, and many other things. A wide range of real- world issues can be addressed by recognizing gender and expression.

Jaiswal et al.[2022] describe the process of emotion detection, which basically consists of three main steps: This paper proposes a deep learning architecture for emotion classification, face detection, and feature extraction for emotion detection from images that is based on convolutional neural networks (CNN). Two datasets, the Japaness female facial emotion (JAFFE) and the Facial emotion recognition challenge (FERC-2013), are used to assess the effectiveness of the proposed method. For the FERC-2013 and JAFFE datasets, the proposed model achieves 70.14 and 98.65 percent accuracy, respectively.

Due to its practical application in a variety of human- computer interaction systems, including friendly robotics, medical treatment, and driver fatigue detection, automatic facial expression analysis has been the subject of numerous studies.

Asbaily et al.[2020] have indicated an accurate and robust FER remains a challenge for computer models due to the variety of human faces and photos, as well as their varying lighting and positions. Out of all FER methods, deep learning models have shown the most promise due to their powerful automatic feature extraction and computational efficiency. In this paper, they achieve the highest classification accuracy by making use of the FER2013 dataset utilized a system that made use of both Classic Neural Networks and the VGG 16 model. On the FER-2013 dataset, where it was used to extract features and categorize using Classic Neural Networks, the VGG16 model had the highest level of accuracy—89.31 percent.

Author / Technique	**Investigation**
D. Chirag et al. [2021] / AI-based FER techniques	comprehensive evaluation of AI-based FER methodologies, includingdatasets,
	feature extraction techniques, algorithms.
W. Mellouk et al.'s[2020] / CNN and CNN-LSTM	described different architectures of CNN and CNN-LSTM recently proposed by different researchers, and presented some different database containing spontaneous images collected from the real world and others formed in laboratories
A. R. Khan et al.[2022] / Conventional machine learning	a holistic review of FER using traditional ML and DL methods to highlight the future gap in this domain for new researchers.
R. A. Borgalli et al.[2022] / convolutional neural network (CNN)-based deep learning systems	This paper focuses on training and testing various custom and standard CNN architectures.
Y.Gao et al.[2015] / deep learning algorithm	Experiments show that the recognition accuracy of the proposed framework is superior to that of conventional algorithms.
A.Jaiswal et al.[2020] / convolutional neural networks (CNN)	The proposed model achieves 70.14 and 98.65 percent accuracy, respectively.
X. Lu et al.[2022] / CNN-BiLSTM algorithm	With an accuracy of 98.75%, the experiments showed that the CNN-BiLSTM algorithm is at least 3.15 percent more accurate than other algorithms.
T. K. Arora et al.[2022] / Convolutional Neural	The existing paper uses optimization to classify multiple facial reactions in a

Networks (CNN)	manner that is comparable to the FACS's seven emotions,
D. K. ReddyGaddam et al.[2022]/Convolutionalneural networks	The proposed model performed significantly better than other models.
P. Jain et al.[2021] / convolutional neural networks	The development of a neural network model that can classify human emotions into seven distinct categories is the primary focus of this work. Image data are used to train, validate, and test the model.
S. K. Lalitha et al.[2021] /deep learning algorithm	The proposed model had a training accuracy of 78% and a validation accuracy of 67%.
N. Naik et al.[2018] / Recurrent Neural Network (RNN)	They propose identifies more advanced feelings like confidence, decision- making, fear, shame, and okay.
S. Kumar et al.[2022] /CNNs	This study will suggest a useful approach for recognizing anger, disgust, happiness, fear, sadness, calmness, and surprisingness using convolutional neural networks (CNNs).
N. C. Brintha et al.[2022] /CNNs	This work helps robots and narcotics officers capture and identify a variety of emotions by providing a supportive mechanism.
V. S. Harsha Sai et al.[2021] /CNNs	A wide range of real-world issues can be addressed by recognizing gender and expression.
A. Jaiswal et al.[2020] / convolutional neural networks (CNN)	The proposed model achieves 70.14 and 98.65 percent accuracy, respectively.
S. A. Al-Asbaily et al.[2022] /Classic Neural Networks	Deep learning models have showed tremendous promise among all FER techniques because to their powerful automatic feature extraction and computational efficiency. On the FER2013 dataset, they attain the greatest classification accuracy in this paper.

LOCAL BINARY PATTERN TECHNIQUE

Local Binary Pattern (LBP) is a texture operator that labels the pixels in an image by thresholding the area around each pixel and treating the result as a binary number. It is a simple has but very computational gained effective popularity simplicity texture I a as operator. well variety as of its The LBP applications discriminative texture due operator to power. its

It can be seen as a common method for texture analysis's historically disparate statistical and structural models. In real-world applications, the LBP operator's resistance to monotonic changes in gray-scale, such as those brought about by variations in illumination, may be its most important property. Its computational simplicity is another important feature, making it possible to analyze images in difficult real-time settings

TEMPLATE MATCHING

Template matching was used in to perform face recognition using the LBP-based facial representation: a template is

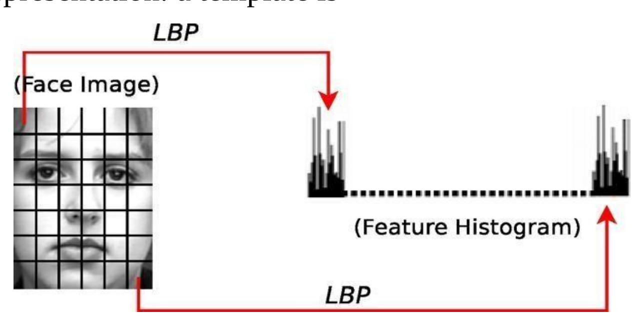

Fig.3 A face image is divided into small regions from which LBP histogram are extracted and concatenated into a single, spatially enhanced feature histogram [W.M,2020]

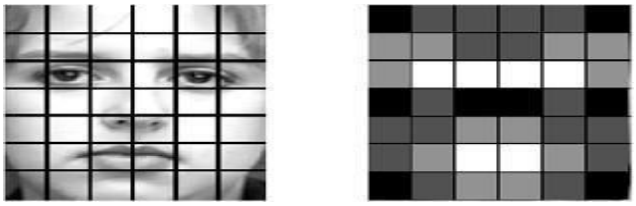

Fig 4: (Left A face image divided into 6x7sub-region. (Right) the weights set for weighted dissimilarity. black squares indicate weight 0.0, dark grey 1.0, light grey 2.0 and white 4.0[W.M,2020]

Formed for each class of face images, then a nearest- neighbor classifier is used to match the input image with the closest template. Here we first adopted template matching to classify facial expressions for its simplicity. In training, the histograms of expression images in a given class were averaged to generate a template for this class.

Following, we also selected the Chi square statistic ($X2$) as the dissimilarity measure for histograms:

Where S and M are two LBP histograms. It is observed that some local facial regions contain more useful information for expression classification than others. For example, facial features contributing to facialexpressions mainly lie in regions such as eye and mouth regions. Therefore, a weight can be set for each sub-region based on its importance. The particular weight set we adopted was shown in Fig. 4, which was designed empirically based on the observation. The weighted X^2 statistic is then given as

$$X^2_W(S,M) = \sum_{ij} W_J \frac{(S_{ij} - M_{ij})^2}{S_{ij} + M_{ij}}$$

Where S and M are two LBP histograms, and wj is the weight for region j

CHALLENGING IN FACE RECOGNITION

- In the face images dataset, images that contain biometric data and enter a secure biometric system typically have low quality and noise.
- Existing work has a face matching issue due to inconsistency between individual details and face images.
- LBP, PCA, NN, and other filtering and wavelet techniques are used for matching in the current research. However, each of these counter measures has a price, which frequently affects user convenience, hardware costs, or matching accuracy.
- While PSNR and MSE are utilized in the proposed work to measure the accuracy of the research, the various other parameters such as support vector machine (SVM) are used to measure the accuracy of the work.

LBP ALGORITHM

Step 1: Inspect the data set images of various pixel sizes

Step 2: All Dataset images are in common size

Step 3: Calculate mean value of image and subtract fromtraining image

Mean Image = mean (img, 2);

Step 4: Use that image as an input image to PCA

Img = ((img – mean Image * ones (1, numImage));

Step 5: Low dimension face space construction: [C, S, L] =princomp(img, ’econ’);Eigen Range = [1, 30]

Define which Eigen values will be selectedC = C (: Eigen Range)

Step 6: Read test image (query image) and project on facespace

Img = zeros (image Size (1)*(image Size (2),numTestImage));

Step 7: Projected Test = img *C;

Step 8: Calculation of distance from Neutral Mean Neutral

=mean (S (Neutral Images, Eigen Range), 2); **Step 9:** Repeat following step until End of image

Dat2Project =1: numTestImage

Test Image = Projected Test (Dat2Project,);

Picking image #Dat2projectEucl_Dist (Dat2project) = sqrt ([Test Image’-mean Neutral]

*[Test
image'-mean neutral]);

Step 10: Result for all test images stored in result.txt file

Step 11: End

Output: Test Image with its exact emotion is detected anddisplayed.

CONCULSION

The features of the human face can be viewed as a complex, dynamic structure whose properties can change significantlyover time. This plays a significant role in identifying individuals and can be considered the primary focal point of social life. This paper also briefly introduced some popular databases related to FER consisting of both video sequences and still images. In a traditional dataset, human facial expressions have been studied using either static 2D images or 2D video sequences. However, because a 2D-based analysis has difficulty handling large variations in poses and subtle facial behaviors, recent datasets have considered 3D facial expressions to better facilitate an examination of the fine structural changes inherent to spontaneous expressions. Furthermore, evaluation metrics of FER-based approaches were introduced to provide standard metrics for comparison. Evaluation metrics precision and recall have been analyzed in the field of recognition However, it is required a new evaluation method for recognizing consecutive facial expressions, or applying micro-expression recognition for moving images. Although studies on FER have been conducted over the past decade, in recent years the performance of FER has been significantly improved through a combination of deep-learning algorithms. Further, FER is an important way to infuse emotion into machines, it is suggested its future scope to be investigated for advanced FER applications.

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