

A Survey on Facial Emotion Recognition (FER) using Machine Learning and Deep Learning Methods

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Abstract: Humans have traditionally found it simple to identify emotions from facial expressions, but it is far more difficult for a computer system to do the same. Emotions possessed by humans can be detected by machine and has a vast scope of study in the computer vision industry upon which several research have already been done. Facial emotion analysis is efficiently used in surveillance videos, expression analysis, gesture recognition, smart homes, computer games, depression treatment, patient monitoring, anxiety, detecting lies, psychoanalysis, paralinguistic communication, detecting operator fatigue and robotics. The literature is collected from different reputable research published during the current decade. The purpose of this paper is to make a study on recent works on facial emotion recognition via Deep learning and Machine Learning to highlight the future gap in this domain for new researchers. In conclusion, this review work serves as a guide and is highly beneficial for researchers in the field of Facial Emotion Recognition (FER), offering a broad understanding and foundational knowledge of the state-of-the-art methodologies now in use.

Keywords: facial expressions; facial emotion recognition (FER), Deep learning, Machine Learning

I. INTRODUCTION

Emotional recognition is one of the most crucial and challenging techniques nowadays. Emotion recognition is used in a wide range of applications, like helping to evaluate blood pressure, stress levels, etc. & facial features using emotional techniques include the functions of the application of happy, sad, calm, and neutral. Many of the techniques and algorithms help to detect the interior workings of the human body.

Emotional recognition detects the human being's thoughts at an instant level. It prevents human beings from major infections or diseases just because of the early detection of diseases using emotional recognition. & the main advantage of emotional recognition is that it helps to identify human mentalities without asking them [1]. Facial expression analysis uses two methods: feature extraction and action unit identification from the facial action coding system (FACS). Ekman et al. suggested the framework known as FACS.

Deep learning is a component of machine learning techniques that can be used for facial expression analysis and emotion recognition. The sizes of facial expression datasets are currently insufficient for deep learning applications. Several research employ augmentation techniques, including cropping, scaling, translating, or mirroring, during the preprocessing stage in order to increase the variance and, consequently, the amount of data. These preprocessing techniques are excellent in boosting deep learning's capabilities.

Face detection is the first step of locating or detecting face(s) in a video or single image in the FER process. Indeed, human beings can easily predict facial emotions and other facial features of an image, but these are difficult tasks for machines without excellent training [2,3]. Facial emotions like sadness and stress are accurately calculated by machine

learning algorithms. This paper provides a holistic review of facial emotion recognition using the traditional ML and DL methods to highlight the future gap in this domain for new researchers.

II. FACIAL EMOTION RECOGNITION USING MACHINE LEARNING TECHNIQUES

This section includes a detailed literature review for the traditional machine learning approaches:

Siddiqi et al. [4] detected and extracted the face portion via the active contour model. The researchers used Chan–Vese and Bhattacharyya’s energy functions to optimize the distance between face and context, and reduce the differences within the face. In addition, noise is reduced using wavelet decomposition, and the geometric appearance features of facial emotions and facial movement features using optical flow are extracted.

The machine learning techniques for the Facial Expression Recognition (FER) approach has been proposed by Harihara Santosh Dadi & Gopala Krishna Mohan[5] in which, pre-processing is employed to 23 diminish the noise. Feature extraction has been performed through the Histogram of Oriented Gradients (HOG) which basically store the edges of the face and the directionality of those edges.

Automatic Facial Expression Recognition (FER) system by Lajevardi & Hussain 2012[6] has been developed based on the feature extraction, feature selection and classification. AdaBoost algorithm is employed for face detection and feature extraction with the help of Gabor filter. The performance results carried out on Cohn-Kanade and JAFFE database shows greater improvement in the classification accuracy, compared with some traditional methods.

Facial expression Recognition system has been proposed by Mavani et al. 2017[7] where they are using convolution neural network trained on the visual recognition images. In which, the result of the edited faces and their visual saliency maps are processed utilizing the Deep Multi-Layer Network for saliency prediction and forwarded to the facial expression recognition CNN.

Visual features of images are examined and some of the classifier techniques are discussed in [8,9] which is helpful in the further inspection of the methods of emotion recognition. As a result, facial expression detection as a sub-field of image processing is quickly expanding. Some of the possible applications are human-computer interaction, psychiatric observations, drunk driver recognition, and the most important is a lie detector. In this paper, a review of recent advances in sensing emotions by recognizing facial expressions using different machine learning architectures is provided.

III. FACIAL EMOTION RECOGNITION USING DEEP LEARNING

Despite the notable success of traditional facial recognition methods through the extracted of handcrafted features, over the past decade researchers have directed to the deep learning approach due to its high automatic recognition capacity.

Mollahosseini et al. [10] propose deep CNN for FER across several available databases. After extracting the facial landmarks from the data, the images reduced to 48x 48 pixels. Then, they applied the augmentation data technique. The architecture used consist of two convolution-pooling layers, then add two inception styles modules, which contains convolutional layers size 1x1, 3x3 and 5x5. They present the ability to use technique the network-in-network, which allow increasing local performance due to the convolution layers applied locally, and this technique also make it possible to reduce the over-fitting problem.

Lopes et al. [11] Studied the impact of data pre-processing before the training the network in order to have a better emotion classification. Data augmentation, rotation correction, cropping, down sampling with 32x32 pixels and intensity normalization are the steps that were applied before CNN, which consist of two convolution-pooling layers ending with two fully connected with 256 and 7 neurons. The best weights gained at the training stage are used at the test stage. This experience was evaluated in three accessible databases: CK+, JAFFE, BU-3DFE. Researchers show that combining all of these pre-processing steps is more effective than applying them separately.

In 2018, for the disappearance or explosion gradient problem Cai et al. [12] propose a novel architecture CNN with Sparse Batch normalization SBP. The property of this network is to use two convolution layers successive at the beginning, followed by max pooling then SBP, and to reduce the over-fitting problem, the dropout applied in the middle of three fully connected. For the facial occlusion problem Li et al. [13] present a new method of CNN, firstly the data introduced into VGG Net network, and then they apply the technique of CNN with attention mechanism ACNN. This architecture trained and tested in three large databases FED-RO, RAF-DB and AffectNet.

Deep learning (DL) algorithms have revolutionized the computer vision field in the current decade with RNN and CNN [14–16]. Li et al. [17] proposed a 3D CNN architecture to recognize several emotions from videos. They extracted deep features and used three benchmark datasets for the experimental evaluation, namely CASME II, CASME and SMIC. Li et al. [18] performed additional face cropping and rotation techniques for feature extraction using a convolutional neural network (CNN). Tests were carried out on the CK+ and JAFFE databases to test the proposed procedure. In this paper, a review of recent advances in sensing emotions by recognizing facial expressions using different deep learning architectures is provided.

IV. DIFFERENT EMOTIONS THAT CAN BE DETECTED

- A. Neutral
- B. Happy
- C. Anger
- D. Disgust
- E. Surprise
- F. Fear
- G. Sad

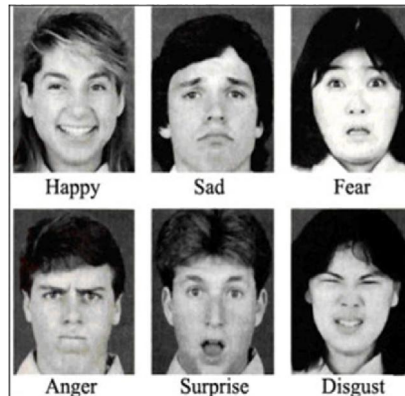


Fig 1: Face emotion

V. CONCLUSIONS AND FUTURE WORK

In this paper, a detailed analysis is presented on FER approaches under two major groups conventional ML-based approaches and DL-based approaches. As a conclusion facial emotion recognition based on 2D data is unable to handle large variations in pose and subtle facial behaviors whereas 3D facial emotion datasets have been considered to provide better results. FER performance has increased due to the combination of DL with ML approaches. In this modern era, the production of sensible machines is recognizing the facial emotions of different individuals and performing actions accordingly. It has been also recommended that emotion-oriented DL approaches can be designed and fused with IoT sensors to predict various aspects that will be very helpful in healthcare, investigation, security and surveillance.

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