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Human Behavior Analysis through Facial Expression Recognition in Images using Deep Learning

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Abstract*: *Facial Expression Recognition is an important undertaking for the machinery to recognize different expressive alterations in individual. Emotions have a strong relationship with our behavior. Human emotions are discrete reactions to inside or outside occasions which have some importance meaning. Involuntary sentiment detection is a process to understand the individual's expressive state to identify his intensions from facial expression which is also a noteworthy piece of non-verbal correspondence. There are seven essential emotions which incorporate Cheerful, Gloomy, Anger, Terror, Astonish, Hatred as well as Unbiased. In the present period of Human-Computer Interaction (HCI), making machines to analyze and recognize emotions is a difficult task. Recent FER systems are lacking of sufficient training data and other problems like illumination and head pose to identify emotions. Inside this article, we provide a comprehensive learning of Facial expression detection with Deep Learning methods which includes different Neural Network Algorithms used with different datasets and its efficiency result. Also we will provide current challenges and current opportunities in this field to develop robust FER using Deep learning.

Index Terms*: *Face Detection, Face Recognition, Deep Learning, Deep Neural Networks, Facial Expression Datasets

I. INTRODUCTION

Individual action examination and detection is immense and tricky research subject in the meadow of computer visualization and prototype identification. Behavioral examination is currently an important spot of explore in computer visualization which helps in solving many problems in indoor as well as outdoor surveillance system. The numbers of video surveillance systems have been increasing every day in order to monitor, track and analyze the behaviors in different areas. In day to day scenario using in different applications like visual traffic monitoring, home securities, luggage thief detection, people counting, in exam hall or in college/organization campus are applications where behavioral analysis is useful. The increasing need of behavioral analysis from surveillance in our basic life also increase research efforts behind improvement in this behavioral analysis field [1].

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In our daily life communication plays a major role. Inside this period of innovation, individual Computer Interaction (HCI) and robotization, Emotion detection has turned into an essential pasture of learn. Non-verbal communication by human carried out through facial expressions and body gestures. 55% role is comprised of human body actions [2]. In setting up inter personal relations; role of facial expression is important. Seven basic types of emotions are there which includes fear, neutral, anger, surprise, disgust, happy and sad. Every other emotions are after effect and diverseness of these basic emotions[3].

Some huge commitments are made in the research of Facial phrase detection with Local Dual Prototype. [4]. Researchers have studied various process for facial phrase detection using binary decision tree [5], with Convolutional Neural Networks [6], Sentiment categorization using NN and HMM [7], Sentiment study in illustration and auditory prompt [8], joining several core methods [9]. However these computational strategies contain a long ways following than individual precision like their establishment did not rely on the working concept of individual deep learning as well as training.

Goal of our study is to observe the sentiment recognition in still imagery through the help of Convolutional Neural Network (CNN). CNN be a popular neural network for deep learning area that gives solutions of problems regarding large training is required in image recognition. Large amount of training is required to correctly identify or recognize emotion in a face. For example, it is difficult to determine whether a person's emotion is sad or angry without proper training. [10]

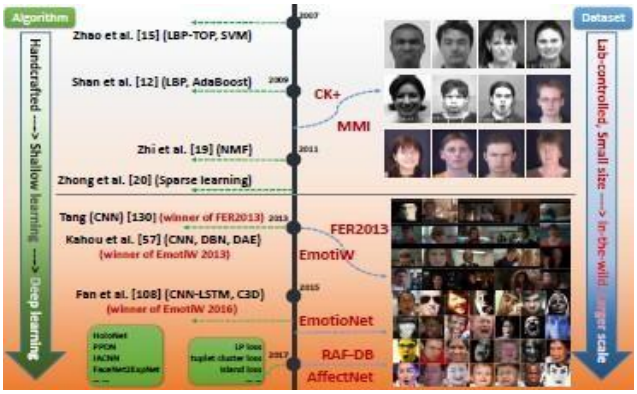

Fig 1. Facial Expression recognition in terms of database with methods [62]

Many reviews have been carried out by researchers on automatic emotion recognition recent years [11], [12], [13], [14]. These reviews have set up a lot of standard algorithmic pipelines for FER which will be helpful to carry out proper classification result analysis. Still many researchers have focused on traditional methods compared to deep learning methods and trying to improve the result based on current challenges in FER. Recently review on FER with the help of deep learning carried out which contains brief review on FER datasets and technical details of different methodologies. Also systematic review represented on different datasets with static images and real time videos covered with its methods as shown in figure 1. [15] It will be very useful for any newcomer to analyze important information in this area. Also it will give modern analysis of deep learning methods inside FER.

Some of the problems identified in FER using deep learning though it has powerful feature of learning ability. A huge quantity of training data require in deep neural network to avoid over fitting problem. To prepare renowned neural network through deep structural design to facilitate attained a large amount significant results in object recognition, existing facial expressions databases are not adequate to train this networks. Also subject varieties exist because of various characteristics like age, masculinity, cultural surroundings and intensity of articulacy [16]. Also pose variations, enlightenment in addition to occlusions are universal factors in unimpeded emotion recognition circumstances. These aspects be involved with facial appearances scenario and consequently to perform better classification, necessity of deep systems is there with huge intra-class changeability in addition to study efficient classification phrase scenario.

Rest of the article is structured like follows. Section II presents Related Work, Section III presents different Dataset details used in FER, Section IV represents Challenges in FER and Section V represents Comparison of methodologies used in FER followed next to Conclusion along with References

II. RELATED WORK

Different kinds of conservative advances contain carried out for Automatic FER systems. To generate a feature vector for training, association among facial apparatus is employed for geometric characteristics found lying on place and viewpoint of 52 degree of facial marker spots. Here primary viewpoint and Euclidean distance is calculated involving every duo of landmarks inside a framework and then distance along with angle values be deducted as of the matching space plus angle values of primary frame in record string. Two classifiers techniques are used here: multi class AdaBoost in the company of dynamic time warping and SVM on the boosted feature vectors. [57]

Diverse face expanses contain diverse styles of detail so look features are habitually mined on or after universal face area. Happy et al.[58] used an approach of Local Binary Pattern (LBP) histogram with dissimilar chunk ranges as of a universal facade region as a characteristic vector plus after that categorized diverse facial expression via Principal Component Analysis (PCA). Though this technique is applied in instantaneous environment, its precision is corrupted as of not able to mirror local differences of facial sections to characteristic vector. Diverse face regions contain poles apart intensities of significance. For instance, compare to forehead plus cheek, eyes in addition to mouth contains additional information. Ghimire et al.[59] divided whole face region hooked on domain precise local expanses to extract appearance features and using an incremental search method, important local regions were identified which provides improvement in recognition accuracy and reduction in feature dimensions.

Many researchers have identified different feature extraction methods and classifiers for conventional approaches. For facial expression recognition well known methods for characteristic mining like Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), distance along with angle relation flanked by facial landmarks plus classifiers for instance Support Vector Machine (SVM), AdaBoost, Random Forest are employed founded on mined characteristics. Benefits of conservative approaches are that they oblige inferior computing control with remembrance compared to Deep learning based procedures. Thus these procedures are tranquil mortal employed in real time organizations since of their lower computational difficulty along with higher accuracy [60].

Now days, deep learning area has revealed tremendous presentation in the computer vision meadow other than very less amount of work has been carried out for Facial Expression Recognition [17]. Deep Belief Network (DBN) has been utilized widely to achieve facial expression detection chores. No image pre- processing is required while analyzing the facial picture through DBN, directly face image be able to be concerned [18]. For instance, Ranzato et al. used gated Markov Random field approach to study discrimination facial expression [19]. In addition to this, DBN identifies facial expression on huge set of facial imageries. In addition it is used on pre-trained guiding data examples wherever a Gabor Filter was applied with deep structure framework to carry out feature extraction. An additional technique for facial expression detection is AU-aware deep network where appearance differences can be described by several limited facial Action Units (AU) with followed by it will be used by DBN to discover several characteristics for executing ultimate facial expression recognition [20]. Recently many researchers have been found out that facial expression recognition can perform well with Convolutional Neural Network (CNN) for candid and non- posed pictures through multi-scale CNN approach and also via uniting a Facial Coding System (FACS) through CNN [22]. Another approach carried out is to combine CNN and SVM classifier with deep network assembled through a heap of SVMs [23].

CNN has additionally demonstrated its superior performance within challenges. It was used with the champions of a 2014 challenge demonstrating extensive enhancement in their outcomes as of the preceding challenge [24]. A different viewpoint employed in CNN in the company of Softmax classifier instead of SVM classifier for succeeding the FER confront in 2013 [25]. Ensemble techniques have been designed for FER except not into deep learning framework.

However they have been consolidated with DBN for time series forecasting and object tracking purpose [26]. Additionally Restricted Boltzmann Machines (RBM) is coordinated to make a lot increasingly precise individual classifier. Though, these group training strategies aren't suitable meant for FER [27].

For enhanced performance of FER, different Deep Belief Network (DBN) models have been combined with audio-video signals to extract important features for Emotion recognition. Also boosted DBN approach suggested discovering and picking important characteristics as well as designing the required categorizer [28]. With the help of different deep learning techniques, complex approach is used to recognize emotion from videos on different modes. For this approach, DBN and CNN are used to implement the representation of audio stream and to capture visual information from detected faces respectively [29]. In other approach different CNNs were combined where individual CNN was implemented for varying input features with varying initializing weights of Neural Network with the use of Fusion function across all classifiers to calculate maximum value of the outputs. Another study of CNN by applying pre processing of inputs with different methods then by averaging results of all CNNs final recognition results were generated [30]. Further improvement is by Fusion and adjusting weighting method where based on accuracy of validation set weight of each network defined [31].

Some ensemble methods of CNNs were proposed for focused appliances. For instance, during a learning by Lyksborg et al., to segment tumor tissue 3 CNNs were guided on 46*46 images [32], while Haibo et al. to perform biological cell detection a cascaded procedure united by a CNN model along with handcrafted characteristics [33]. Another method proposed for ensembles of CNNs to detect polyp with specialization of individual CNN as a feature. Though the entire assembly techniques of DBNs plus CNNs were not found efficient in support of Facial Expression Recognition [34].

A novel proposed method with CNN which has 2 Convolutional layers in which each layer pursued by Max Pooling along with 4 Inception levels are applied in favor of Facial Expression Recognition which is not related to Ensemble Learning method [35]. Based on hierarchical committee of CNN is newly proposed method of FER which has improved 2.14% accuracy with its classifier whereas ensemble methods improved accuracy by 2.81% which proves that ensemble method is more effective. But based on its hierarchical architecture which is composed of CNNs making it more complex [36].

Precision, Recall, Accuracy and F1-Score are four major parameters used to evaluate metrics of FER. Precision (P) is described the same as (True Positive) / (True Positive + False Positive) and Recall (R) is described the same as (True Positive) / (True Positive + False Negative) wherever True Positive is the numeral of true positives and False positive is the numeral of false positives in given dataset. Divisions of automatic footnotes of emotion to facilitate are appropriately identified is known as Precision. Accurate detections of emotion in excess of actual numeral of imagery through emotion are known as Recall. Accuracy is described by the proportion of true outcomes via entire numeral of images mentioned below in Eq. (1) to find the same [61].

$$\text{Accuracy} = \frac{(\text{True Positive} + \text{True Negative})}{\text{Total Images}} \quad (1)$$

III. DATABASE DETAILS

Various databases are used for Facial Expression Recognition which includes KDEF (Karolinska Directed Emotional Faces 2018) [46], JAFFE (Japanese Female Facial Expressions 2017) [37], CK (Cohn Kanade 2017) and CK+ (Extended Cohn Kanade) [38], MUG (Multimedia Understanding Group 2017) [40], TFEID (Taiwanese Facial Expression Image Database 2017) [41], MMI Dataset (MMI Database 2017) [39], AR Face database (AR 2018) [43], Yale Face database (Yale 2017) [42].

In many research JAFFE database is widely used which contains 10 Japanese feminine's expressions through 7 different facial expressions in addition to contain total 213 gray imagery with resolution of 256*256 pixels for each image. Many researchers have used this dataset in different methods and algorithms meant for facial expression recognition in addition to attained higher precision. It is a laboratory trained small dataset which will be helpful to carried out your evaluation for the given task effectively and giving good result. But still many researchers are trying to carry out good accuracy on real time dataset. JAFFE and CK+ both are laboratory trained dataset and MMI, MUG, TFEID, KDEF contains real time images in their database repository. Sample of JAFFE database is revealed inside figure 2.

Fig 2. Example imagery from JAFFE Database [37]

Another database which is widely used by researchers is CK database which contains 7 expressions for 132 subjects including neutral and smile posed. Total 486 gray images are there with 640*490 resolutions. Example imagery of this database are shown below into Figure 3

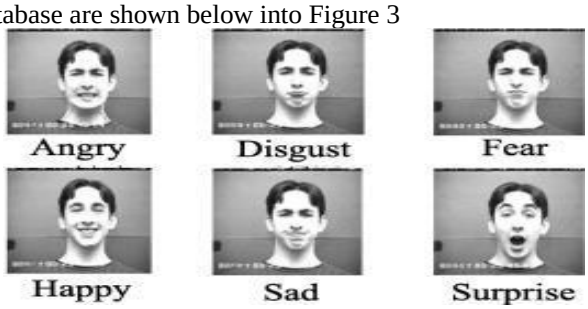

Fig 3. Example imagery from CK Database [38]

Diverse datasets meant for facial expression recognition with necessary details are mentioned inside below Table 1.

Table 1. FER Databases Description

Name of Database	Details of Expressions	Total No. of Images	Detail of Resolution
Japanese Female Facial Expressions (JAFFE) [37]	Smile, Sad, Surprise, Anger,Fear Disgust, Neutral	213	256*256
Yale Face Database [42]	Happy, Normal, Sad, Sleepy, Surprised, Wink	165	168*192
Cohn Kanade (CK) [38]	Joy, Surprise, Anger, Fear, Sad Disgust	486	640*490
Extended Cohn Kanade (CK+) [38]	Neutral, Sad, Surprise, Happy,Fear Anger, Contempt, Disgust	593	640*490
MMI Facial Expression Database[39]	Disgust, Happy, Surprise, Neutral, Sad, Fear	250	720*576
Multimedia Understanding Group (MUG)[40]	Neutral, Sad, Surprise, Happy,Fear Anger, Disgust	1462	896*896
Taiwanese Facial Expression Image Database (TFEID)[41]	Neutral, Anger, Disgust, Fear, Happy, Sad, Surprise	7200	600*480
Karolinska Directed Emotional Faces (KDEF)[46]	Angry, Fear, Sad, Disgust, Happy, Surprise, Neutral	490	762*562

IV. CHALLENGES IN FER

Facial Expression Recognition is very trending research subject now a day and many researchers are dealing with many challenges to reduce complexity and improving the accuracy in favor of Facial Expression Recognition. Various confronts are listed below:

- To advance the robustness of algorithm in FER
- Many datasets are created in lab environment but facial expressions in real life are more challenging because they are changing constantly and also complex
- Affects differences in expressions based on culture and geography
- Expressions differ in gender and in real time environment

Field of Machine Learning and Artificial Intelligence giving opportunities to build Computer as well as Robots to recognize emotion expressions be fond of individuals which will create a strong bond in the process of Human Computer Interaction which is also known as HCI. Also such type of applications will be useful for security purpose and many others. Recently several investigators are working on following major concerns:

- 3-D Facial Expression Recognition
- Robust classification algorithms for FER
- To improve Deep learning models and architectures

V. COMPARISON OF METHODS IN FER

Many researchers have worked on Facial Expression Recognition with different methods and datasets. They have achieved accuracy in their result based on different datasets and algorithms. Below Table No. 2 summarizes facial expression recognition techniques that have been used by multiple researchers along with their pros and cons. Many researchers have carried out their work and based on that we can listed them out with advantages and disadvantages categories.

Table 2. Facial Expression Recognition Techniques

Author Name	Methods	Advantages	Disadvantages
Mistry & Zhang [48]	1)Modified LBP 2)Embedded POS 3) SVM	1) 100% accuracy over CK+ Database 2) 94.6% accuracy for MMI database	1)Further work needed on Embedded POS method
Goyani & Patel [49]	1)Multi level Haarwavelet based approach	1) It achieves 90.4%,88.5%& 96.8% accuracy on CK, JAFFE & TFEID dataset respectively	1)It has more computational Complexity
Qayyum at el. [50]	1)Stationary Wavelet Transform (SWT)	1)An average recognition rate 98.8% for JAFFE and 96.6% for CK+ dataset achieved	1)Face recognition computation time was high

Radlak& Smolka [51]	1)Dlib Detector 2)Gradient Boosting	1) Tests Performed on real time settings 2)Best Accuracy is 36.93%	1) Bad results in Disgust and Fear expressions
Pu at el. [52]	1)Two fold Random Forest 2)Active Appearance Model	1)Expression recognition Accuracy up to 96.38%	1)Not tested on real time environment
Manisha at el. [53]	1)Artificial Neural Network	1)Found to be 76% accurate in analyzing emotions	1)Training time was high 2)Not suitable for large datasets
Saini at el. [54]	1)Principal Component Analysis (PCA) 2)Singular Value de-composition (SVD)	1)Gives good classification Accuracy	1)Time complexity was a big problem
Khan at el. [56]	1)Feature extraction by PLBP 2)Extraction of Salient features using tracker of eyes	1)PLBP is computationally efficient 2)Improved performance on images with lower resolution	1)Change in Camera angle is not much effective
Dornaika at el. [55]	1)Exploited Head Poses 2) Principal Component Analysis (PCA) 3) Spatio Temporal Texture Map (STTM)	1)Maximum recognition was 90% 2)Dynamically learns online face appearance 3)PCA+LDA have provided better performance	1)Disgust expression gave 44% 2)Face detection, Facial action, Face tracking is not in the scope of paper

VI. CONCLUSION

This paper presents a survey of different facial expression recognition techniques and architectures used to extract important facial features. Detailed information of different datasets used in facial expression recognition explained with necessary information. Recent feature extraction techniques with comparison and recent challenges are covered which will be helpful for other researchers to overcome problems of existing methods and improve the results in terms of accuracy.

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