

Facial Emotion Recognition and Implementation: A Survey

Yashaswini K¹, Mamatha G²

¹(Student, Department of ISE, JSS Academy of Technical Education, Bangalore, India)

²(Assistant Professor, Department of ISE, JSS Academy of Technical Education, Bangalore, India)

Abstract: An increasing amount of research has been carried out on Facial Emotion Recognition in the past few decades, due to its significant impact on Human-Computer interaction. Recognition of Facial expressions are essential for a variety of automated applications, especially in the field of computer-vision, security, education, social media, healthcare, AI based applications. Good amount of work and effective methodologies are proposed for Facial Emotion Recognition (FER), intended for static images and motion images. Conventionally, to recognize Facial emotions, researchers used methods such as Multilayer Perceptron (MLP), K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Valence-Arousal Dimensional features (VAD), a hybrid approach HOG and visual descriptors such as, Local Binary Pattern (LBP), Eigen faces, Face-landmark, and Texture Features. However, Convolution Neural Network has achieved milestones in terms of accuracy for recognizing Facial emotions. As part of the survey, we even studied standard datasets used for Facial Emotion identification. In addition to human-computer interaction, facial expression recognition technology is used in many real world applications such as intelligence control, fatigue detection; public/ political meeting analysis, etc. Man-Machine interactions are the real necessity of the present day in various fields and FER plays a very important role in that requirement.

Keywords – Facial emotion, CNN, Artificial Intelligence

I. Introduction

Computers now automate every task, and Facial emotion recognition is happening to be a trendy research topic in Computer vision. Facial expressions are used in the field of Security surveillance, Teaching, Neuromarketing, etc. When we accurately predict Human facial expression, one can accomplish a great deal. Human language is composed of oral language and body language but facial expression is part of both. Understanding one's facial expression is essential for a successful Human-computer interaction. People can spot the same facial expression on a variety of people's faces, which is known as Facial expression recognition. Facial expression is one of the easiest ways for humans to communicate their intention and emotion. Expressions observed during interpersonal contact can serve as important communication channels. Some of the basic feelings like anger, sadness, contempt, fear, happiness, surprise, etc revealed through Facial expression are as shown in fig. 1. Facial expressions are made available for studies in the form of different datasets such as CK+, FER 2013, Emotic, Google facial expressions, JAFFE, KDFE, etc.



Fig. 1 Facial expression for seven basic emotions

II. Literature Survey

For identifying landmarks and texture features, researchers have traditionally utilized SVMs (Support Vector Machines), MLPs (Multi-Layer Perceptron Models), and k-NNs (K-Nearest Neighbors). A range of other techniques are also used like Histogram of Oriented Gradients (HOG), a hybrid approach, Gradient feature mapping, Eigen vectors, etc. To extract features, we can use a number of techniques like, Local Binary Patterns (LBP), Gabor filters, Eigenfaces, and Linear Discriminant Analysis (LDA). Research on Facial emotion detection performed using these methods are considered as Traditional approaches and the steps followed by them as shown in the fig. 2.

A. Traditional / Conventional Approaches

For automatic FER systems, various types of conventional approaches have been studied. The commonality of these approaches is detecting the face region and extracting geometric features, appearance features, or a hybrid of geometric and appearance features on the target face

Limuel Z [9] an Artificial Neural Network was developed to model the relationship between Human facial expression and emotions, which was conveyed through Visual representations. [9] Model classified the images based on emotions. They used the JAFFE Dataset to detect 7 emotions; Principal Component Analysis (PCA) was used to obtain image feature vectors based on dimension reduction.

Charvi Jain [1], proposed a Support Vector Machine (SVM) model that detects facial features (prominently eyes and lips) from any given image and classifies them based on emotions (happy, fear, neutral, sadness, anger, disgust). Training data is then filtered, refined by Grid Search, and classified by the SVM method. After testing the data and their labels, a classification report assesses the accuracy of the testing data. In order to enhance the classification of data, several approaches can be followed such as, training images can be passed through Gabor filters or transforming them using Histogram of Oriented Gradients or Discrete Wavelet Transforms.

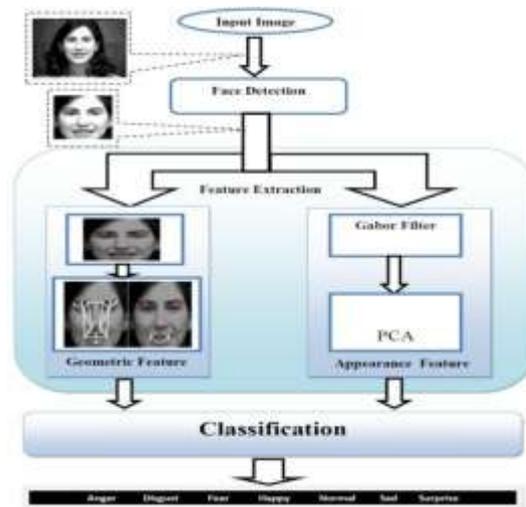


Fig. 2 Facial Emotion Recognition by Traditional Approach

Sanjay Gurav [6] they examined different FER methods, such as CNN, HOG features, AUs, Gabor features, salient regions, and feature-point movement, and proposed a method for improving facial emotion recognition's accuracy and latency with the help of supervised Machine Learning methods.

Yacine Yaddaden [10] in their hybrid approach, two different feature types is combined to identify emotions from facial expressions: Geometric (facial fiducial points) and Appearance-based (discrete wavelet transform coefficients) the six basic emotions were described by specific types of features. In order to classify Facial expressions in three benchmark datasets: JAFFE, KDEF, and RaFD, the researchers propose to use multi-class SVM architecture and a feature selection technique known as Extremely Randomized Trees.

Jing-Ming Guo [11], proposed a Hybrid-RNN network based system for recognizing facial expressions, from both CK+ and Oulu-CASIA datasets. The combination of RNN models with the feature sets "C + A + L" performed optimally compared to current state-of-the-art methods for Facial expression recognition.

B. Deep Learning Approach using CNN

The most common Deep Learning method used for Face expression recognition is Convolution Neural Networks (CNNs), the general architecture is as shown in fig. 3. Many Research works on Facial emotion detection uses CNN as the central component.

Deep learning methods have the advantage of being trained on large amounts of data, which allows them to learn the Face representation that is robust to variations in the data. CNNs can learn these characteristics from training data as well. In FER, CNN algorithm is used to occupy the place of specialized features that are robust to variations within a class (e.g. facial expression, age, illumination, pose, etc.). CNN is composed of nine hidden layers: one input layer and one output layer. An image of a Facial expression in grayscale is used as input to the input layer. A 64*6*6 Feature map is generated by the algorithm using four Convolution layers and three Pooling layers, for local feature detection and sparse feature extraction.

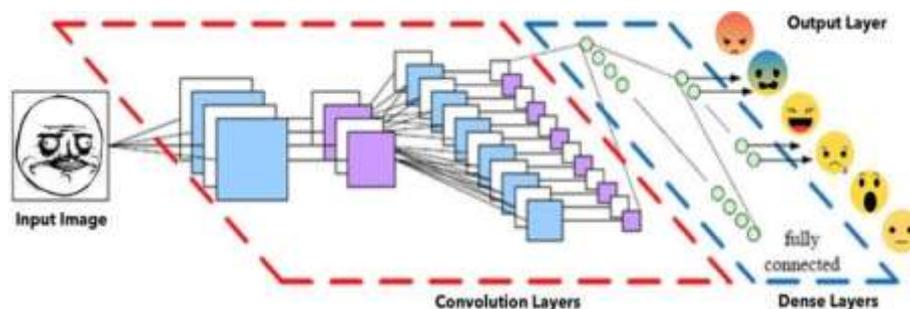


Fig. 3 Facial Emotion Recognition by Deep Learning approach using CNN

Sabrina Begaj [7] investigated how they can handle FER Datasets and experiment with different parameters and various architectures of CNN, to detect seven human emotions (anger, fear, disgust, contempt, happiness, sadness, surprise). [7] Makes use of an interesting and challenging dataset, iCV MEFED (Multi-Emotion Facial Expression Dataset), Task was divided into two parts: Dataset generation and CNN constructions. [7] Future plan is to use the same dataset and "Action units" to detect the muscles of the face as features and feed that information to the CNN model.

Pranav E [5] Their work used a two-layer CNN model to identify five different facial emotions from a dataset of images; Python was used to program the project, and Jupyter Notebook was used to simulate the entire process. Based on emotion image data, a DCNN was trained with a loss function that is based on Adam's optimization and categorical cross entropy optimization. The model had a comparable accuracy in training and validation, which indicates that it is a good fit and that it has been generalized. The loss function was reduced using Adam's optimizer, and the accuracy was 78.04.

Shuang Liu [4] proposed a valence-arousal dimensional emotion model to identify facial expressions. It used CNN to predict valence dimensions. Face detection, feature extraction, and valence grade prediction were all incorporated in the [4] system. Nine levels of annotations were provided for facial expressions. CNN model was trained using CK+ and Fer2013 datasets, performance of the system was evaluated by observing facial expressions of volunteers watching videos.

Arjun Singh [8] CNN and ResNet50 structures were proposed with deep learning to identify facial emotions. Results obtained were far better than their competitors. Kaggle dataset had an accuracy of 67.2%, and KDEP dataset had an accuracy of 78.3%.

Zadeh [2] proposed a framework that used Gabor filters for identifying features, and CNN for classification. Framework greatly enhanced the performance of CNN. By extracting the image sub-features,

Gabor filter fed the convolution neural network with a variety of sub features. Using the list of sub-features, CNN then extracted the emotions of the face. According to some of the experiments, the proposed methodology increased both the training speed and recognition accuracy of CNN.

Mehendale [3] The FER model uses an Expression Vector (EV) to determine the type of normal facial expressions. Data were gathered from 10,000 images (154 people) with 96% accuracy. After testing it extensively the extended datasets such as CMU, Caltech faces, NIST, and Cohn– Kanade expression were tested for more than 750K images.

III. Overview Of Datasets Used In Facial Emotion Recognition

Facial Emotion Recognition uses a range of datasets, each with its own exceptional characteristics. Researchers must use large datasets in order to thoroughly understand the facial expression. But most of the face expression samples in datasets are purposely crafted by the dataset creator; however they need to be administered by psychologists who are more versed in recognizing emotional responses. Researchers are working hard at creating new, enhanced, and useful datasets during the past few years, limited to static images in two dimensions or image sequences of 2D videos, showing expressions in a variety of dimensions, with a few rare cases studying 3D models.



Fig. 4 Sample images in various Datasets

FER experiments are conducted using a variety of datasets as shown in the table 1 , namely, Cohn – Kanade , Extended Cohn – Kanade (CK+), MMI, Multimedia Understanding Group (MUG), Japanese Female Facial Expressions (JAFFE), Taiwanese Facial Expression Image Database (TFEID, 2017), Yale, AR face database (AR), Google datasets, Real-time database , Own database, FER2013, Kaggle and Karolinska Directed Emotional Faces (KDEF).

Several experiments used the JAFFE database. There are ten Japanese female expressions with seven facial expressions as shown in fig. 4: a total of 213 images, each 256 x 256 pixels. Additionally, the Real-time dataset has nearly 2250 images for six expressions, along with 687 image-pair dataset that measures 640 x 480 pixels.

Table- 1 Dataset Description

Database name	Origin	Expressions	No of images	Resolution
Cohn Kanade (CK)	United states	Joy, surprise, anger, fear, disgust, sadness	486	640*490
Multimedia Understanding Group (MUG)	Caucasian	Neutral, sadness, surprise, happiness, fear, anger, and disgust	1462	896*896
Japanese Female Facial Expression(JAFFE)	Japan	Smile,sad, surprise, anger, fear, disgust, neutral	213	256*256
Yale	California	Happy, normal, sad, sleepy, surprised, wink	165	168*192
Extended Cohn Kanade (CK+)	United states	Neutral, sadness, surprise, happiness, fear, anger, contempt and disgust	593	640*490
Taiwanese Facial Expression Image Database (TFEID)	Taiwan	Neutral, anger, contempt, disgust, fear, happiness, sadness, surprise	7200	600*480
MMI	Netherlands	Disgust, Happiness, surprise, neutral, surprise, sad, fear	250	720*576
Karolinska Directed Emotional Faces (KDEF)	Sweden	Angry, Fearful, Disgusted, Sad, Happy, Surprised, Neutral	490	762*562

IV. Applications Of Facial Emotion Recognition

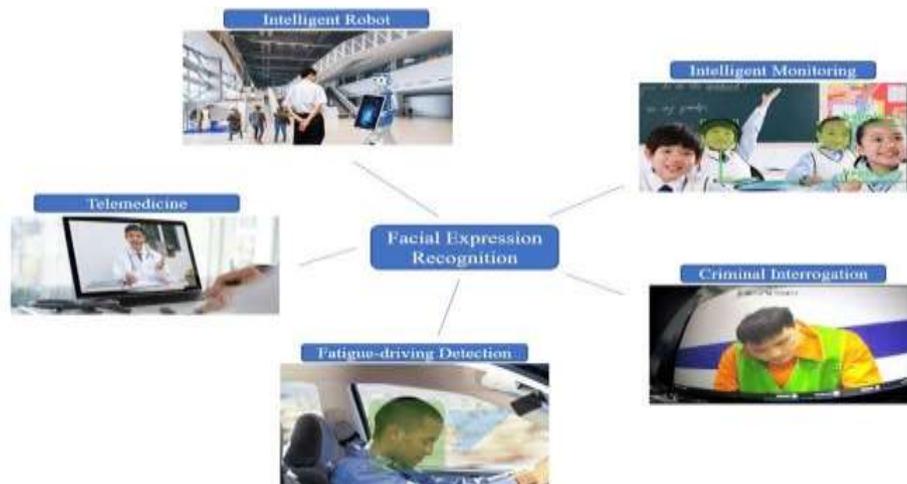


Fig. 5 Applications of Facial Emotion Recognition

In our day to day life, a number of situations arise where we require using Facial Emotion Recognition; some of the very familiar applications of FER are as shown in fig. 5,

- Non-verbal communication such as facial expressions play a significant role in helping us understand human behavior, mood, mental disorder , etc
- Computer-vision or monitoring facial expressions at significant places like - driver cabinet, classroom, passenger terminals, shopping mall, meeting hall, etc can reveal lot of information which needs to be assessed
- During a marketing survey on a particular target group based on age, gender. FER can be used to determine the response of customer for a product or idea
- FER is useful during Crime investigation, while interrogating criminals

- Face recognition is used as Biometric, for attendance purpose at Work place like office, factories, etc and for Security purpose extensively in devices like Mobile phones, Laptops, safe-lockers, Home security systems, etc
- During Video-conferences and personal Interviews, FER is used to identify the person's behavior and mood. Example to check whether the candidate is nervous or confident etc.

V. Conclusion

We examined conventional methods and Deep learning based CNN approaches for recognizing facial emotion expressions, studied background knowledge for understanding the FER domain, listed some real-world applications of FER. In our study, we reviewed a variety of datasets used to identify basic facial emotion and expressions such as happy, angry, sad, disgusted, neutral, surprise etc. we learnt that most tests are performed in controlled laboratory situations, so few techniques and methods are applicable in the real world, with limited recognition rates, computer interaction, and intelligent control. limitations of deep learning based FER approaches exist, such as the need for large datasets, powerful computing systems, huge memory, and the fact that both training and testing phases are time-consuming.

References

- [1] C. Jain, K. Sawant, M. Rehman and R. Kumar, "Emotion Detection and Characterization using Facial Features," 2018 3rd International Conference and Workshops on Recent Advances and Innovations in Engineering (ICRAIE), 2018, pp. 1-6, doi: 10.1109/ICRAIE.2018.8710406.
- [2] M. M. Taghi Zadeh, M. Imani and B. Majidi, "Fast Facial emotion recognition Using Convolutional Neural Networks and Gabor Filters," 2019 5th Conference on Knowledge Based Engineering and Innovation (KBEL), 2019, pp. 577-581, doi: 10.1109/KBEL.2019.8734943.
- [3] Mehendale, N. Facial emotion recognition using convolutional neural networks (FERC). SN Appl. Sci. 2, 446 (2020). <https://doi.org/10.1007/s42452-020-2234-1>
- [4] S. Liu, D. Li, Q. Gao and Y. Song, "Facial Emotion Recognition Based on CNN," 2020 Chinese Automation Congress (CAC), 2020, pp. 398-403, doi: 10.1109/CAC51589.2020.9327432.
- [5] Pranav, E. et al. "Facial Emotion Recognition Using Deep Convolutional Neural Network." 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS) (2020): 317-320.
- [6] Gurav, Abhishek Sanjay and Pramila Chawan. "Real-Time Emotion Classification using Facial Expression Recognition: A Survey." International Research Journal of Engineering and Technology (IRJET), Volume: 07 Issue: 11 | Nov 2020
- [7] S. Begaj, A. O. Topal and M. Ali, "Emotion Recognition Based on Facial Expressions Using Convolutional Neural Network (CNN)," 2020 International Conference on Computing, Networking, Telecommunications & Engineering Sciences Applications (CoNTESA), 2020, pp. 58-63, doi: 10.1109/CoNTESA50436.2020.9302866.
- [8] A. Singh, A. P. Srivastav, P. Choudhary and S. Raj, "Facial emotion recognition using convolutional neural network," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), 2021, pp. 486-490, doi: 10.1109/ICIEM51511.2021.9445346.
- [9] L. Z. Ruiz, R. P. V. Alomia, A. D. Q. Dantis, M. J. S. San Diego, C. F. Tindugan and K. K. D. Serrano, "Human emotion detection through facial expressions for commercial analysis," 2017IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2017, pp. 1-6, doi: 10.1109/HNICEM.2017.8269512.
- [10] Y. Yaddaden, M. Adda, A. Bouzouane, S. Gaboury and B. Bouchard, "Hybrid-Based Facial Expression Recognition Approach for Human-Computer Interaction," 2018 IEEE 20th International Workshop on Multimedia Signal Processing (MMSP), 2018, pp. 1-6, doi: 10.1109/MMSP.2018.8547081.
- [11] J. -M. Guo, P. -C. Huang and L. -Y. Chang, "A Hybrid Facial Expression Recognition System Based on Recurrent Neural Network," 2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), 2019, pp. 1-8, doi: 10.1109/AVSS.2019.8909888.