[1]Husna Shaikh

[2]Sanam Kazi

[3]Wasim Jasani

[4]Viraj Sawant

[5]Naser Shaikh

[6]Pranav Jinturkar

# A Survey on Facial Emotion Recognition and Fake Emotion Detection Techniques

***Abstract: -*** Facial expressions play a crucial role in depicting the thoughts and feelings of any human. Moreover, they might even serve as the distinguishing factor in categorizing whether a person is genuine or not. In this survey, the authors have carried out a systematic literature review of the past work done on facial emotion recognition and discrimination of genuine and fake emotions. Various datasets that are previously and currently being used in this field have been surveyed. The main objective of this paper is to study the state-of-the-art techniques that are being used to analyze and identify facial emotions and to distinguish between their genuineness. For this purpose, papers from distinguished publications have been researched and a comprehensive review of the literature has been fulfilled.

***Keywords:*** Facial expressions, facial emotion recognition, fake emotion detection, deep learning, survey.

## I. INTRODUCTION

Facial expressions are fundamental in conveying human emotions and the non-verbal language is incomplete without it. Expressions provide vital clues that allow one to comprehend the various psychological states involved in interpersonal communication. However, human beings understand and can discern these complex facial signs and that is why simulating this has proved a problematic endeavor in the realm of artificial intelligence and computer vision.

FER is an area of research that focuses on computer processing of facial expressions in order to understand the emotions that these expressions represent. By using new technologies such as advancement in computer vision, machine learning, and deep learning, researchers and technologists have gone very far in helping computers interpret our emotion through our face signs.

Facial Emotion Recognition tends to be a series of stages. Pre-processing takes place during the primary stage which entails detection of the facial features like eyebrow, eye, nose, mouth and chin from the video frames or images. In turn, fine-grained and specific features are mostly extracted which improve the data quality and hence make emotion classification correct. The following step involves training of a classifier model using the labeled data sets that have the facial expressions coupled with the emotional tags. For example, machine learning models such as CNNs, SVMs, and RNNs can be used to recognize facial features and emotions. Therefore, a trained classifier is used to generate emotion labels for new, unseen facial expressions so that recognizing and categorizing emotions is possible.

[1] Student, Information Technology Department, M.H. Saboo Siddik College of Engineering, Mumbai, India, husnas2933@gmail.com

[2] Assistant Professor, Information Technology Department, M.H. Saboo Siddik College of Engineering, Mumbai, India, sanam.kazi@mhssce.ac.in

[3] Student, Information Technology Department, M.H. Saboo Siddik College of Engineering, Mumbai, India, jasaniwasim2002@gmail.com

[4] Student, Information Technology Department, M.H. Saboo Siddik College of Engineering, Mumbai, India, sawantviraj465@gmail.com

[5] Student, Information Technology Department, M.H. Saboo Siddik College of Engineering, Mumbai, India, mohammednaser1572@gmail.com

[6] Student, Walchand Institute of Technology, Solapur, India, pranavjinturkar452@gmail.com

[1] *Corresponding author: husnas2933@gmail.com

Human experiences are always accompanied by emotions that are complex and multifaceted. This has a wide range of thoughts on the mental status of an individual that affect their moods, behaviors, and reactions to stimuli. Emotions are frequently involved with attitudes, temperaments, dispositions, and inspirations, which influence human relation and decision making. Human perception naturally understands emotions but still machines find it difficult to differentiate the authenticity of expressed emotions. The digital age where most people interact virtually emphasizes the necessity for precise emotion detection.

Authenticity of emotions conveyed in online environments is important in ensuring that users trust, minimize misinformation and interact sincerely. With the rise of AI in different spheres the question of how to improve the emotional intelligence in machines is gaining more and more attention. This has a lot of consequences in customer service, cyber security, and mental health. Future systems powered by AI should be able to identify and respond to real emotions. This would change how customers are served taking into consideration the emotions shown.

Additionally, in terms of cybersecurity, detecting fake emotions can help identify bad actors that are trying to fool automated systems. Legitimate emotions must be distinguished from false or fake expressions in legal activities. The evaluation of testimonies and statements, especially the emotional authenticity of the people involved, is crucial in properly assessing the credibility of the testimonies. Due to this ability, a case can be influenced towards a particular course in legal cases and court processes. Besides, recognizing emotions is also a necessity in mental health and therapy domain. With this, therapists can determine more accurately where individuals are in terms of their mental state so they can give them proper care.

The purpose of this paper is:

1. To carry out a detailed review about all the datasets used in facial emotion recognition (FER) and discrimination of fake versus real emotions spread over various research studies.
2. To distinguish these datasets based on certain criteria and features, considering categories such as age groups, estimating their characteristics, sizes and diversity, in the research.
3. To analyze the methodologies and techniques used for facial emotion recognition and distinguishing between real and false emotions.
4. To examine the problems and limitations in the field of FER concerning fake and real emotions.

Through this survey we aim to provide a general view on the current state of affairs concerning FER and identification of false emotions. The methodology used for conducting this literature review has been depicted in Fig. 1.

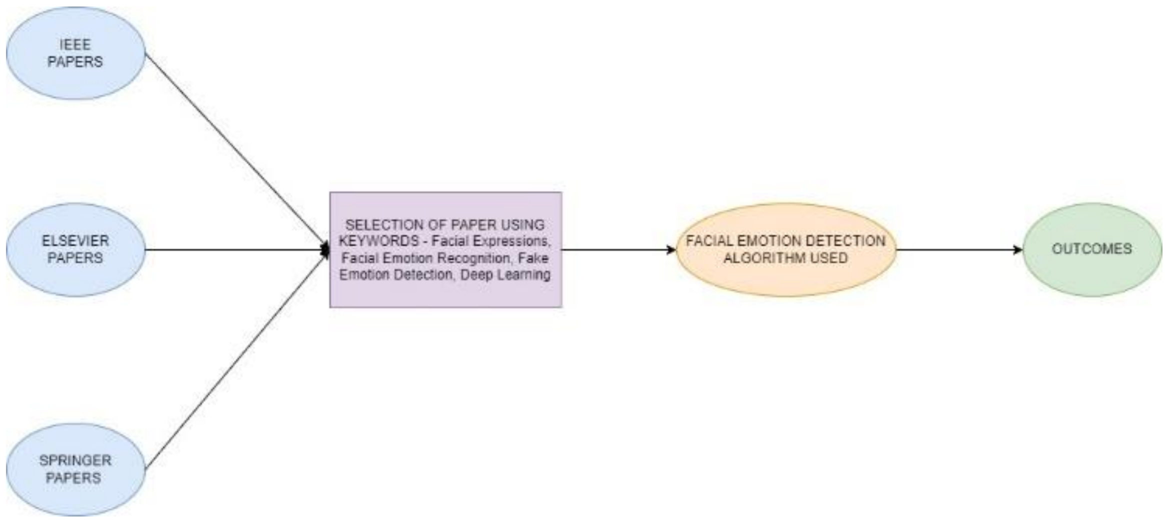


Fig. 1. Methodology utilized to conduct the survey.

## II. DATASET DICUSSION

There has been a boom in different datasets for emotion recognition from images or videos, which has led to a change of the landscape of datasets. These datasets are different in terms of acquisition settings, expressive variation, subjects' demographics, and image's quality. With the passage of time, addition was made on these datasets. They were extended to include aspects such as sex, race, age and picture qualities, hence their quality and the computation of the model too. A correct dataset is essential to ensure strong, data-driven learning for emotion recognition. It is important to understand what make up each set of data because they are crucial for developing efficient computational methods for facial emotional analysis. A wide range of datasets have been studied from numerous research papers. While some papers utilize only one dataset in their experiments for training and testing, there are numerous studies that make use of more than one database for their research. The datasets that have been studies are discussed below:

### *A. FER2013 (Facial Expression Recognition 2013)*

This open-source dataset [21] is popularly used in facial emotion recognition systems. The FER2013 was created by Pierre-Luc Carrier and Aaron Courville for one of their projects. They later made it publicly available just before the ICML 2013. The dataset contains 48 x 48-pixel grayscale face images, totaling up to 35887 images with a range of 7 distinct emotions that are labelled from 0 to 6. The images are split into a training, public testing and private testing set.

### *B. JAFFE (Japanese Female Facial Expression)*

This is yet another widely used public dataset. It [22] is a collection of 213 images displaying various facial expressions of 10 distinct Japanese female individuals. There are 7 posed expressions (6 fundamental expressions + 1 neutral) namely Happy, Sad, Angry, Fear, Surprise, Disgust and Neutral. The grayscale images have a resolution of 256 x 256 pixels with each image being annotated on an average semantic rating on 6 facial expressions by 60 Japanese viewers. The images were collected by Michael Lyons and his colleagues at the Hyushu University in Japan.

### *C. Cohn Kanade (CK)*

The dataset [23] was created by Paul Ekman, Cohn, Kanade and colleagues. It contains labelled facial expression images. 327 sequences from 123 subjects have been recorded. In each sequence, a person's face is shown moving from a neutral position to the highest point of an emotion. It includes 6 elementary emotional expressions. The images are grayscale with regards to lighting, attitude, and degree of facial expressions within different sequences. The annotation of each image sequence specifies emotion label and facial action unit describing muscle movement for every expression.

### *D. Extended Cohn Kanade (CK+)*

This is an addition of the original CK dataset and was introduced due to various limitation found in the dataset. CK+ dataset [24] has the basic 6 emotions but also introduces the neutral expression. It consists of 593 videos from an overall of 123 diverse people. These subjects lie between 18 to 50 age range from a variety of distinct heritages and genders. Each video captures shifts in facial expressions from neutral to a peak as they are recorded at 30 FPS and 640x490 or 640x480 resolutions. The CK+ database, is a prevalently utilized facial expression classification database.

### *E. Cha Learn dataset for Real versus Fake emotion*

In 2017, a competition [25] was organized as part of the IEEE International Conference on Computer Vision (ICCV) to differentiate true from fake facial expressions of emotions and this dataset had been specifically created for this purpose. The dataset includes video recordings of 50 individuals in RGB contributing 12 videos, each representing 6 fundamental emotions expressed in both real and acted forms. The videos last around 3 to 4 seconds. Within each video, participants transitioned from a neutral emotional state. In summary, the dataset has 600 videos separated into a training set of 480 videos with 40 actors plus both a validation and test set of 60 videos with 5 actors each.

### *F. Karolinska Directed Emotional Faces (KDEF)*

The dataset is available to the public and contains 4900 images of human expressions of 70 people ranging from the age of 20 to 30 years. Each individual displays 7 different emotions (6 fundamental + neutral) and every image can be observed from 5 distinct angles. The images feature individuals without beards, moustaches, earrings, or eyeglasses, and it was preferred that no visible makeup was applied. The images are 32-bit colored, 562 x 762 pixels with a resolution of 72 x 72 dpi and a compression quality of 94%.

### *G. MAHNOB database*

The dataset [26] is a repository of data designed to help understand people's social behaviors. It comprises of audio as well as physiological signals that have captured people's faces, gestures, and other social activities. It contains videos of different resolutions found in cameras including the standard definition (640×480) and high-definition videos (1280x720). This dataset is important source of information for the researchers and developers. It helps in understanding emotions people have while in social settings.

### *H. Acted Facial Expressions in the Wild (AFEW)*

The database consists of challenging clips extracted from feature films totaling up to 600 videos. It offers per-frame annotations for valence and arousal levels, including 68 facial markers. These annotations allow a detailed analysis of emotions, aiding researchers in developing and evaluating algorithms for emotion recognition and understanding facial expressions in video content.

### *I. Multimodal Multi-Party Human-Computer Interaction Dataset (MMI)*

In 2002, the database was developed, to provide considerable amount of visual information on different faces and facial expressions. It addresses the absence in current databases which portray only the recordings of each phase: neutral to onset, peak, offset, and back to neutral face. Unlike those databases which only concentrate on primary emotions, this database consists of regular expressions besides standard activation specifications for individual AUs and different ADs. It provides more than 2900 videos with HD images of 75 subjects with annotations for AU in video and free to the scientific community for research.

### *J. IMPA – FACE3D*

The 2008 founded IMPA-FACE3D database supports research in facial animation by providing information on how the facial expression is analyzed and synthesized. The face is a neutral one and 6 universal expressions covering their geometric and color data are provided. The detail of the captured spatial facial features along with color information gives researchers the opportunity to delve deep into facial animation, expression analysis, as well as computer graphics.

### *K. M-LFW-FER*

The M-LFW-FER dataset has 4757 images showcasing 3 different emotions: 2538 positive, 423 negative, and 1796 neutral expressions. The dataset features a combination of side and front views as well. The front view subset comprises of 2078 positive, 338 negative and 1268 neutral images. The dataset is segregated into training and validation sets in the ratio of 7: 3 for every subset. The dataset has been employed for recognizing facial expressions for masked faces.

### *L. Caltech Faces*

Caltech Faces Dataset has been assembled at the California Institute of Technology, designed for research purpose on face detection and recognition tasks. With about 450 images of 27 people's faces, it captures different facial attitudes, light intensities, and so on. The images focus on the individual, showing face details captured through controlled set ups for studying facial analysis using computer vision.

### *M. CMU Multi-pie face database*

The database consists of around 750, 000 images taken of 337 different people between 4 and 5 months. High-resolution frontal photos, varied facial expressions, different poses from 15 viewpoints and 19 illumination conditions. The database contained 20 images for every of the 15 cameras used with 18 flashes taken rapidly one after another, covering various expressions and lighting versions. Secondly, frontal full-face pictures were captured with a 6.3 mega pixel camera which gave 3072 x 2048 sized pictures expressing different facial poses in each sitting.

### *N. NIST Mugshot Identification Database*

This is a database for developing and testing automated mugshot identification system composed of 3,248 PNG-format photographs and their attached TXT-formatted metadata files. It consists of 1,573 people (1495 men, and 78 women), including both front and side views. The sample contains 131 cases with several front views, and 1,418 cases with solitary front view. There are 89 cases for profiles with multiple profiles and 1,268 cases for profiles with one personality. Furthermore, there are instances presenting both sides as well as frontal views, for example, 89 with multiple of both sides and frontals; 27 with multiple frontals and one profile; and 1,217 one frontal and one profile.

A thorough comparison of the several datasets has been given in Table 1.

TABLE 1. Comparative Analysis of Different Datasets

| References | Dataset Name | Emotions in Dataset | Number of Images/ videos | Category | Subjects | Other Information |
|---|---|---|---|---|---|---|
| [3], [8], [10], [11], [12], [14], [15], [20] | FER2013 (Facial Expression Recognition 2013) | Happy, Angry, Disgust, Neutral, Fear, Sad, Surprise | 35,887 | Adults | N/A | Images are 48 x 48 pixels, grayscale |
| [2], [8], [10], [15] | JAFFE (Japanese Female Facial Expression) | Happy, Sad, Angry, Surprise, Disgust, Fear, Neutral | 213 | Adults | 10 | Images are 256 x 256 pixels, grayscale |
| [6], [16], [17], [18] | Cohn Kanade (CK) | Anger, Disgust, Fear, Happiness, Sadness, Surprise | 327 sequences | Adults | 123 | Contains sequences showing emotion progression |
| [1], [2], [7], [18], [19] | Extended Cohn Kanade (CK+) | Anger, Happy, Surprise, Sadness, Fear, Disgust, Neutral | 593 filmed sequences | Adults | 123 | Videos recorded at 30 FPS, 640x490 resolution |
| [5], [6], [9], [13] | ChaLearn Real vs Fake Emotion | Anger, Happiness, Sadness, Disgust, Contempt, Surprise | 600 videos | Adults | 50 | Videos captured at 100 FPS |
| [4] | Karolinska Directed Emotional Faces (KDEF) | Angry, Fear, Disgust, Sad, Happy, Surprise, Neutral | 4,900 images | Adults | 70 | Images are 562 x 762 pixels, 32-bit coloured |

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|---|---|---|---|---|---|---|
| [16] | Multimedia Understanding through the Huge Amount of Social Behaviour Data | Social behaviour understanding, Emotion recognition | Videos of different resolutions | Adults | N/A | Synchronized HD and SD videos |
| [16] | Acted Facial Expressions in the Wild (AFEW) | Facial expressions within video content | 600 videos | Adults | N/A | Per-frame labels for valence and arousal |
| [16] | MMI Face Expression Database | Facial expressions, Regular expressions | 2,900+ videos | Adults | 75 | Annotations for AUs in video |
| [17] | IMPA-FACE3D | Neutral face, 6 universal expressions | N/A | Adults | N/A | Geometric and colour data provided |
| [18] | M-LFW-FER | Positive, Negative, Neutral expressions | 4,757 images | Adults | N/A | Contains side and front views |
| [19] | Caltech Faces | Faces with different attitudes | 450 images | Adults | N/A | Captures varied facial attitudes |
| [19] | CMU Multi-PIE face database | Varied facial expressions, poses, lighting | 750,000 images | Adults | 337 | Images captured under various conditions |
| [19] | NIST Mugshot Identification Database | Mugshots that contain front and side views | 3,248 images | Adults | 1,573 | Contains metadata files for each image |

## III. TECHNIQUES USED

We have explored all of the methods that have been used to create the various distinct models in detail, carefully extracting and assembling the accuracy rates that correspond to each method depending on the dataset used. The methods used in every research paper have been comprehensively listed in Table 2.

TABLE 2. Techniques Used

| **Paper No.** | **Techniques Used** | **Accuracy** |
|---|---|---|
| [1] | Modified Convolution Neural Network (MCNN) along with Artificial Bee Colony Algorithm (ABC) & Uses Empirical Wavelet Transform (EWT) to extract features | N/A |
| [2] | Custom CNN Model with 6 Convolution, 3 Maxpool, etc. layers | JAFFE - 95.23%<br>CK+ - 93.24% |
| [3] | Face Detection - Voila Jones Algorithm<br>Emotion Detection - Custom CNN Model | N/A |
| [4] | Face Detection - Haar Cascade<br>Facial Landmark Detection - Dlib Library<br>Emotion Classification - Used Multiple Algorithm<br>RFC, SVM, SAG, RTC, NBC | SVM - 87.31%<br>RFC - 73.4%<br>SAG - 78.58%<br>SMO - 77.76%<br>RT - 47.81%<br>NBC - 67.59% |
| [5] | Support Vector Machine (SVM) | 76.66% |
| [6] | Attribute Extraction - Custom CNN Model | N/A |

| | | |
|---|---|---|
| | Emotion Classification - Custom CNN Model | |
| [7] | Local Binary Pattern (LBP), Autoencoders, Custom CNN Model | 96.5% |
| [8] | Custom CNN Model with Conv2D, Maxpool, etc. layers | Training - 97.22%<br>Testing - 59.06% |
| [9] | Facial Action Coding System (FACS)<br>Feature Extraction Using Normalized Mean<br>SVM along with LASSO Regularization | 82% |
| [10] | Custom CNN Model (Based Upon Trial & Error) | 70.14% |
| [11] | Facial Landmark Detection, ResNet | 99.96% |
| [12] | Shallow CNN with Conv2D, MaxPool2D, etc. layers<br>Deep CNN with Conv2D, MaxPool2D, etc. layers | 89.98% |
| [13] | Face Detection - Haar Feature Face Detector & MOSSE based Object Tracker<br>Facial Landmark Detection - Dlib Library<br>Emotion Detection - LSTM PB (Long Short-Term Memory - Parametric Bias) | 66.7% |
| [14] | Custom CNN Model with Conv2D, MaxPool2D, Batch Normalization, etc. layers | Training - 93.5%<br>Testing - 86% |
| [15] | Face Detection – Local Binary Pattern (LBP)<br>Feature Extraction – Histogram of Oriented Gradients (HOG)<br>Emotion Classification – Convolutional Neural Networks (CNN) | JAFFE - 91.2%<br>FER2013 - 74.4% |
| [16] | Feature Extraction - RNN<br>Face Tracking - Cascaded CNN<br>Emotion Detection - BiLSTM with Attention Mechanism | 98% |
| [17] | For Facial Landmark Detection - Haar Cascade Classifier<br>K- Means Algorithm to analyze the database<br>K- Nearest Neighbors & Backpropagation Neural Network to classify emotions | N/A |
| [18] | Dlib Hog Face Detection Technique, SVM, Local Binary Pattern (LBP) | 86.65% |
| [19] | Two Level CNN Framework Technique | Caltech Faces - 85%<br>CMU - 78%<br>NIST - 96% |
| [20] | Face Recognition - Deepface Algorithm, Emotion Detection – VGG | 97% |

## IV. LIMITATIONS

First and foremost, the heart of these issues is the FER datasets containing emotion images which are unbalanced, causing problems to methods for detecting emotions and thus hampering progress on these issues [1], [14], [15]. Some investigations are too narrow by focusing only on particular muscles that are used for the expression; these neglect the important role played by other crucial facial movements [5]. In addition, several publications reveal that most researchers focus only on particular emotions such as happiness or sadness. The researchers did not develop holistic models comprising of many emotions including happiness and sadness [3], [5], [16].

A major impediment is related to the inherent subjectivity built into some models which limits its use in a wide range of testing scenarios, reducing their applicability and accuracy [6]. In general, comparative analyses always indicate that CNN is better than RNN when it comes to the classification of real smile authenticity. Hence, we should use more efficient methods [3], [6]. One of the setbacks emanates due to lack dedicated datasets to differentiate genuine emotions from fake ones. This is a critical disadvantage that greatly impedes model training and accuracy, suggesting the need for extensive datasets to promote progress in this field [3].

Additionally, the cumulative error of poor accuracies in several studies reflect hardware limitations and basic model failings requiring solid upgrades [12], [16]. Many of the datasets are also highly unbalanced, particularly

FER2013, in which emotions like disgust and fear see a great reduction in emotion detection accuracy. This collection of different papers stresses the problems associated with unbalanced data sets, narrow-down testing, subjective methodology, and critical facial movements supervision. As one can see their collected knowledge brings into sharp focus the need to improve techniques for authenticate smiles, the use of better datasets, improved modelling procedures and taking a look at smiles in the context of an overall facial expressions for better success on this front.

## V. CONCLUSION

Ultimately, this paper is a detailed study of various features of FER and fake emotion detection methods that are employed in modern-day researches. In this study, we focus mostly on an all-inclusive assessment of the main datasets made use of in the reviewed literature, the methods, limitations, and challenges in this field. For the most part we undertook a detailed investigation into datasets in FER studies that form the main core of such studies. We carefully cut apart the methodologies used and unveiled their effectiveness. However, critical evaluation of these methods highlighted the issues arising from different contexts and the adequacy of datasets for the successful growth of reliable emotion classification systems. Hence, this study sheds light on the crucial impact of these datasets in determining the FER techniques as well as the implications of sparse dataset diversity, lower resolution, and absence of spontaneous utterances. Limitations of current methodology create an opportunity for future research on how to develop more complete datasets and new techniques to increase robustness and generality of FER models. Therefore, this paper explores the uses of FER in different sectors, including their impacts on different fields and society at large. It refers to emergent trends and possible lines of future developments pointing at the need for improvements in dataset building, methodological elaboration, and bringing about adaptations to practice. This further pushes the need for improved methodologies, diversification of datasets and innovative techniques in designing more adaptable and situation-specific FER and fake emotion detection algorithms.

## VI. FUTURE SCOPE

Future research on emotion detection could progress into many interesting directions. One area of focus is the development of more robust and reliable techniques to separate real from fake emotions. This could involve adding more data modes to emotion detection models, such as physiological motions or contextual data. Additionally, researchers need to examine the moral aspects of emotion detection technologies and put in place safety measures against misuse. Some of the potential applications of this model are:

1. **Improving the accuracy of fake emotion detection:** This will mean creating new methods for inspecting facial expressions, speech patterns, and other cues which give away false emotions.

2. **Expanding the range of emotions that can be detected:** At present, the models for fake emotion detection usually concentrate on a few emotions - seven basic emotions, such as happiness, sadness, anger, and fear, etc. However, there are many other emotions besides those that humans express, and it is vital to be able to detect these emotions as well.

3. **Developing more robust models that are less susceptible to noise and bias:** There are many kinds of factors that can fool fake emotion detection models, like background noise, poor lighting, and cultural differences. We must build models that are not so vulnerable to these factors in order to ensure their accuracy when used.

4. **Exploring the ethical implications of fake emotion detection:** The ability to detect fake emotion detection can be used both positively and negatively. Before this technology is widely applied, the ethical issues involved should be carefully understood.

5. **Understanding the distinction between genuine and fake emotions:** Better diagnostic devices and treatments in the field of mental health can be achieved through this. It could help in the treatment of conditions like depression, where patients often disguise their true emotions.

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