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# EMOTION RECOGNITION FOR MENTAL HEALTH PREDICTION USING AI TECHNIQUES: AN OVERVIEW

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***Abstract:*** Human facial expressions are a mirror of human thoughts, feelings and human mental states. Facial Emotion Recognition (FER) can provide a social advantage. It's like a form of silent communication. Emotion recognition technology will help to automatically detect the patient's emotions during illness and avoid external acts such as suicide, mental disorders or mental health problems. If we understand all the signs of emotions, we can solve many problems for human beings. Emotion recognition and detection is also useful for healthcare. Through emotional state recognition, we can get information about patients. Recognizing a patient's emotions for a specific disease using artificial intelligence techniques is a challenging task. This article presents recognition, detection and methods for mental health patients. Using artificial intelligence techniques with an emotion detection library and matching emotions to mental health. This article uses an emotional scale to show that there is a link between negative emotions and mental health problems. In this paper, she provided a comprehensive review of AI-based FER methodology, including datasets, feature extraction techniques, algorithms, and recent breakthroughs with their applications in facial expression recognition. In the future, all aspects of FER for different ages would significantly influence the health research community.

***Keyword:*** Emotion Recognition (ER), Emotion Classification, Positive and Negative Emotions, Emotion Mapping, Feature Extraction.

## 1. INTRODUCTION

Human expressions or emotions indicate the way we communicate and play an important role in our daily lives. Facial emotion recognition technology can be used in healthcare, security, commercial analysis and feedback analysis. Recognizing human emotions is a very complex and demanding task for machines to understand, but it is easy for humans to understand [1]. Albert Mehrabian, a famous psychologist, found through his research that the emotional data that people classify as emotions is divided into sections. According to Mehrabian, they found that only 7% of emotional data passes through language and 38% is conveyed by (our language aids) paralinguistics, which vary from culture to culture, such as tone, pitch and rhythm of speaking. 55% of emotional data is shown by facial expression. This suggests that sensitive emotional data can be obtained using facial emotion recognition. It effectively understands every human state of mind and action that is directly related to emotions [2,3]. Thus, human facial emotion recognition can be widely used in human-computer interaction, such as intelligent control systems, behavioural studies, pattern searching, psychology, and other fields [4,5]. Through emotional recognition, we can solve many problems such as business, health and safety issues.

Ekman gave six basic models of emotions which consist of happiness, sadness, surprise, anger, fear and disgust. These can be divided into two parts: positive and negative emotions. Positive emotions include happiness and surprise, and negative emotions include sadness, anger, fear, and disgust [6,7]. Positive emotions are related to improving work efficiency and human health. Negative emotions under the influence of various factors cause stress and reduce concentration [8,9]. We can say that positive emotions are very beneficial for human health, and negative ones are harmful and indicate some dangerous condition, either psychological or physical [10]. Effects on emotional health include depression, anxiety, loneliness, mental breakdowns and other similar problems. To solve this problem, we first detect human emotions and map them to the field of psychology. Like – trait/symptoms of depression emotions.

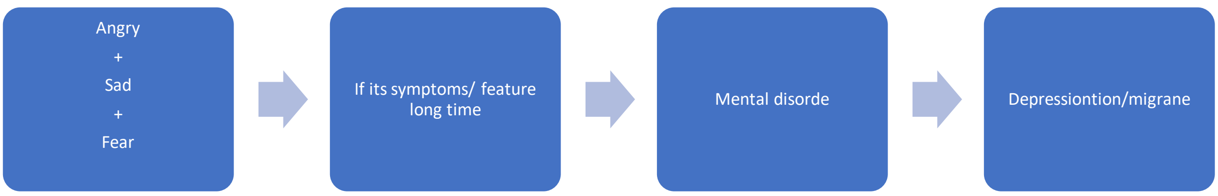



**Fig:1 Negative emotions mapped process.**

Recognizing human emotions is a very ambitious task for human reactions and behaviour. It connects several fields – e.g.,psychology, electronics/sensors, signal processing and machine learning [11].

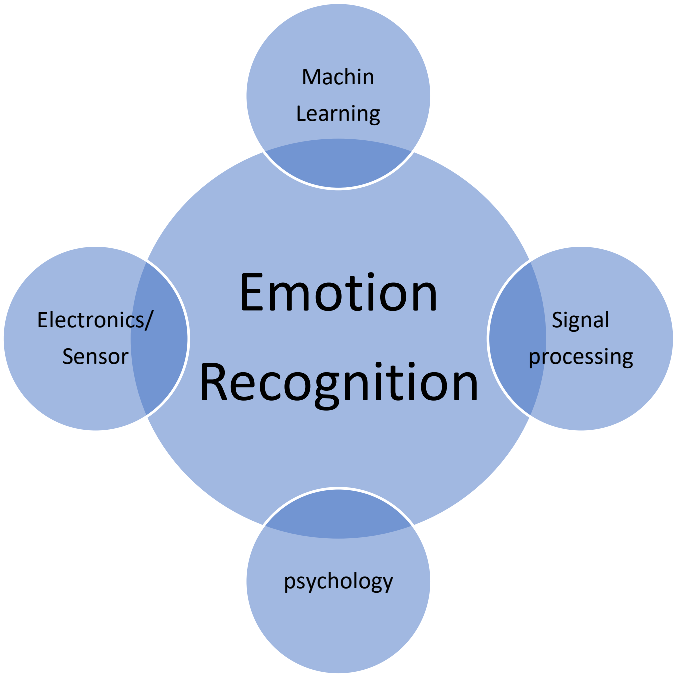



**Fig: 2 The interdisciplinary background of emotion recognition.**

In this post, we are dealing with mental disorders related to human health. So, our primary focus is on recognizing negative emotions and mapping them to psychological behaviour. We can solve mental health problems by detecting emotions. In this article, we used Python EDA technology with AI concept and provided a negative emotion percentage chart.

## 2 METHODOLOGY

In this section, we described the methodology of emotion detection from image data. In this work, we first use artificial intelligence techniques for image data detection and recognition. In the field of computer science, AI is the best technological option. We can get amazing solutions related to classification of image and text data. After the classification, we compared the negative emotions with the possible diseases of the patients. Like with depression. Use Python EDA or image data and also describe how human emotions can be analysed for healthcare purposes.

### 2.1 Collection of image data related to human emotions

Our first step is to collect the image data and dataset. We then select a dataset of images of negative emotions related to health data. We then performed a basic pre-processing step.

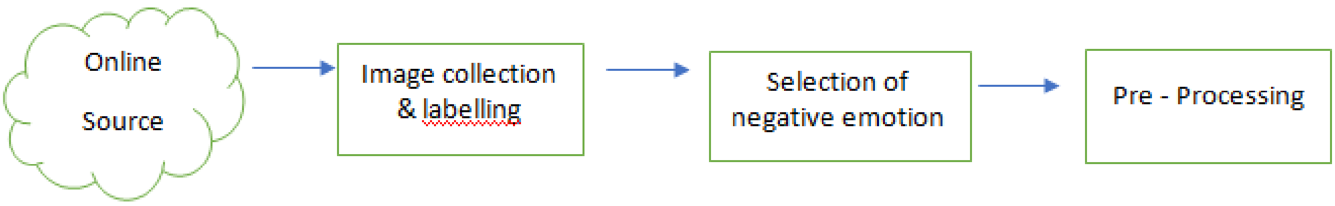



**Fig:3 Data Generation.**

### 2.2 Emotion models.

Together with the study of the brain, the theories gave rise to new models of emotions. Which helps to understand people's inner feelings. Early signal processing models for communication were developed around the world to aid in the analysis of communication. These early models of communication provided the basis for the emotion model. This later led to more complex emotional models. And emotional models are involved at different levels. Emotion models also influenced the field of computer technology [31].

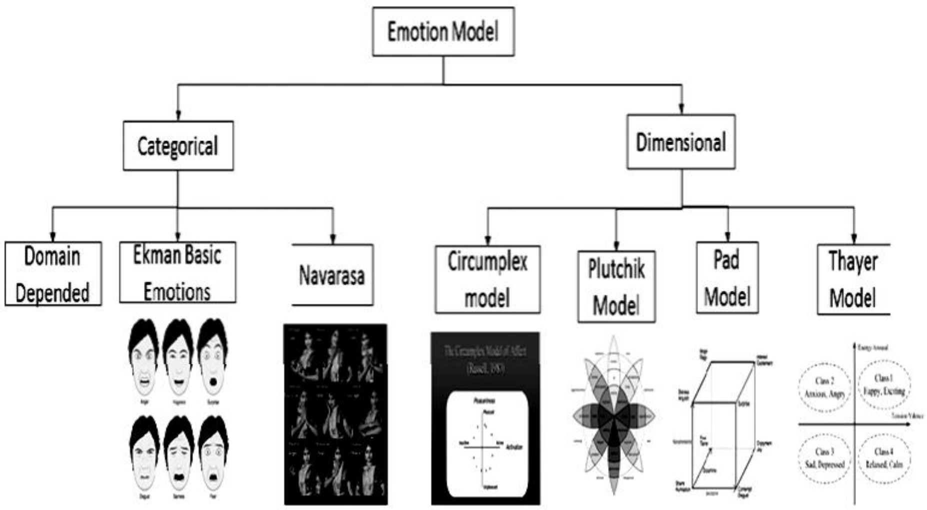



**Fig.4 Models of emotions.**

**a) Domain-dependent –** Emotional intelligence can basically be divided into five domains, knowing emotions, managing emotions, motivating oneself, recognizing emotions in others and dealing with relationships.

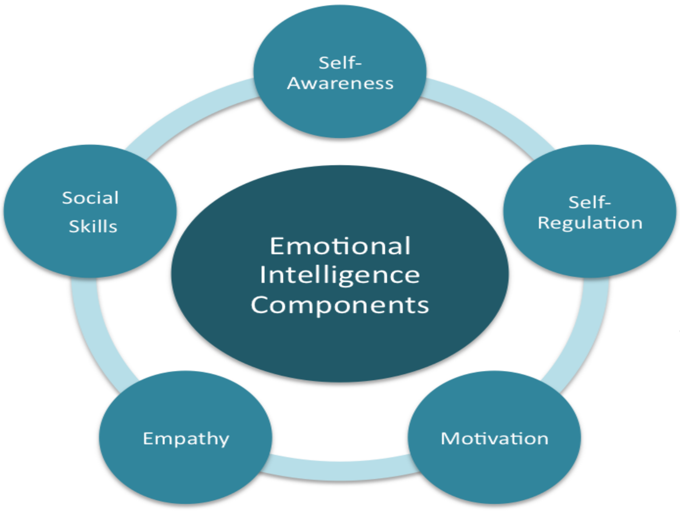



**Fig.5 Domain-dependent model.**

**b) Ekman Basic Emotions -** Six basic emotions is a term and his theory refers to the American psychologists "Pal Ekman" and "WallanceV.Friesen".

Ekman and Friesen identified six basic emotions. In 1972, it is based on the study of the isolated culture of the people of the Lori tribe in Papua New Guinea. The tribe members were able to identify these six emotions in the pictures – anger, disgust, fear, happiness, sadness and surprise.

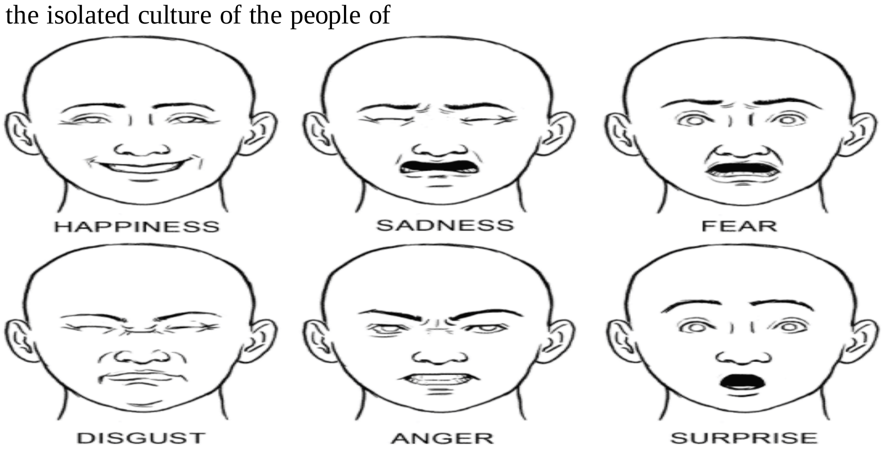



**Fig.6 Ekman Six basic models**

**c) Navarasa based model –**Navarasa means nine emotions; rasa means an emotional state of mind. The nine emotions are Shringara (love/beauty), Hasya (laughter), Karuna (sadness), Raudra (anger), Veera (heroism/courage), Bhayanaka (horror/fear), Bibhatsa (disgust), Adbhutha (surprise/wonder),Shantha (Pea or Calm), (October 18, 2020, Trupti Paikaray in tea with life, India, TOI). By Radhika lyer in story/ December 6, 2021 (Nine Human Expressions). There are many datasets available for research on human emotion recognition. However, we have limited information and have not found an emotion corpus in the above nine basic emotions.


**Fig.7 Model based on Navaras.**

**d) Circumplex Model –** The Russell's (1980) Circumplex Model focuses on determining how traits and emotions are structurally similar, and its basic premise is that a relatively unproblematic circular arrangement, or circumplex, is an economic description of the relationships between traits and emotions. James Russell asked research participants to sort 28 emotion words into categories based on perceived similarity [70]. Then Russell used a statistical technique to evaluate emotions. It is based on positive correlations.

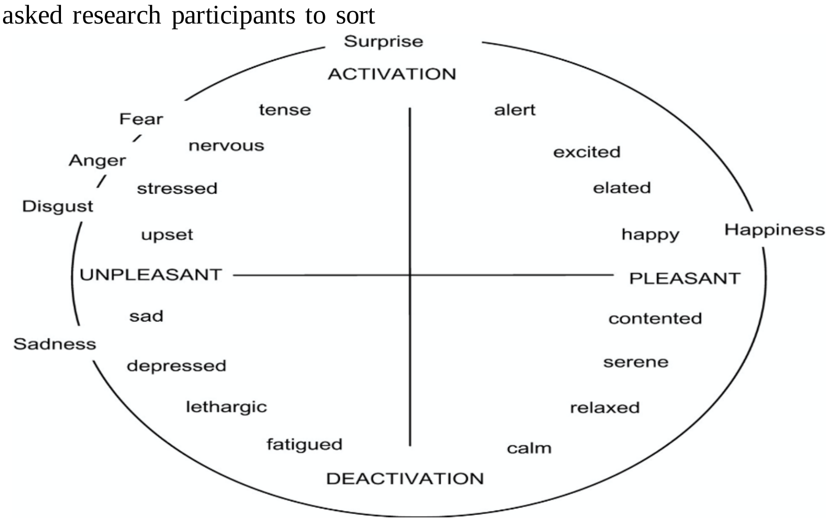



**Fig.8 Circumplex model.**

**e) Plutchik model –** American psychologist Dr. After studying emotions, Robert proposed that there are eight primary emotions that underlie all others: joy, sadness, acceptance, disgust, fear, anger, surprise, and anticipation (Pollack, 2016). The Plutchik model is more useful for understanding all 34,000 different emotions and identifying primary emotions.

They were first described in 1980.

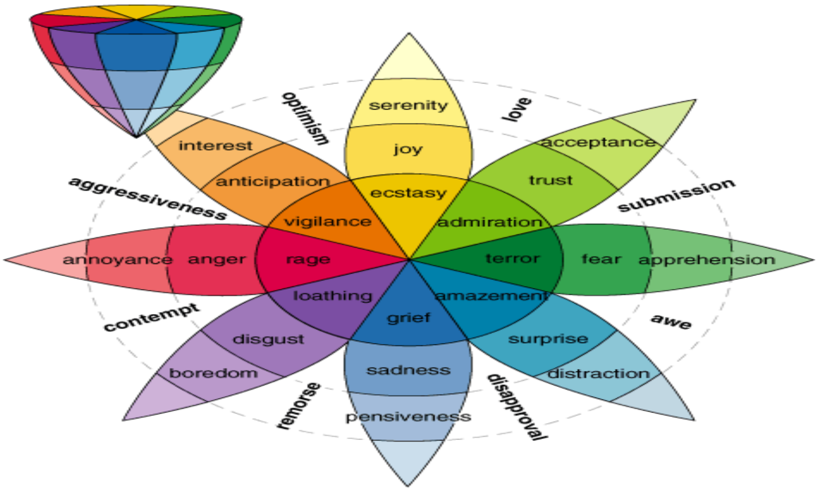



**Fig.9 Plutchik model.**

**f) Pad Model-**The Pad Model of Emotional State is a psychological model developed by Albert Mehrabian and James A. Russell (1974 and later) to describe and measure emotional states.

The PAD model uses three numerical dimensions, Pleasure, Arousal and Dominance, to represent all emotions. (Pleasure-arousal-dominance (PAD) model), the PAD model is mainly used to study non-verbal communication such as body language in psychology.

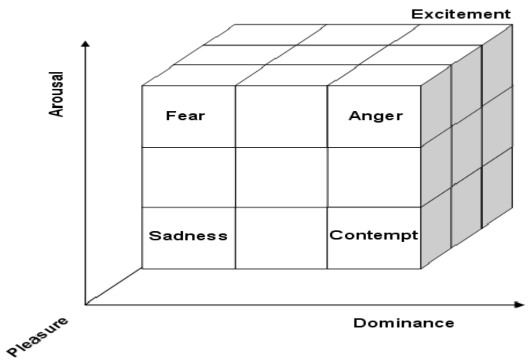



**Fig. 10 PAD model.**

**g) Thayer's model -** Thayer's model (Friedman and Thayer, 1998), which includes disorders of affect, including anxiety disorders.

Thayer's theory is an appraisal theory and a theory of depression, the researcher emphasized the mathematical model of dynamic mood, which reflects the relationship between mood, health and adaptation to the environment.

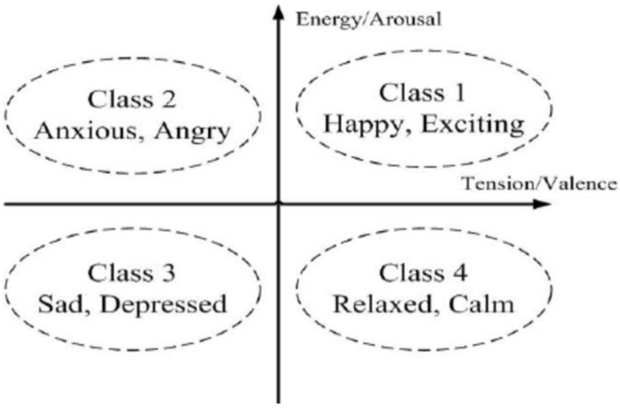



**Fig.11 Thayer's model.**

### 2.3 Database for emotions.

A database of facial expressions or emotions is a collection of images and video clips. This picture and video represent a range of emotions. According to Researcher, a well-annotated media context of facial behaviour is essential for training, testing and validating algorithms for developing expression recognition systems. The expression database displays various basic emotional expressions.

Many publicly available databases are divided into categories. Here are some important details of facial expression databases.

| Database | Facial expression | Number of Subjects | Number of images/videos | Gray/Color | Resolution, Frame rate | Ground truth | Type |
|---|---|---|---|---|---|---|---|
| FERG-3D-DB (Facial Expression Research Group 3D Database) for stylized characters [32] | angry, disgust, fear, joy, neutral, sad, surprise | 4 | 39574 annotated examples | Color | | Emotion labels | Frontal pose |
| Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) [33] | Speech: Calm, happy, sad, angry, fearful, surprise, disgust, and neutral.<br><br>Song: Calm, happy, sad, angry, fearful, and neutral. Each expression at two levels of emotional intensity. | 24 | 7356 video and audio files | Color | 1280x720 (720p) | Facial expression labels<br><br>Ratings provided by 319 human raters | Posed |
| Extended Cohn-Kanade Dataset (CK+)[34] | neutral, sadness, surprise, happiness, fear, anger, contempt and disgust | 123 | 593 image sequences (327 sequences having discrete emotion labels) | Mostly gray | 640* 490 | Facial expression labels and FACS (AU label for final frame in each image | Posed; spontaneous smiles |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | | sequence) | |
| Japanese Female Facial Expressions (JAFFE)[35] | neutral, sadness, surprise, happiness, fear, anger, and disgust | 10 | 213 static images | Gray | 256* 256 | Facial expression label | Posed |
| MMI Database[36] | | 43 | 1280 videos and over 250 images | Color | 720* 576 | AU label for the image frame with apex facial expression in each image sequence | Posed and Spontaneous |
| Belfast Database[37] | Set 1 (disgust, fear, amusement, frustration, surprise) | 114 | 570 video clips | Color | 720*576 | | Natural Emotion |
| | Set 2 (disgust, fear, amusement, frustration, surprise, anger, sadness) | 82 | 650 video clips | Color | | | |
| | Set 3 (disgust, fear, amusement) | 60 | 180 video clips | Color | 1920*1080 | | |
| Indian Semi-Acted Facial Expression Database (iSAFE)[38] | Happy, Sad, Fear, Surprise, Angry, Neutral, Disgust | 44 | 395 clips | Color | 1920x1080 (60 fps) | Emotion labels | Spontaneous |
| DISFA[39] | - | 27 | 4,845 video frames | Color | 1024*768; 20 fps | AU intensity for each video frame (12 AUs) | Spontaneous |
| Multimedia Understanding Group (MUG)[40] | neutral, sadness, surprise, happiness, fear, anger, and disgust | 86 | 1462 sequences | Color | 896*896, 19fps | Emotion labels | Posed |
| Indian Spontaneous Expression Database (ISED)[41] | sadness, surprise, happiness, and disgust | 50 | 428 videos | Color | 1920* 1080, 50 fps | Emotion labels | Spontaneous |
| Radboud Faces Database (RaFD)[42] | neutral, sadness, contempt, surprise, happiness, fear, anger, and disgust | 67 | Three different gaze directions and five camera angles (8*67*3*5=8040 | Color | 681*1024 | Emotion labels | Posed |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | images) | | | | |
| Oulu-CASIA NIR-VIS database | surprise, happiness, sadness, anger, fear and disgust | 80 | three different illumination conditions: normal, weak and dark (total 2880 video sequences) | Color | 320×240 | | Posed |
| FERG (Facial Expression Research Group Database)-DB[43] for stylized characters | angry, disgust, fear, joy, neutral, sad, surprise | 6 | 55767 | Color | 768x768 | Emotion labels | Frontal pose |
| AffectNet[44] | neutral, happy, sad, surprise, fear, disgust, anger, contempt | | ~450,000 manually annotated<br>~ 500,000 automatically annotated | Color | Various | Emotion labels, valence, arousal | Wild setting |
| IMPA-FACE3D[45] | neutral frontal, joy, sadness, surprise, anger, disgust, fear, opened, closed, kiss, left side, right side, neutral sagittal left, neutral sagittal right, nape and forehead (acquired sometimes) | 38 | 534 static images | Color | 640X480 | Emotion labels | Posed |
| FEI Face Database | neutral,smile | 200 | 2800 static images | Color | 640X480 | Emotion labels | Posed |
| Aff-Wild[46][47] | valence and arousal | 200 | ~1,250,000 manually annotated | Color | Various (average = 640x360) | Valence, Arousal | In-the-Wild setting |
| Aff-Wild2[48][49] | neutral, happiness, sadness, surprise, fear, disgust, anger + valence-arousal + action units 1,2,4,6,12,15,20,25 | 458 | ~2,800,000 manually annotated | Color | Various (average = 1030x630) | Valence, Arousal, 7 basic expressions, action units for each video frame | In-the-Wild setting |
| Real-world Affective Faces Database (RAF-DB)[50][51] | 6 classes of **basic emotions** (Surprised, Fear, Disgust, Happy, Sad, Angry) plus Neutral and 12 classes of **compound emotions** (Fearfully | | 29672 annotated examples | Color | Various for original dataset and 100x100 for aligned dataset | Emotion labels | Posed and Spontaneous |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Surprised, Fearfully Disgusted, Sadly Angry, Sadly Fearful, Angrily Disgusted, Angrily Surprised, Sadly Disgusted, Disgustedly Surprised, Happily Surprised, Sadly Surprised, Fearfully Angry, Happily Disgusted) | | | | | | |

### 2.4 Feature extraction methods for emotion recognition.

In Emotion Recognition, the researcher used different types of methods. Such as emotion recognition algorithm, emotion classification algorithms and quantitative data analysis methods.

#### I. Emotion Recognition Algorithm.

Emotion recognition or emotion detection is a specialized version of object detection where objects are detected by human faces. Many object detection algorithms (engati.medium.com) [24] are used for emotion detection and recognition, such as

**OpenCV (Haar-Cascade)**

Haar-Cascade implementation of OpenCV, it is an open library for image manipulation in C. OpenCV is very fast for inference in real-time systems.

**MT CNN**

The MT CNN algorithm is based on deep learning methods. It uses Convolutional Neural Network for face detection and provides test accuracy compared to OpenCV &Haar – Cascade method.

**YOLOV3**

You look only once (YOLO) is a state-of-the-art Deep Learning algorithm for object detection. It has many convolutional networks. Creating a Deep CNN model. The YOLO model can detect 80 different types of object classes with high accuracy. And it is faster than MTCNN.

**SSD**

Single Shot Detector (SSD) like YOLO model and it is also a deep convolutional model. SSD can detect many positions and lighting. His speed is good.

**BlazFace**

This is a fast face detection algorithm released by Google. It accepts a 128 × 128 image. The BlazFace algorithm is optimized for use in facial recognition on mobile phones. It works on mobile cameras to detect facial images. It doesn't work well for CCTV footage.

**Face boxes**

For the latest facial recognition algorithm, researchers can use Face Boxes. Its inference time is real-time CPU fast, its accuracy and speed are very fast compared to other algorithms.

**Fig. 12 Face boxes**

#### II. Emotion Classification Algorithm.

**RF**

(Developed by Breiman (2001) Breiman, L.) Classification of random forests consists of a large number of trees. RF involves the processing of many decision trees. Each tree predicts the probability value of the target variables. RF classification is used for large data sets. if users input complex datasets, it takes longer to evaluate them.

**SVM**

(Presented by Vladimir N. Vapnik and Alexey Ya. Chervonenkis) Support Vector Machine (SVM) classifiers use an exciting change that makes them suitable for evaluating non-linear decision boundaries, and given that this is possible by increasing the given variable space using a special function called cores. The decision boundary of SVM considers that it allows to label a variable as a function to the target variable. The math function it uses to evaluate the bounds is given by -

$$f(x) = \beta 0 - \sum_{i\,\epsilon s} aiK\,(x, xi)$$

Here, K represents the kernel function and **f(x)=β0** and **aiK** beta are the training parameters.

The SVM classification algorithm is basically used for face detection, image classification and handwritten character recognition.

**Naive Bayes Classifier**

(Rev. Thomas Bayes). It is one of the simplest and most effective classification algorithms for machine learning. It is based on Bayes' theorem, which describes how the probability of an event is evaluated based on prior knowledge of the conditions that may be associated with the event. Mathematically this sentence says-

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$$

Where P(Y|X) is the probability of event Y assuming that X has already occurred.

.

P(X) is the probability of event X,

P(Y) is the probability of event Y,

P(X|Y) is the probability of event X given a fixed value of Y.

Naive Bayes classification algorithm is used in various applications like –

Spam classification for email identification.

Live Prediction system for target variables in real time.

Sentiment analysis to recognize products and classify positive or negative sentiment.

Multi-Class Prediction for Multi-Class Machine Learning Problems.

**KNN**

(Evelyn Fix and Joseph Hodges are credited with the initial ideas around the KNN model in this 1951.) The K-Nearest Neighbor classification algorithm works by identifying the K nearest neighbours to predict and a given observation point. It then evaluates the proportions of each type of target variable using K points and then predicts the target variable with the highest ratio. KNN classification helps with contour detection and identification of similar documents.

**LDA**

(By Jasom Brownlee on Sep 28, 2020 in Python Machine Learning) Linear Discriminant Analysis is a linear machine learning classification algorithm. The LDA algorithm involves developing a probabilistic model per class based on a specific distribution of observations for each input variable. The LDA classification algorithm is mostly used in speech emotion recognition.

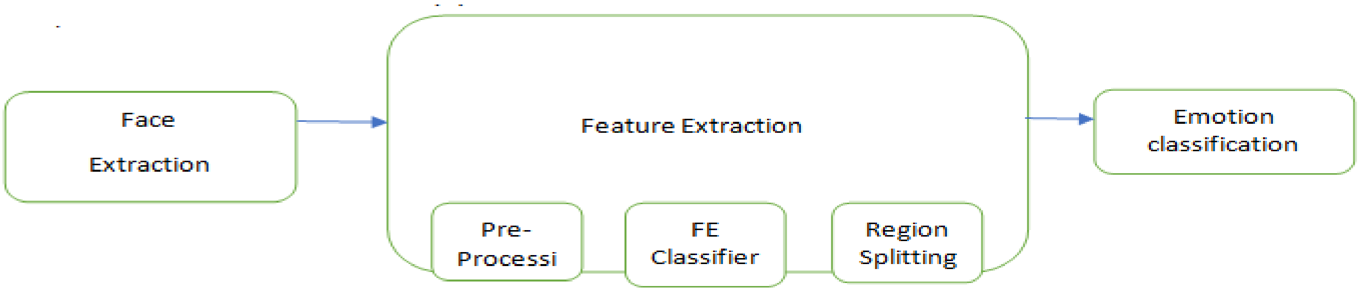



**Fig.13 Emotion Recognition Classification step.**

**DNN (Deep Neural Network)**

In current research, video is used for input and detection of frontal faces of people. Video streams are used for image pre-processing. Analysis of acquired images and videos is done using Deep Neural Network, Deep Convolution Network in combination with traditional classifiers like – KNN, LDA, SVM and others. Finally, the system analyses the emotions obtained in images, videos and messages. The development of emotions detected over a certain period of time [52]. The general structure of the Deep Learning system process is shown in Fig.

In a system -

First stage: In the first stage of the system, video and images related to facial expressions are inserted.

Second stage: In the second stage, the video is converted to 3600 frames.

Third stage: In this stage, pre-processing technique is applied to the input image. This stage has two main operations – removing unnecessary images and resizing the image.

Fourth stage: After the pre-processing stage, deep learning networks are required in which traditional classifiers are used for classification. After this step, we get the Emotions of facial expressions of each type.

**CNN (Convolutional Neural Network)**

Convolutional neural networks (CNNs) are a type of deep learning network. Other traditional classification algorithms can be used on CNN when comparing Deep Learning Network Pre-Processing. CNN has input layer, output layer, hidden layers, pooling layers and fully connected layers. This improves data classification and the accuracy of analysis results. Researchers can deeply study facial emotion recognition for healthcare and get better results through this concept.

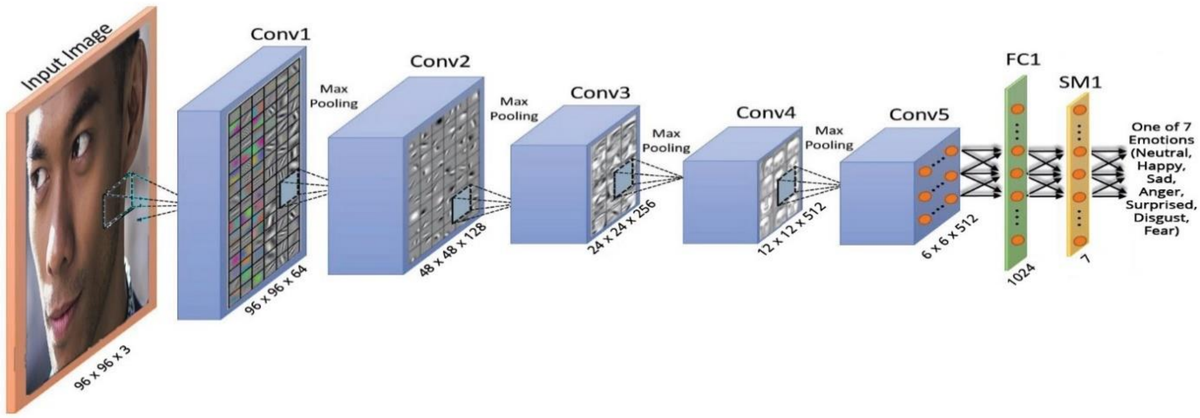



**Fig:14 Structure of Deep Convolution Network.**

**III. Qualitative Analysis.**

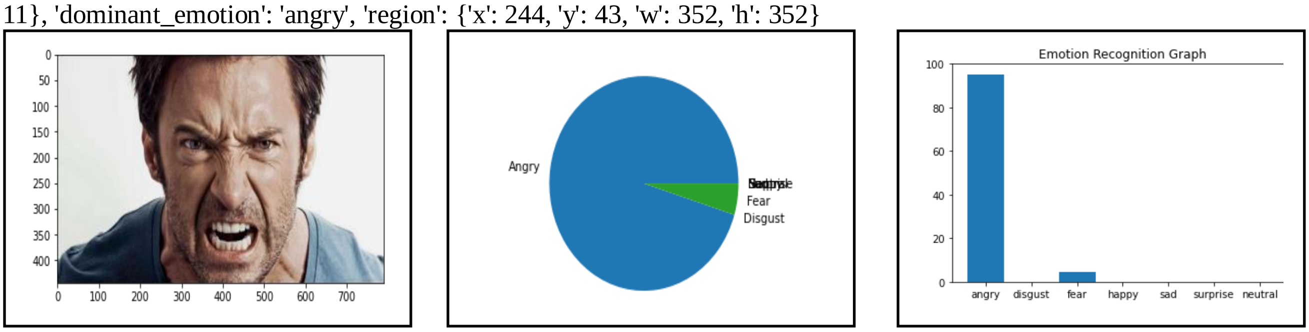
we now describe our quantitative data analysis for emotion detection and recognition [53]. And using the appropriate library functions –

**2.4.1 Emotion Image Detection & Emotion Recognition**

In this step, first of all, the dataset is created by detecting the image. Image action library functions are used in all images.

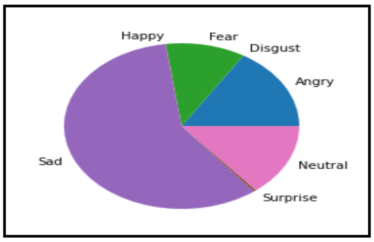
Emotion recognition graphs and emotion recognition charts have been used for image action range labels.

Angry - {'emotion': {'angry': 95.26973962783813, 'disgust': 8.8512946971874846e-08, 'fear': 4.730259254574776, 'happy': 4.215117160475887e-12, 'sad': 3.3450870517981457e-06, 'surprise': 2.507935916232218e-10, 'neutral': 8.429262604754684e-11}, 'dominant_emotion': 'angry', 'region': {'x': 244, 'y': 43, 'w': 352, 'h': 352}

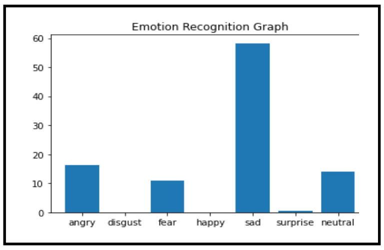



(a) (b) (c)

Sad - {'emotion': {'angry': 16.204548930579552, 'disgust': 0.014108574897146238, 'fear': 10.944237000437141, 'happy': 0.054549145761606604,'sad': 58.27235480876508, 'surprise': 0.42716660101215825, 'neutral': 14.083027650949044}, 'dominant_emotion': 'sad', 'region': {'x': 110, 'y': 59, 'w': 120, 'h': 120}}



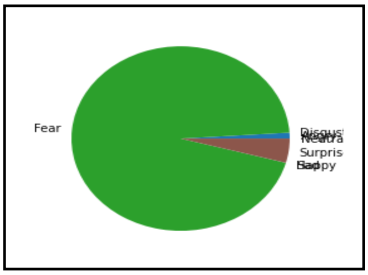

(a)



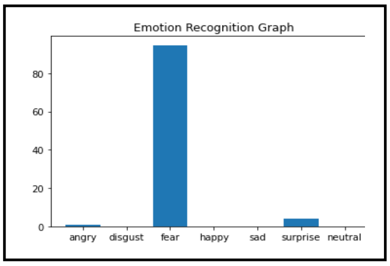

(b)

(c)

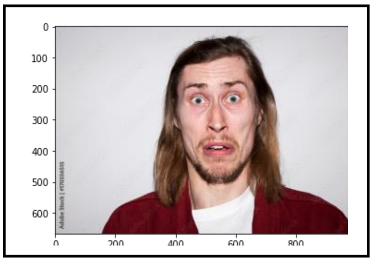
Fear - {'emotion': {'angry': 1.0241676732401652, 'disgust': 0.0017911020380612745, 'fear': 94.74108187801134, 'happy': 0.0036320578492728085, 'sad': 0.01290095319334511, 'surprise': 4.2164324502010615, 'neutral': 1.5240947191233057e-07}, 'dominant_emotion': 'fear', 'region': {'x': 361, 'y': 101, 'w': 344, 'h': 344}}




**(a)**




**(b)**



**(c)**

**Fig.15** (a) Input image emotion detection, (b) Emotion recognition action graph, (c) Emotion Recognition range labels charts.

### 2.4.2 Emotion dataset for analysis

There are many different emotion definition systems from psychological and mental/sensitive science [54],[55]. In this analysis work, we use the emotion-defined tabulated dataset, which is used for negative emotion analysis and psychological study.

```
In [2]: Emotion_data = pd.read_csv (r"C:\Users\sonal\Downloads\data.csv")

In [3]: Emotion_data
Out[3]:
```

| | Unnamed: 0 | path | label |
|---|---|---|---|
| **0** | 0 | Surprise/1bd930d6a1c717c11be33db74823f661cb53f... | Surprise |
| **1** | 1 | Surprise/cropped_emotions.100096~12ffff.png | Surprise |
| **2** | 2 | Surprise/0df0e470e33093f5b72a8197fa209d684032c... | Surprise |
| **3** | 3 | Surprise/cropped_emotions.260779~12ffff.png | Surprise |
| **4** | 4 | Surprise/cropped_emotions.263616~12ffff.png | Surprise |
| **...** | ... | ... | ... |
| **15448** | 15448 | Angry/cropped_emotions.571245~angry.png | Angry |
| **15449** | 15449 | Angry/cropped_emotions.232257~angry.png | Angry |
| **15450** | 15450 | Angry/cropped_emotions.232276~angry.png | Angry |
| **15451** | 15451 | Angry/0aa9ec997e4faa4499e0aa3efac5ab97db109423... | Angry |
| **15452** | 15452 | Angry/7fdcf428267020e7b1b063745c0834ae6ccb9125... | Angry |

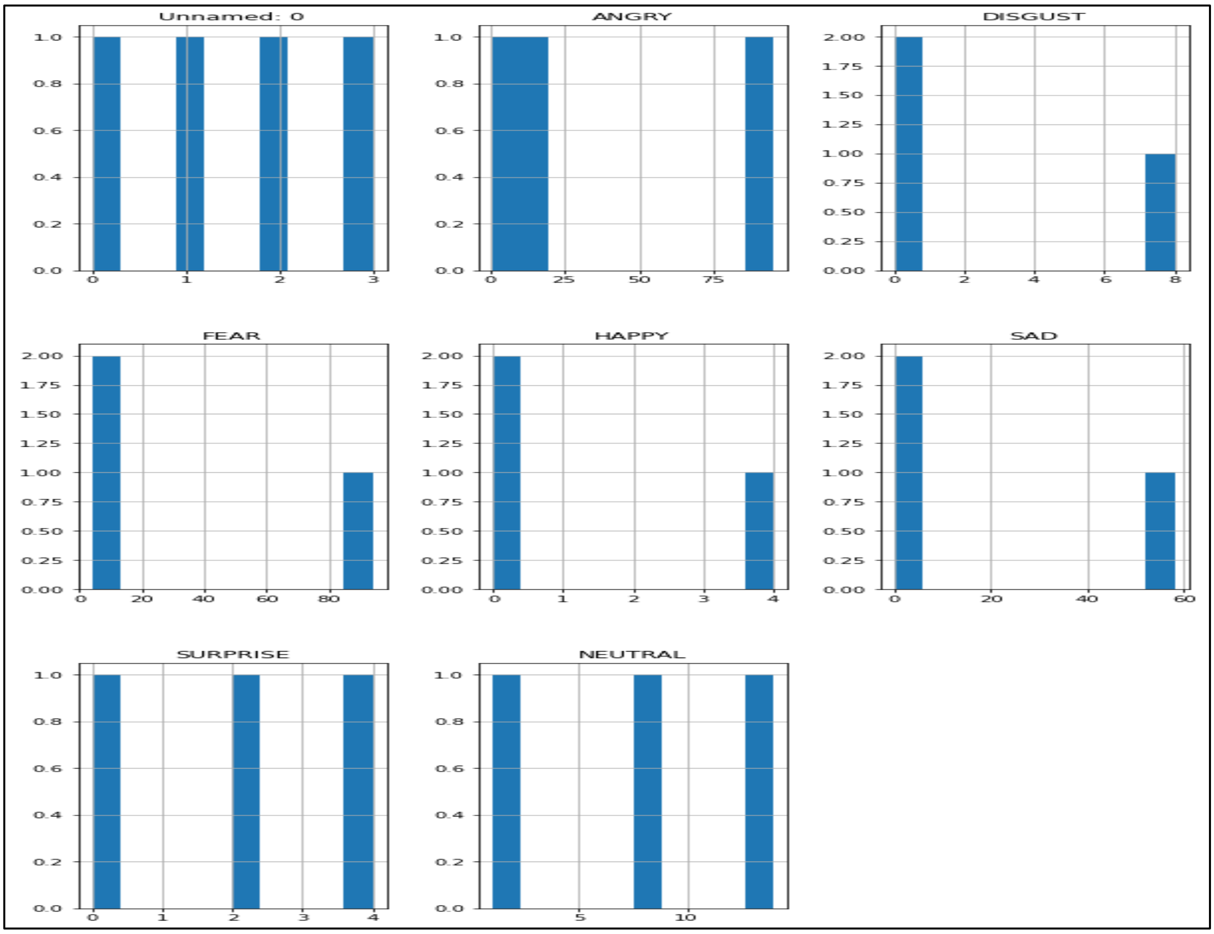
15453 rows × 3 columns

Print summary statistics of the dataset using the **describe ()** function.

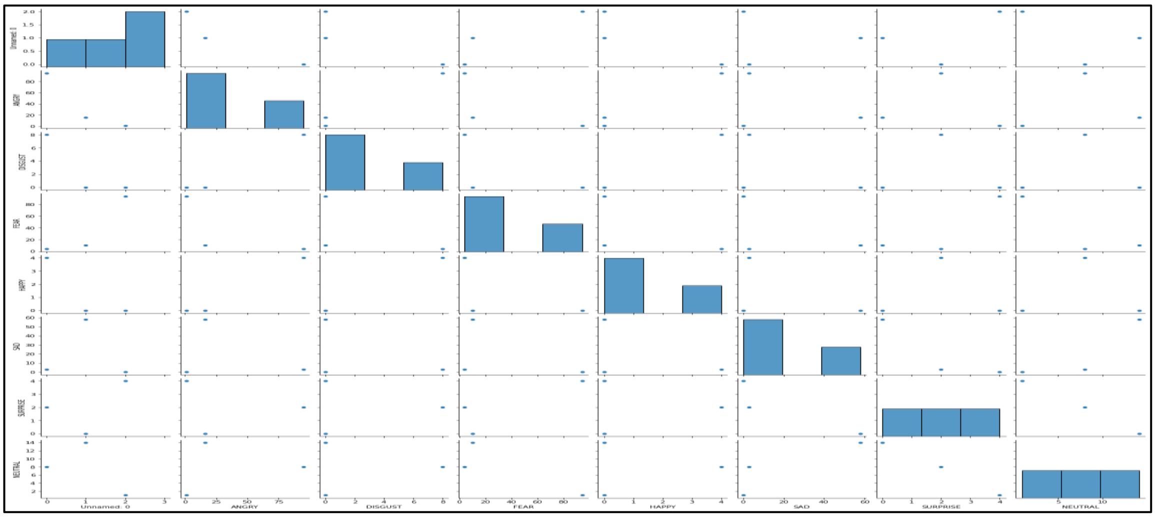
Out[5]:

| | Unnamed: 0 | IMAGE | ANGRY | DISGUST | FEAR | HAPPY | SAD | SURPRISE | NEUTRAL |
|---|---|---|---|---|---|---|---|---|---|
| count | 4.000000 | 3 | 3.000000 | 3.000000 | 3.000000 | 3.000000 | 3.000000 | 3.0 | 3.000000 |
| unique | NaN | 3 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| top | NaN | C:\image for paper\img1.jpg | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| freq | NaN | 1 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| mean | 1.500000 | NaN | 37.333333 | 2.666667 | 36.000000 | 1.333333 | 20.333333 | 2.0 | 7.666667 |
| std | 1.290994 | NaN | 50.500825 | 4.618802 | 50.318983 | 2.309401 | 32.654760 | 2.0 | 6.506407 |
| min | 0.000000 | NaN | 1.000000 | 0.000000 | 4.000000 | 0.000000 | 0.000000 | 0.0 | 1.000000 |
| 25% | 0.750000 | NaN | 8.500000 | 0.000000 | 7.000000 | 0.000000 | 1.500000 | 1.0 | 4.500000 |
| 50% | 1.500000 | NaN | 16.000000 | 0.000000 | 10.000000 | 0.000000 | 3.000000 | 2.0 | 8.000000 |
| 75% | 2.250000 | NaN | 55.500000 | 4.000000 | 52.000000 | 2.000000 | 30.500000 | 3.0 | 11.000000 |
| max | 3.000000 | NaN | 95.000000 | 8.000000 | 94.000000 | 4.000000 | 58.000000 | 4.0 | 14.000000 |

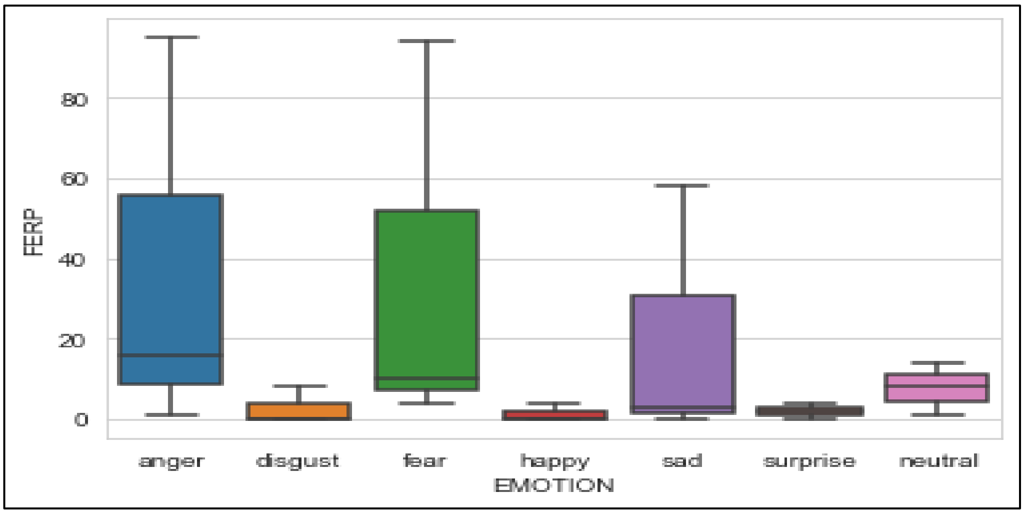
**Plot Histogram for All Variables -** Plot histogram is a graph that shows the distribution of numeric variable values as a series of bars. Here, the histogram chart covers a range of numerical values and shows the highest frequency of emotional data.




**Build a pairwise graph using the seaborn library -** A pairwise graph plots the pairwise relationship in a dataset. Let the Pair-Plot function create a grid. In addition, all dataset variables are displayed on the Y-axis in one row and on the X-axis in one column. Shown here is a Pair-Plot marine library map of emotional longitude and latitude.



Box plot for visualizing the relationship between emotions and FERP-Box-Plot is a method to graphically represent the spread of a numerical variable through quartiles. The bottom of the box is the 20% percentile and the top of the box is the 80% percentile of the negative emotion data.




**2.5 Appearance-based methods.**

**a) Optimalization**

An optimization algorithm is related to a branch of mathematics used to solve a mathematical problem based on a minimization and maximization function. And they act as important sources for engineering and machine learning problems [56].

Given an algorithm **f(x)**, the optimization algorithm helps to either minimize or maximize the value of **f(x)**. In deep learning content, we use optimization algorithms to train the neural network by optimizing the cost function **J**. The cost function is defined as: $j(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathrm{L}\,(\mathrm{y}'^{\mathrm{i}}, \mathrm{y}^{\mathrm{i}})$

The value of the cost function j is the average of the loss L between the estimated value of y^' and the actual value of y. the value y^' is obtained during the forward propagation step & uses the weights w and basis b of the optimization algorithms; we minimize the value of the cost function j by updating the values of the trainable parameters. W and b. Use of the optimization algorithm in machine learning and deep learning. So, we can improve the job of analyzing facial emotion or expression recognition data using an optimization algorithm. Because optimization provides a toolkit for modelling/formulation and algorithmic techniques [63].

**b) Feature extraction using an optimization algorithm**

The feature extraction method is associated with the sum of rows and columns of white pixels of the edge-identified image. A row sum pattern (Mh) along a column and a column sum pattern (Mv) along a row of white pixels are defined as a feature of each region. These patterns are known as projection profiles. f (m, n) represents a binary image of m rows and n columns. Then the vertical profile is defined as the sum of the white pixels of each column perpendicular to the x-axis, which is represented by the vector Mv of size n x (1)

$$\boldsymbol{Mvj}\sum_{i=1}^{m}\boldsymbol{f(i,j)} \qquad \boldsymbol{j} = \mathbf{1,2,3,\dots\dots}$$

The horizontal profile is the sum of the white pixels of each row perpendicular to the y-axis, which is represented by the vector Mh of size m and is calculated using (2).

$$Mhi \sum_{i=1}^{m} f(i,j) \qquad i = 1, 2, 3, \dots \dots .$$

The shape of the human eye is more like an ellipse (we call it a regular ellipse) as shown in Fig. The minor axis is a feature of the eye that changes for each emotion. The main axis of the eye is more or less fixed in different emotions for a particular person. The ellipse is parameterized by its minor and major axes, serially, as ``2a" (fixed) and ``2b" (to be calculated) is described in (3).

$$\frac{x^2}{a^2} + \frac{y^2}{b^2} = 1$$

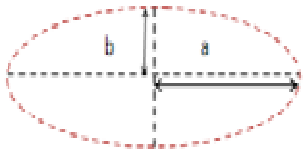



**Fig.16 Regular ellipse.**

The shape of the human lip is towards a combination of two ellipses, which is called an irregular ellipse, as shown in Fig. The word 'irregular' means that the ellipse has two different minor axes, while the major axes remain the same. And the edge detected image of the lip is considered as an irregular ellipse. The minor axis lengths of the lip element for each emotion are calculated. The major axis is "2a" (considered fixed) and the two minor axes are "2b1" and "2b2" (to be calculated). The appropriate values of bl and b2 are replaced by the upper and lower parts in series. The state of the spirit in the image or picture strongly depends on the facial expression b1, b2 as the lip expression and b as the eye expression. In the next section, the pso algorithm adopted to optimize these expressions [A. Habibizad navin1+, Mir Kamal Mirnia2][63].

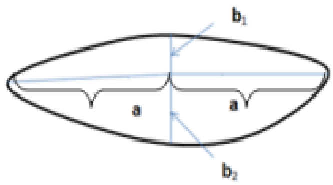



**Fig.17 Irregular ellipse.**

**c) EigenFace**

The eigenface method is an algorithm used for general face recognition. It is based on own face techniques. This uses principal component analysis (PCA) [57]. Mathematically, the principal components of a proper surface divide the surface element vector. And the face Eigen matrix creates a multi-dimensional model, so the facial expression can be easily understood. The idea of Eigen face is to convert a face feature into a mathematical form instead of a mathematical meaning for mathematical features and changes [58]. Custom Face prepares a practice set of images, focusing on making sure all parts of the image have normal light. And normalized the eyes, mouth and other parts of the face. Convert each image into a row and column and parse the image into a basis of the original images, a vector of length into the basis R x C.

- Connect the lines of pixels of the original image; the length is set to the R × C vector.
- If the image is a set of rows, then these form a matrix.
- Where none of the rows = N and the length of each row is R × C and each row is represented by an image vector. This step represents an image A of N mean vectors.
- For the next step, A is subtracted from each row of M to find the matrix M. The covariance S is the matrix that represents the transposed matrix T.
- S = TT
- The researcher can calculate the S Eigen Vector and Eigen value. And reach the highest value using R × C. To identify it by face space [59].

**d) Fisher face**

Fisher's face algorithm gives a successful result for face recognition. LDA (Linear Discriminant Analysis) method demonstrated in (Belhumeur et al., 1997, zhau et al. 1999, chen et al., 2000 Yu and Yang, 2001, Liu and Wechsler, 2002, Lu et al. 2003 a,b; Ye and Li, 2004). Each used LDA to search a set of images that shows the maximum ratio between different class variances. The disadvantage of LAA is that the class variance matrix is always unique because the number of pixels in an image is greater than the number of images. So, it can easily detect the error in the image. Many algorithms are proposed for this. The Fisher face class takes advantage of variance and reduces the difference in this scat so it can handle conditions like lighting and differences in pose conditions. And it helps to identify the image [57]. The Fisher face algorithm by Belhumeur et al. uses both principal component analysis and linear discriminant analysis to create a subspace projection matrix. Fisher's face algorithm is able to receive "emotion" information within the - class [71]. This report reduces the differences between classes. Fisher face maximizes class variation within each class. And the self-face construction process first executes each (N × M) array of images and provides a new shape in the ((N × M) × 1) vector.

Next, using the X k values, calculate both the class mean μ k and the mean of all μ samples

$$\boldsymbol{\mu}_{\mathbf{k}} \frac{1}{k} \sum_{R=1}^{N} \mathbf{X}_{\mathbf{K}} = \textbf{Mean}$$

$$\boldsymbol{\mu}_{\mathbf{k}} = \frac{1}{N\,k} \sum_{m=1}^{N} \mathbf{X}_{\mathbf{k}}$$

where:

N = Total number of frames

Nk = Number of images in class K

X km = Image at index m of class K [58].

**e) LBPH**

Local Binary Pattern Histogram (LBPH) is used for extraction by many techniques. Those that provide important steps to face recognition, local binary pattern is one of the methods used for feature extraction. In 1996, he was led to a new approach by Ojala et al. Shape and texture are achieved using LBPH. Divide the image into several small parts. And its function includes a binary pattern to represent the image space and pixel. Images in LBPH can be separated by evaluating based on the distance between their histograms. The LBPH operator works between eight-pixelneighbors. This means that the value of the center pixels holds them. When the graycenter pixels are higher than the value of the center pixels, the neighboring pixels become one. This condition occurs when the value is equal. LBPH is then created by concatenating the binary code to zero [60].

This is an example of a texture spectrum photo type used to classify the texture of an image. When LBP is combined with the Histogram of Oriented Gradients (HOG) descriptor, the enactment in the Recognition database [61] is increased.

The following steps to achieve this goal are:

• Creating a data set

• Getting a face

• Feature extraction

• Classification

The LBPH algorithm is part of the open CV.

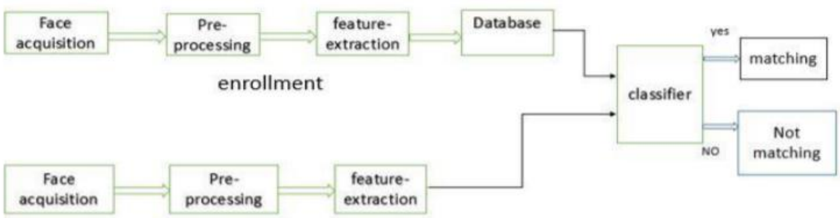
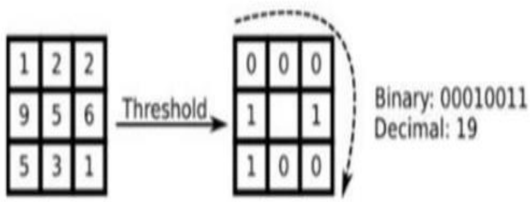



**Fig. Classification of LBPH.**

An LBP feature vector can be generated with the following type-

1. The window under test is divided into cells or split.

2. And LBPH compare each test cell than 8 pixels around it. (Left-Top, Left-Middle, Left-Bottom, Right-Top, Right-Middle, Right-Bottom, etc.), and with these pixels we will assume a circular path that moves clockwise and counter clockwise.




3. If the value of the middle pixel is greater than the value of the nearest pixel, it is marked from zero or from 1, here one byte indicates a binary number and this number is converted to decimal.

4. From each number, calculate a histogram for the regularity of the generated cells.

5. Normalize the histogram.

6. Connect and normalize the histogram of each cell.

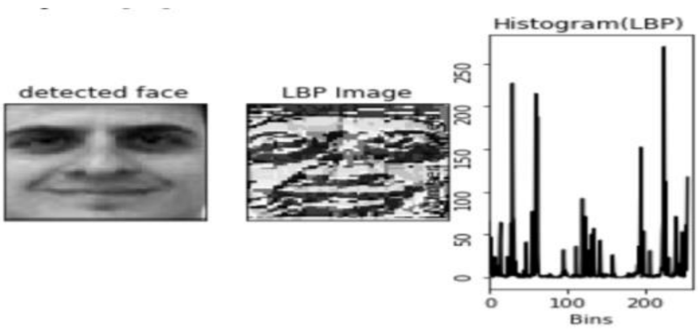



**Fig. 18 LBPH.**

7. Provides a vector of elements for the entire window.

Its classifiers can be used for face recognition or texture analysis [61],[63].

### 2.3.3 Methods based on geometric elements.

In the geometric emotion detection and recognition approach, local features such as mouth, eyes, eyebrows, and nose are first extracted or detected from face images, as shown in the following figure, which is used for emotion classification [64],[65].

Active Appearance Models (AAM) [66] are a successful geometric method.

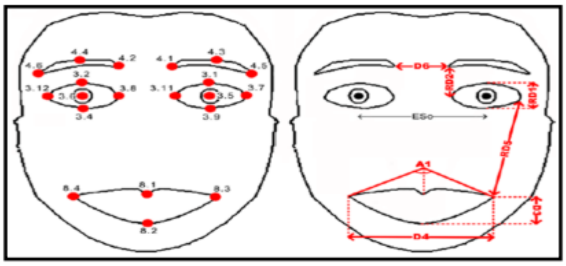


**Fig.19 Properties of landmarks.**

The Lucas-Kande optical flow algorithm is used to transmit each position of the virtual marker to track its position during the subject's emotional display, and ten characters are derived as the distance between each marker and the point, as shown in the following figure. All distance data were calculated using " Pythagorean Theorems", then saved in CSV format for further processing during the data acquisition process.

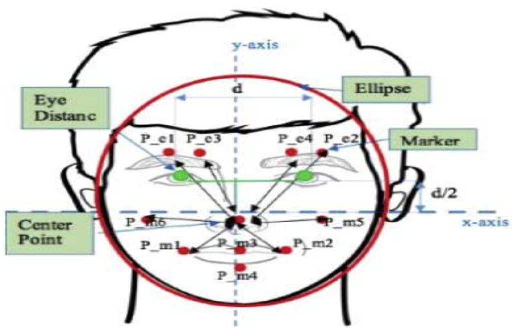



**Fig.20 Emotion marker point.**

In the column of the right mouth, the line m1 represents the hypotenuse of a right triangle, where the line parallel to the X axis is dx [the difference between the coordinates of P-m1 (XP-m1) and the point (xc)], and the line parallel to the axis is dy [the difference between y -'s coordinates P-m1 (yp-m1) and point (yc)]. So, the formula for calculating the distance is given by Eq.

Distance (m1) =

$$\sqrt{(Xc - Xp - m1)2 + (Yc.Yp - m1)2}$$

**2.6 Feature extraction methods for image and emotion in real time.**

Facial expression represents emotion and provides informed information about people's personalities and thoughts. Technology is constantly performing various tasks in order to increase its use in the public. According to the researcher, understanding human facial expressions is a key component to understand emotions and also to find wide application in the field of human-computer interaction [67].

Artificial intelligence and machine learning are successfully used in real-time emotion recognition and other various fields.

Mostly OpenCV, TensorFlow, Haar Cascade, NumPy, Kera's and Pandas libraries used in python for real time emotion recognition.

In this step, we use an online depression analysis test. The system captures video of the person's front face using the system's web camera. This video is converted into frames and from each frame a face is cropped and OpenCV features are extracted in the same way as in the training site.

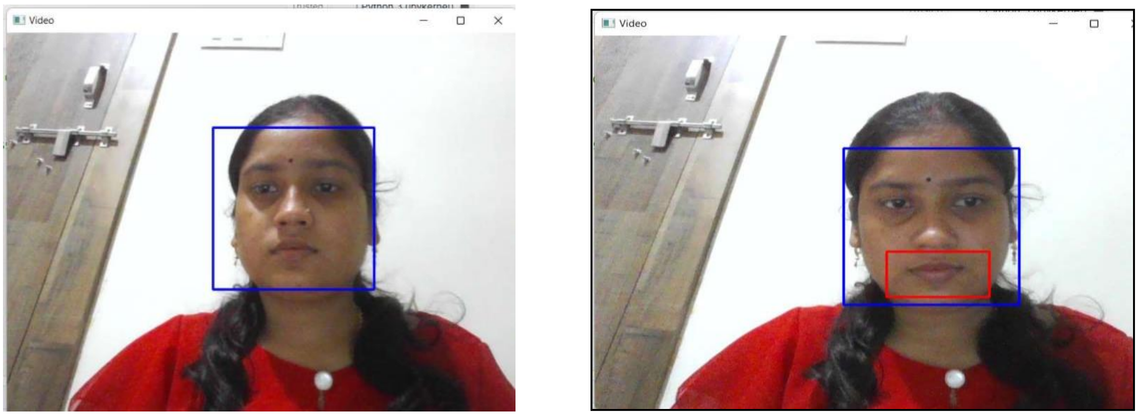



**Fig.22 Detection of emotions in real time.**

**3 Research gap and challenges.**

Emotion recognition (ER) combines knowledge of artificial intelligence (AI) and psychology [apriorit.com]. emotion solving usually detects and recognizes only seven basic emotions Happiness, Surprise, Anger, Sadness, Fear, Disgust, Joy, etc., but in the future, the researcher can solve problems of different types by analysing positive and negative emotions, such as Medical, Educational, Safety, etc.

**Problems with recognizing emotions in images and videos**

It can be difficult for people to define a facial expression as a certain emotion. Various studies have shown that different people recognize different emotions in the same facial expression, and it's even harder for AI.

According to the researcher, recognizing emotions is complicated due to many factors. We can divide these factors into two parts, technical and psychological [68].

**a) TechnicalProblems-**

Emotion recognition shares many problems with the detection of moving objects in video, object identification, continuous detection, incomplete or unpredictable actions, etc.

Some technical issues that follow –

• **Data expansion.**

• **Face occlusion and lighting issues.**

• **Identification of facial features.**

• **Recognizing incomplete emotions.**

• **Capturing the context of emotions.**

• **Racial differences.**

**b) Challenges of the psychologist-**

Psychologists have long been concerned with the connection between facial expressions and emotions. There are still many blind spots. These studies are fundamental to emotion recognition, so it is important to be aware of any shortcomings.

Some of the most psychological challenges are as follows-

• Cultural differences in emotional expression.

• Identification of children's emotions.

• Incorrect emotion indicators.

**4 FER Potential applications in healthcare-**

• Can detect autism or neurodegenerative diseases.

• Researchers can predict psychotic disorders or depression.

• Suicide prevention.

• Can detect depression in the elderly.

• Researchers can observe patients' condition during treatment.

## 5 CONCLUSION

In this article, we have compared different types of emotion classes such as happy, sad, fear, joy, anger and sad and provided a graph, table and percentage of negative emotions. We have analysed all existing points in FER, obtained knowledge about healthcare and provided the obtained results. Describe the accuracy of negative emotions such as anger which is 95%, sadness 58% and fear 94% by accuracy rate, frequency of negative emotion data, mapping and percentile of negative data. We discussed patients' illnesses and also ER, how to map negative emotions and how to help a sick person or patient.

Many researchers have also worked in this area. Researchers provided ML and AI models to analyse mental health – such as depression, using data from Twitter and Facebook. However, the proposed depression and health care models do not have access to information that users do not wish to disclose, or to private information such as direct messages. It is possible that these communications will affect the mental health analysis.

There are some improvements that could be made in the future. First, researchers can create a new ER dataset according to other target diseases. Secondary, additional functions, such as the researcher, can also improve the work of detecting and recognizing negative emotions in real time. Third, the model construction process could be improved using additional data such as real-time emotion recognition (ER) and images. Finally, researchers can extend it using deep learning methods such as DNN, CNN, and AI.

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