Facial Mood Recognition Using Local Gravity Face

Report submitted for the partial fulfillment of the requirements for the degree of
Bachelor of Technology in
Information Technology

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Approval

This is to certify that the project report entitled "**Facial Mood Recognition Using Local Gravity Face**" prepared under my supervision by ***Nayanika Chandra (IT/2014/003)*** *and* ***Subhasmita Chowdhury (IT/2014/031)*** be accepted in partial fulfillment for the degree of Bachelor of Technology in Information Technology.

It is to be understood that by this approval, the undersigned does not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn thereof, but approves the report only for the purpose for which it has been submitted.

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INTRODUCTION

Facial mood recognition is one of the most important cognitive functions that our brain performs quite efficiently. This is only possible because humans are able to recognize moods quite accurately and efficiently. An automatic facial mood recognition system is an important component in human machine interaction. Apart from the commercial uses of automatic facial mood recognition system it might be useful to incorporate some cues from the biological system in the model and use the model to develop further insights into the cognitive processing of our brain.

Human mood or emotions are expressed in different ways such as voice, gesture or 'facial moods or emotions'. Facial expressions are one of the accurate nonverbal communication methods. Facial moods or emotions are commonly categorized by seven classes, such as:

- Anger
- Disgust
- Fear
- Happy
- Sad
- Surprise

Facial moods recognition has a very important application in the field of Human Computer Interface. A set of muscle movements known as Facial Action Units is already there to make the facial moods or emotions more accurate. LG-face has already shown its invariance property in the facial expression domain. Using LG-face facial expressions can be recognized.

Fig1: Various Facial Expressions

PROBLEM DEFINITION

Our project domain is "**IMAGE PROCESSING**" and the project report entitled " **Facial Mood Recognition Using Local Gravity Face**".This is a novel method called local-gravity-face (LGface) for illumination-invariant and heterogeneous face recognition (HFR). LG-face employs a concept called the local gravitational force angle (LGFA). The LGFA is the direction of the gravitational force that the center pixel exerts on the other pixels within a local neighborhood. A theoretical analysis shows that the LGFA is an illumination-invariant feature, considering only the reflectance part of the local texture effect of the neighboring pixels. It also preserves edge information.

Now using this illumination invariant image as a point of correlation we subject the system to various other images from random persons. When the system receives the image it detects the facial points of concerns which play a huge part in determination of the current emotional state of the person which are mainly the eyes and the lips. On detection of these parts we sample 50 distinct points on the image which can be used for correlation with the other images stored in the database. Then we compare these points of the input image to the ones stored in the database and the section with which the highest correlation coefficient is determined is provided as the output emotional expression of the input image.

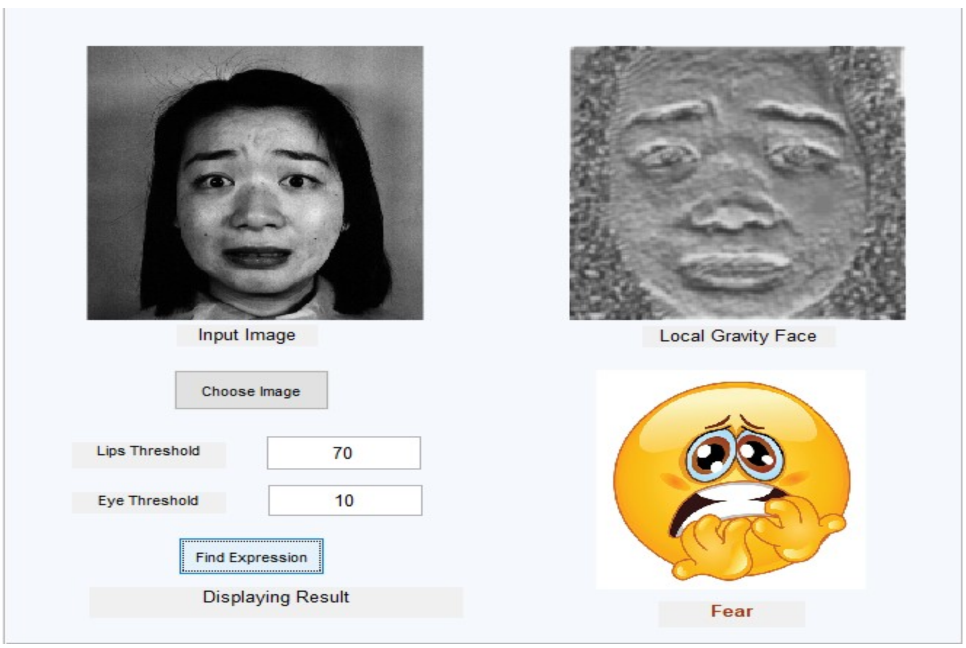


Fig2: Facial Mood Recognition Using Local Gravity Face

LITERATURE STUDY

Facial Mood Recognition is studied using various algorithms. Some of them are:

1. Facial Expression Recognition using Active Appearance Model or AAM
2. Facial Expression Recognition using Data Mining
3. Local-gravity face for illumination invariant for facial mood recognition
4. Artificial neural network

1. FACIAL EXPRESSION RECOGNITION USING AAM ALGORITHM

Facial expression recognition is especially important in interaction between human and intelligent robots. Since the introduction of AAM model, there has been great change in detection accuracy. The recognition is task is based on two parts, one of them is AAM combined with Neural Network, which gives better accuracy but lower speed. The other is AAM combined with point-correlation which is especially fast. Thus it can be integrated in mobile robot platforms.
This algorithm has a disadvantage that it is light dependent.

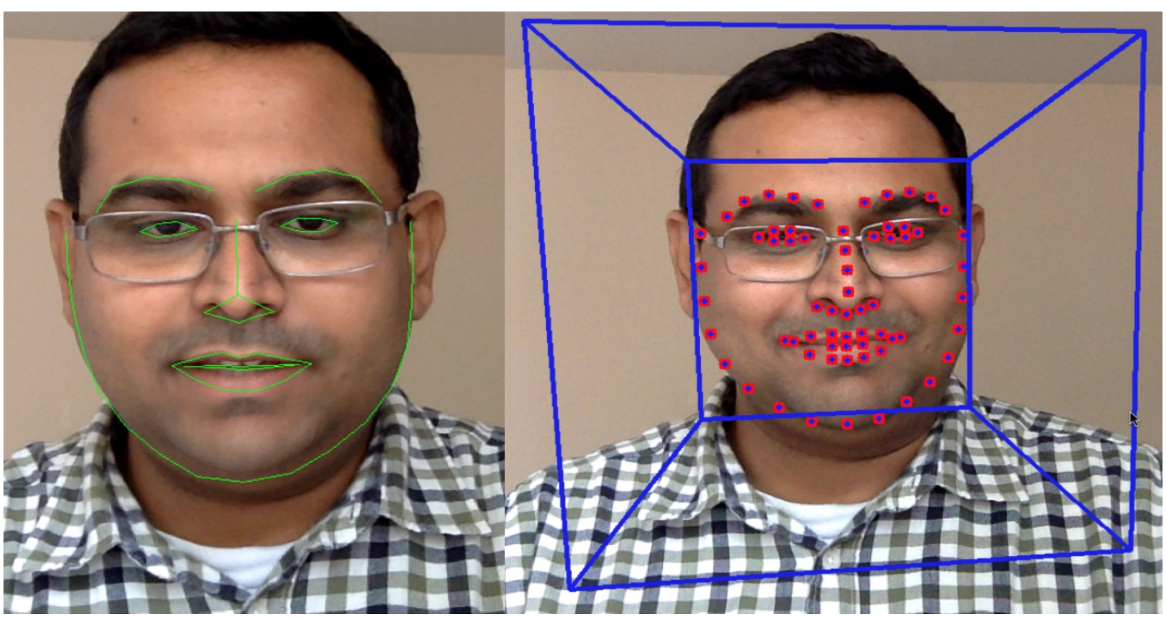


Fig 3: Result of AAM

2. FACIAL EXPRESSION RECOGNITION USING DATA MINING ALGORITHM

Facial expression is one of the most powerful, natural, and abrupt means for human beings which have the knack to communicate emotion and regulate inter-personal behavior. In this algorithm we focus on two different approaches of expression recognition. First template based method, second appearance based method i.e. principle component analysis. In template based we make use of template matching to excerpt templates of different facial components. The facial expression information is mostly concentrate on facial expression information regions, mouth, eye and eyebrow regions areas are segmented from the facial expression images. Using these templates we calculate facial characteristics points (FCP's).Then we define 30 facial characteristic points to describe the position and shape of the above three organs to find diverse parameters which are input to the decision tree for recognizing different facial expressions.

The main problem with this algorithm is that the template values may differ from the ones that are already fed into the system.

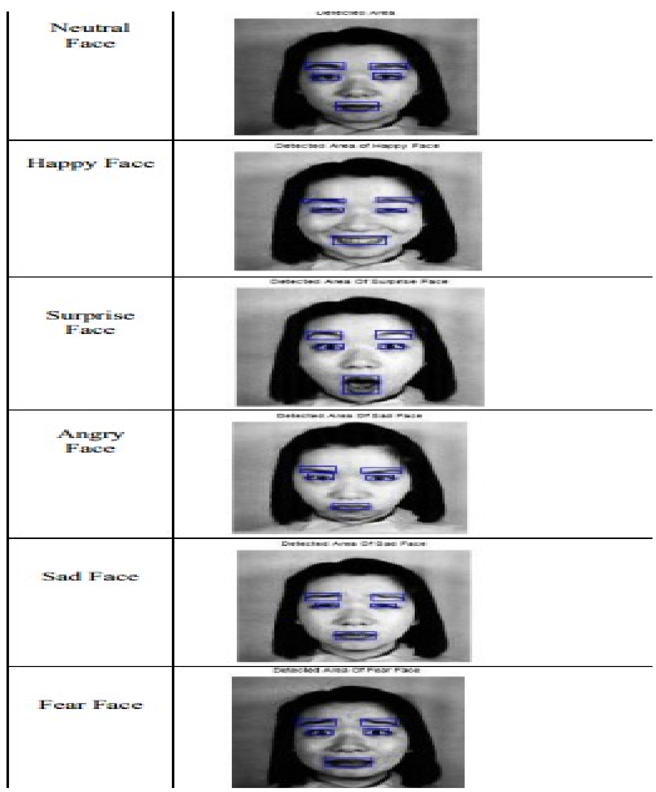


Fig 4: Result of Facial Expression using Data Mining Algorithm

3. LOCAL GRAVITY FACE FOR ILLUMINATION INVARIANT FOR FACIAL MOOD RECOGNITION

In this category, face images are pre-processed to normalize the illumination. The traditional pre-processing methods are histogram equalization (HE), gamma correction, logarithmic transformation, and other similar methods. Several other modern preprocessing techniques for addressing illumination variations also exist and are worth mentioning here. Adaptive histogram equalization (AHE), region-based histogram equalization (RHE) and block-based histogram equalization (BHE) have all been proposed to overcome the problem of non uniform illumination. Lee et al. proposed an oriented local histogram equalization (OLHE) method. Jobson et al. proposed a multi-scale retinex (MSR) method to reduce halo artifacts. Chen et al. proposed a preprocessing method based on discarding low frequency discrete cosine transform (DCT) coefficients. Rather than the global estimation of DCT coefficients, Lian et al. proposed a local estimation of the low frequency DCT coefficients in the logarithmic domain. Shashua and Riklin-Raviv introduced the Quotient Image (QI) method, which generates a pixel-wise linear combination from training samples and then calculates an illumination-invariant albedo ratio between the original face and this linear combination. A similar concept known as a self-quotient image (SQI) is created by dividing a test image using a smoothed version of itself. However, in this approach, sharp edges are lost as a result of the use of a Gaussian filter. Bhowmik et al. proposed a quotient-based multi-resolution fusion of thermal and visual images. Chen et al. proposed an edge preserving logarithmic total variation (LTV) model based on image factorization. A wavelet-domain approach has also been used in [25]–[27] to reduce the illumination effect. Tan and Triggs proposed a chain of preprocessing steps for illumination normalization. Still, these methods do not yield fully satisfactory results. In some cases, preprocessing removes too much useful information, and as a result, the performance in the subsequent recognition phase is degraded

• **Modeling**

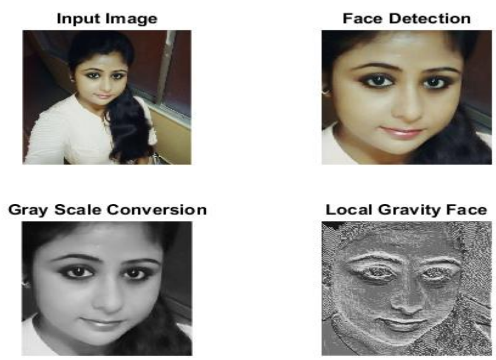
The three major factors affecting illumination variations are the 3-D shape of the human face, lighting from different directions, and varying lighting levels. Most algorithms presented in the literature assume that various lighting conditions have a homogeneous level. Therefore, modeling can be classified into two categories: 3-D face modeling and illumination modeling. Blanz and Vetter proposed 3-D shape and texture models for human faces with different poses and illumination levels. However, this type of modeling suffers from high computational costs. Belhumeur and Kriegman showed that an illumination cone can be approximated by a low-dimensional linear subspace of fixed posed training images under varying lighting conditions. Baseri and Jacobs also showed that a 9-D linear subspace can be used to approximate varying lighting conditions. Bathur and Hayes proposed the use of a segmented linear subspace obtained by segmenting an image into regions of similar surfaces. The disadvantages of these model-based approaches include the need for multiple face images under different illumination conditions and 3-D shape information during training.

• **Invariant feature representation**

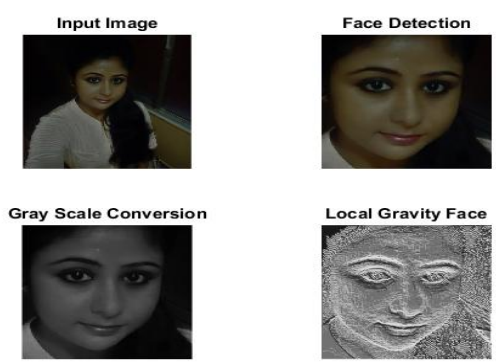
In this category of methods, illumination-invariant features are extracted for the design of a robust face recognition system. The standard illumination-invariant features are the edge map, the derivative of the image intensity, and the Gabor filter. However, these characteristics are somewhat limited and are not useful for coping with large variations in lighting. Local-pixel-difference-based illumination-invariant features have also been proposed, including local binary patterns (LBPs), local ternary patterns (LTPs), enhanced local directional patterns (ELDPs) and local directional number patterns (LDNs). The ELDP and LDN methods use Kirsch compass masks to generate edge maps. Biswas et al. [38] estimated facial albedo to obtain illumination-invariant facial signatures. Zhang et al. showed that "Gradientface" (G-face) is an illumination-invariant representation, and the results are remarkable. Wang et al. proposed another attractive illumination-invariant face representation, called "Weber-face" (W-face), based on Weber's law. Recently, Faraji and Qi proposed a combination of a logarithmic function and fractal analysis to obtain an illumination-invariant logarithmic fractal analysis (LFA) feature. Zhu et al. proposed a logarithmic gradient histogram (LGH) method based on combining the logarithmic domain and the gradient domain. Lai et al. proposed the use of multi-scale logarithm difference edge maps (MSLDE), based on the logarithmic domain and the difference between two pixels in a neighborhood, to obtain illumination-invariant features. Visual images are more strongly affected by changes in illumination than are other types of images, such as thermal, near-infrared (NIR) and shortwave-infrared images. Some researchers have used images of different modalities to minimize the impact of illumination. All of the methods described above consider the common assumption that the wavelengths originating from all radiation sources, including sources of visual light, are the same (i.e., homogeneous). However, in real-world situations, different face recognition applications address faces collected from different sources, and the outputs of these sources are face images of different modalities, such as NIR images, thermal images, sketches, and visible-light (VIS) photographs. The wavelengths captured in these images are different (i.e., heterogeneous); for example, the VIS wavelengths are $0.4 - 0.7\ \mu m$, whereas the wavelengths of NIR radiation are $0.7{-}1.1\ \mu m$. Although sketches are drawn using repeated line strokes and shades to emphasize key features, visual inspection reveals that there are illumination differences between sketches and photographs. To address such images of different modalities, a field of face recognition called heterogeneous face recognition (HFR) is emerging. One of the major problems in HFR is the potential for differences in modality between query and gallery images. Here, we have considered only two scenarios of HFR, i.e., NIR-VIS matching and sketch-photo matching. Facial imaging under VIS and NIR illumination involves illumination sources with different illumination patterns, as discussed in. Therefore, one of the reasons for this modality gap is these differences in illumination patterns. In terms of gray levels, sketches exhibit a constant color, whereas the properties of visual images are completely dependent on the illumination level and the direction of origin of the illumination. Therefore, if a visual image is to be compared with a sketch or vice versa, the influence of the illumination level is enormous. Thus, illumination-invariant face recognition techniques are essential for HFR. Three different categories of techniques are available for HFR: The first is the synthesis category, in which a synthesized face image is generated using a synthesis mechanism and then compared against one or more reference images using existing face recognition techniques. The second is the category of common feature representation, in which images of both modalities of interest are represented using a common feature domain and then compared. The last category is common subspace learning, in which a common subspace is used to classify heterogeneous faces. Recently, Jin et al. proposed a coupled discriminative feature learning method for HFR. In this paper, we propose an illumination-invariant feature extraction method based on the direction of the local gravitational force. We call this directional feature the Local Gravitational Force Angle (*LGFA*), and the method is called Local Gravity Face (*LG-face*). They also proved that the *LG-face* method is illumination-invariant and that its recognition performances on existing challenging databases are quite impressive.

The main features of the proposed ***Local Gravity Face*** approaches are as follows:

1. The features are illumination-invariant.
2. There is no need to estimate the illumination components (*L*); they are automatically discarded.
3. No smoothing preprocessing of the images is performed, and therefore, there is no loss of texture, i.e., the reflection components (*R*) and edges are preserved.
4. Because it is based on the local gravitational force effect, the *LGFA* is considered a local feature.
5. The relative positions of key facial features are not modified.
6. The method reduces the intra-class variations among faces in the same class and enhances the inter-class variations among faces in different classes.



In Bright Light Condition



In Dim Light Condition

Fig 5: Results of normal face after implementing LG-face

4. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is an efficient computing system whose central theme is borrowed from the analogy of biological neural networks. ANNs are also named as “artificial neural systems,” or “parallel distributed processing systems,” or “connectionist systems.” ANN acquires a large collection of units that are interconnected in some pattern to allow communication between the units. These units, also referred to as nodes or neurons, are simple processors which operate in parallel.

Every neuron is connected with other neuron through a connection link. Each connection link is associated with a weight that has information about the input signal. This is the most useful information for neurons to solve a particular problem because the weight usually excites or inhibits the signal that is being communicated. Each neuron has an internal state, which is called an activation signal. Output signals, which are produced after combining the input signals and activation rule, may be sent to other units.

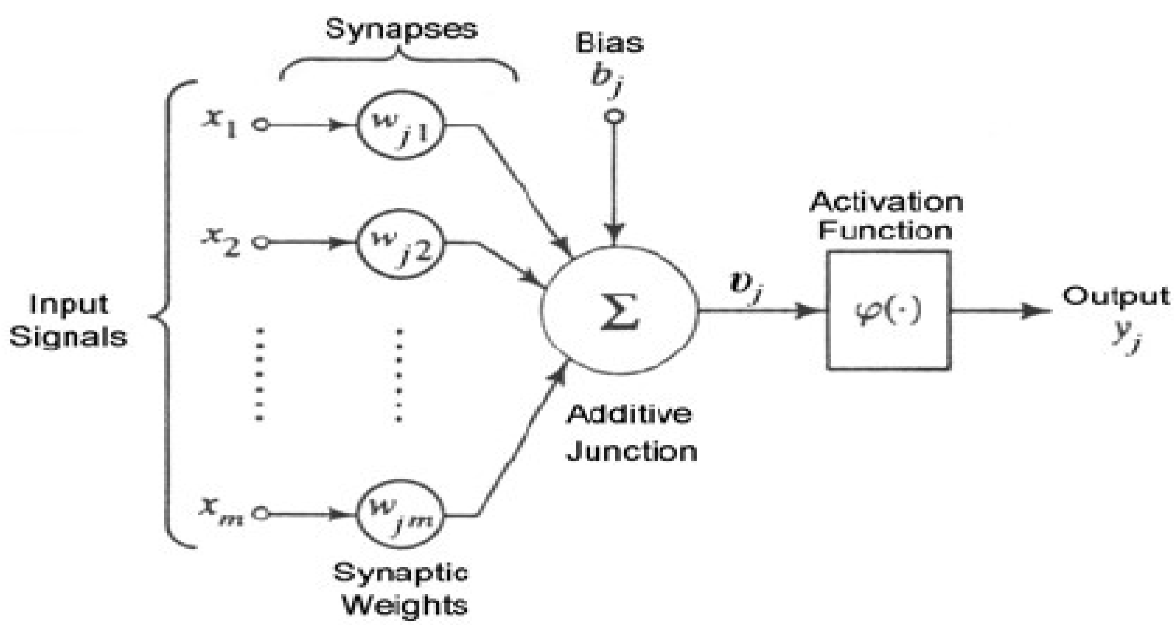


Fig 6: Model of Artificial Network

ARTIFICIAL NEURAL NETWORK - BUILDING BLOCKS

Processing of ANN depends upon the following three building blocks −

- Network Topology
- Adjustments of Weights or Learning
- Activation Functions

Network Topology

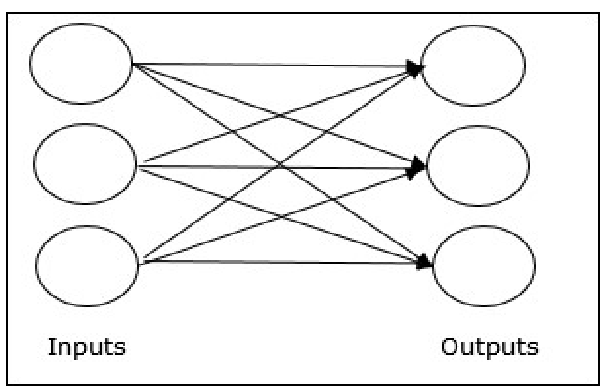
A network topology is the arrangement of a network along with its nodes and connecting lines. According to the topology, ANN can be classified as the following kinds −

- **Feed forward Network**

It is a non-recurrent network having processing units/nodes in layers and all the nodes in a layer are connected with the nodes of the previous layers. The connection has different weights upon them. There is no feedback loop means the signal can only flow in one direction, from input to output. It may be divided into the following two types –

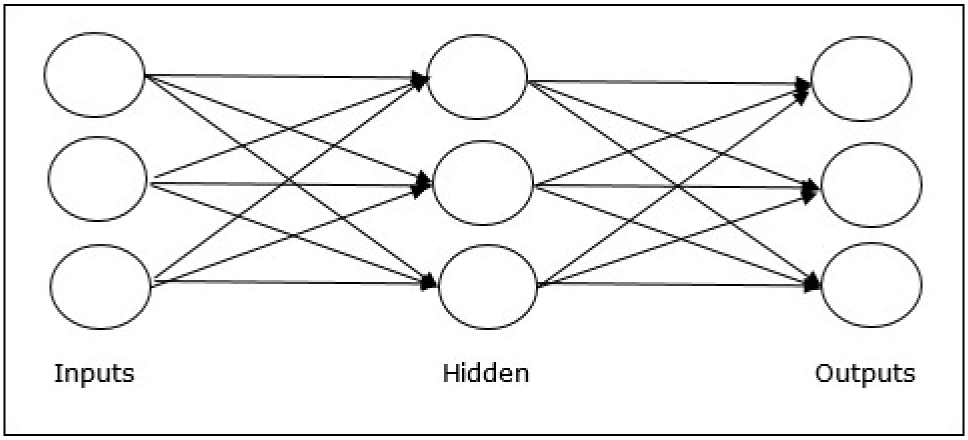
- **Single layer feed forward network**

The concept is of feed forward ANN having only one weighted layer. In other words, we can say the input layer is fully connected to the output layer.



- **Multilayer feed forward network**

The concept is of feed forward ANN having more than one weighted layer. As this network has one or more layers between the input and the output layer, it is called hidden layers.



- **Feedback Network**

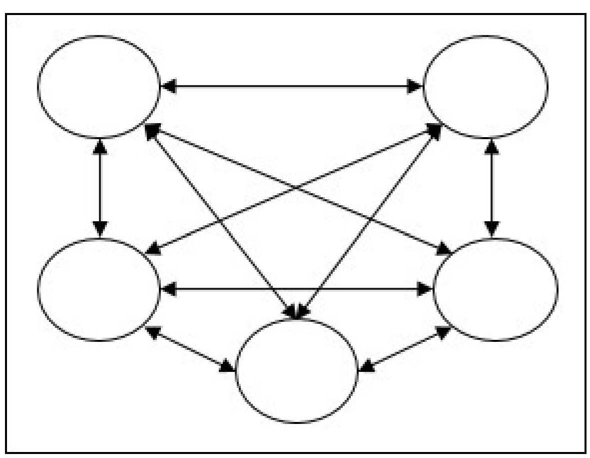
As the name suggests, a feedback network has feedback paths, which means the signal can flow in both directions using loops. This makes it a non-linear dynamic system, which changes continuously until it reaches a state of equilibrium. It may be divided into the following types −

- **Recurrent networks**

They are feedback networks with closed loops. Following are the two types of recurrent networks.

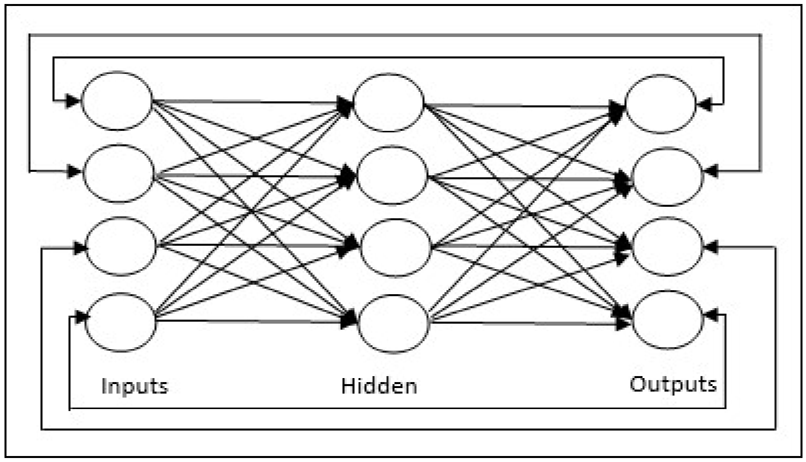
- **Fully recurrent network**

It is the simplest neural network architecture because all nodes are connected to all other nodes and each node works as both input and output.



- **Jordan network**

It is a closed loop network in which the output will go to the input again as feedback as shown in the following diagram.

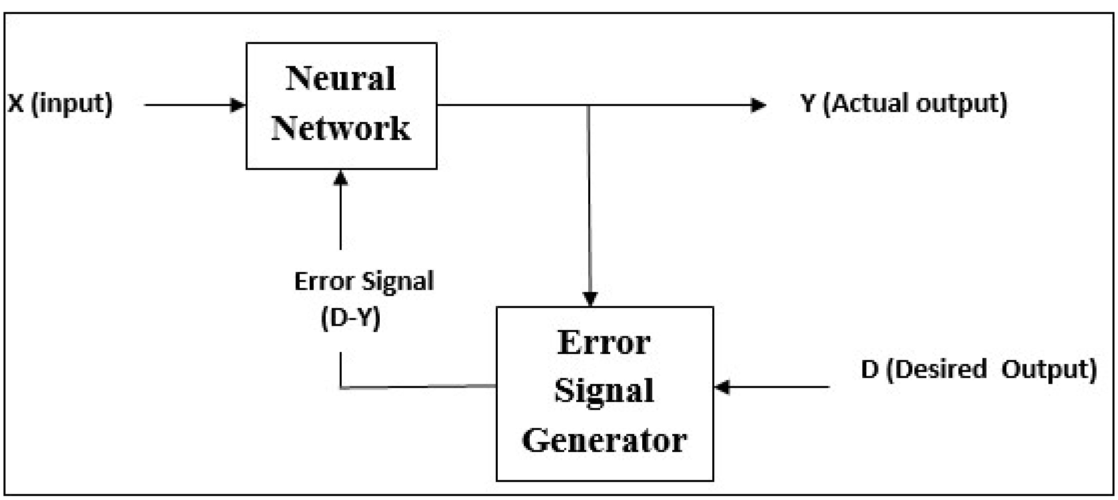


➢ Adjustments of Weights or Learning

Learning, in artificial neural network, is the method of modifying the weights of connections between the neurons of a specified network. Learning in ANN can be classified into three categories namely supervised learning, unsupervised learning, and reinforcement learning.

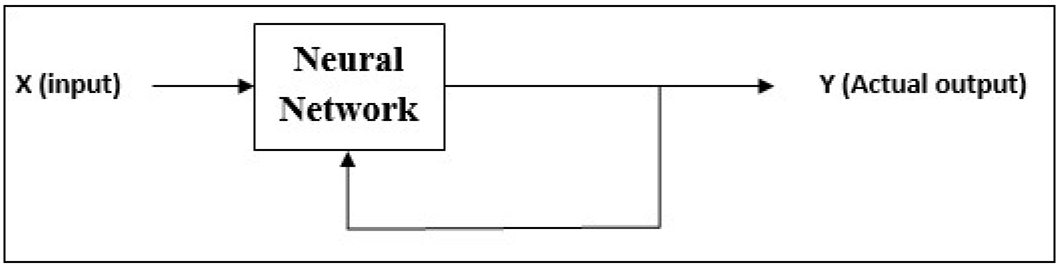
- **Supervised Learning**

As the name suggests, this type of learning is done under the supervision of a teacher. This learning process is dependent.



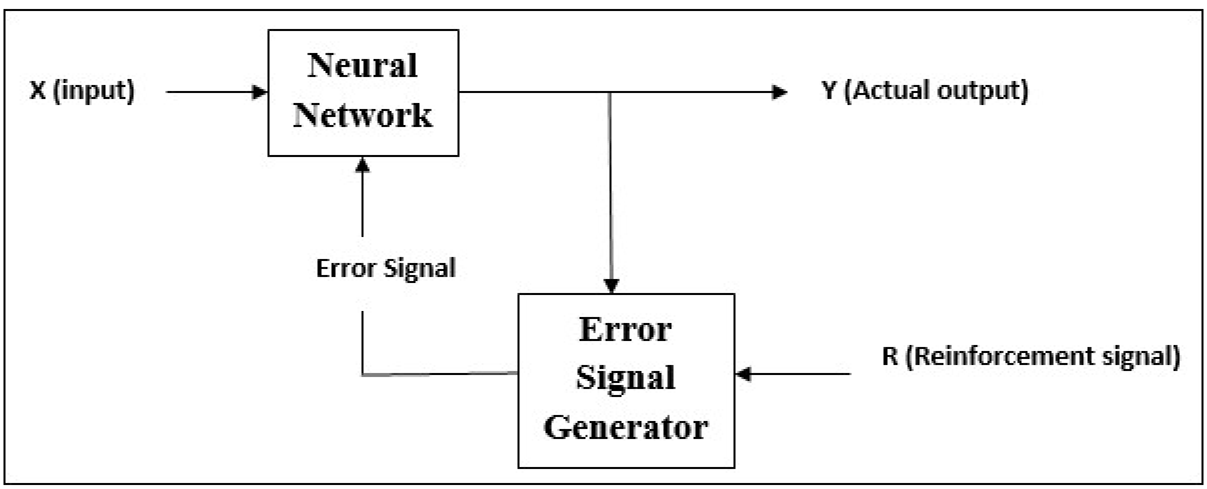
- **Unsupervised Learning**

As the name suggests, this type of learning is done without the supervision of a teacher. This learning process is independent.



- **Reinforcement Learning**

As the name suggests, this type of learning is used to reinforce or strengthen the network over some critic information. This learning process is similar to supervised learning, however we might have very less information.



➢ Activation Functions

It may be defined as the extra force or effort applied over the input to obtain an exact output. In ANN, we can also apply activation functions over the input to get the exact output.

ARTIFICIAL NEURAL NETWORK - APPLICATIONS

Followings are some of the areas, where ANN is being used. It suggests that ANN has an interdisciplinary approach in its development and applications.

Speech Recognition

Speech occupies a prominent role in human-human interaction. Therefore, it is natural for people to expect speech interfaces with computers. In the present era, for communication with machines, humans still need sophisticated languages which are difficult to learn and use. To ease this communication barrier, a simple solution could be communication in a spoken language that is possible for the machine to understand.

Great progress has been made in this field; however, still such kinds of systems are facing the problem of limited vocabulary or grammar along with the issue of retraining of the system for different speakers in different conditions. ANN is playing a major role in this area. Following ANNs have been used for speech recognition −

- Multilayer networks
- Multilayer networks with recurrent connections
- Kohonen self-organizing feature map

The most useful network for this is Kohonen Self-Organizing feature map, which has its input as short segments of the speech waveform. It will map the same kind of phonemes as the output array, called feature extraction technique. After extracting the features, with the help of some acoustic models as back-end processing, it will recognize the utterance.

Character Recognition

It is an interesting problem which falls under the general area of Pattern Recognition. Many neural networks have been developed for automatic recognition of handwritten characters, either letters or digits. Following are some ANNs which have been used for character recognition −

- Multilayer neural networks such as Back propagation neural networks.
- Neocognitron

Though back-propagation neural networks have several hidden layers, the pattern of connection from one layer to the next is localized. Similarly, neocognitron also has several hidden layers and its training is done layer by layer for such kind of applications.

Signature Verification Application

Signatures are one of the most useful ways to authorize and authenticate a person in legal transactions. Signature verification technique is a non-vision based technique.

For this application, the first approach is to extract the feature or rather the geometrical feature set representing the signature. With these feature sets, we have to train the neural networks using an efficient neural network algorithm. This trained neural network will classify the signature as being genuine or forged under the verification stage.

Human Face Recognition

It is one of the biometric methods to identify the given face. It is a typical task because of the characterization of "non-face" images. However, if a neural network is well trained, then it can be divided into two classes namely images having faces and images that do not have faces.

First, all the input images must be preprocessed. Then, the dimensionality of that image must be reduced. And, at last it must be classified using neural network training algorithm. Following neural networks are used for training purposes with preprocessed image −

- Fully-connected multilayer feed-forward neural network trained with the help of back-propagation algorithm.
- For dimensionality reduction, Principal Component Analysis (PCA) is used.

SOFTWARE REQUIREMENT SPECIFICATION (SRS)

Operating System	Processors	Disk Space	RAM	Graphics
Windows 10	Any Intel or AMDx86-64 processor	2GB for Matlab 4-6 GB for typical installation	2GB	No specific graphics card is needed
Windows 8.1	AVX2 instruction set up support is recommended		With Simulink 4 GB is required	Hardware accelerated graphics card supporting OpenGL 3.3 with 1 GB GPU memory is recommended.
Windows 7 service Pack 1	With Polyspace 4 cores is recommended		With Polyspace 4 GB per core is recommended	
Windows Server 2016				
Windows Server 2012 R2				
Windows Server 2012				
Windows Server 2008 R2 Service Pack 1				

Table 1: SRS of MATLAB

PLANNING

- **TEST CASE**

Test Plan

The test plan approach that has been used in our project includes the following:

Design verification or compliance test: These stages of testing have been performed during the development or approval stage of the product, typically on a small sample of units.

Test Coverage

The design verification tests have been performed at the point of reaching every milestone. Test area included testing of various features such as face detection, histogram equalization, convert into LG face, and extract nodal point value, detecting emotion.

Test Method

Testing of diverse features has been performed in Facial Expression Recognition System. For each module, corresponding outputs were checked. For testing each module, the output produced from running the code was checked with the test data set.

Test Responsibility

The team members working on their respective features performed the testing of those features. Test responsibilities also included, the data collected, and how that data was used and reported.

- **GNATT CHART**

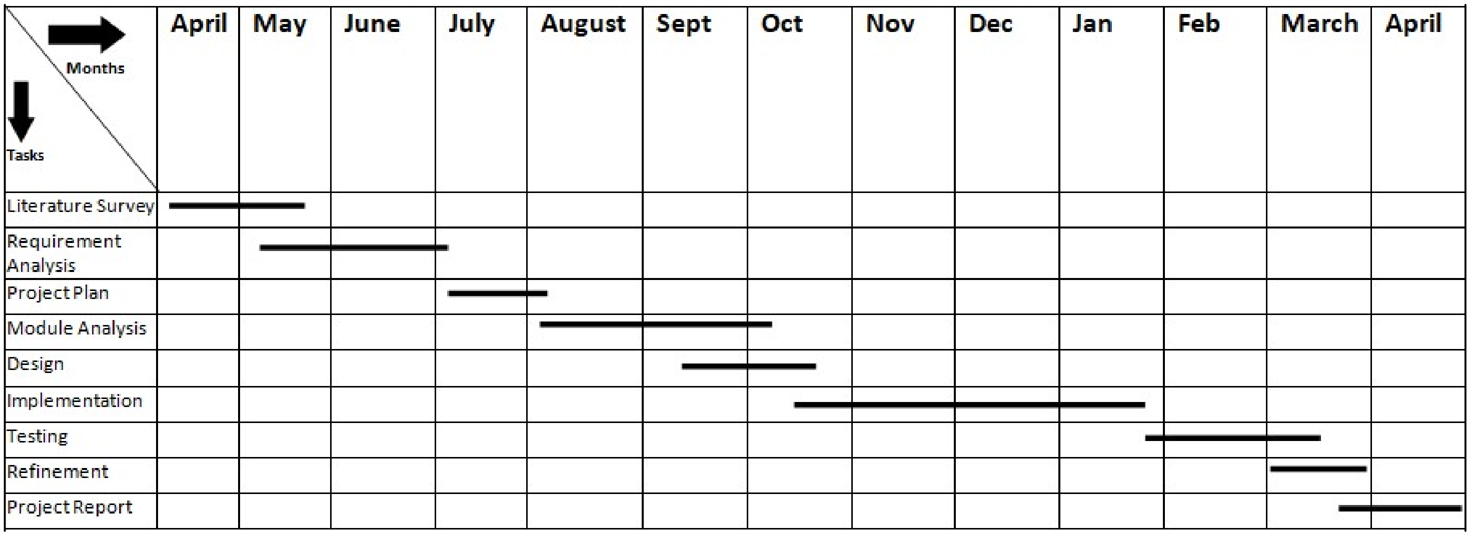


Table 2: Gnatt Chart

- **PROJECT TIME LINE:**

The following table shows the expected flow of work for the accomplishment of the required result.

Serial No	Description	Duration (Weeks)	Status
1.	Literature Survey: Gathering information for Facial Mood Recognition	6	Done
2.	Literature Survey: Various Algorithms	2	Done
3.	Project Plan	3	Done
4.	Design	6	Done
5.	Coding	18	Done
6.	Building UI	1	Done
7.	Testing	12	Done
8.	Refinement	2	Done
9.	Project Report	2	Done

Table 3: Project Time Line

DESIGN

- **LOGIC SEQUENCE:**

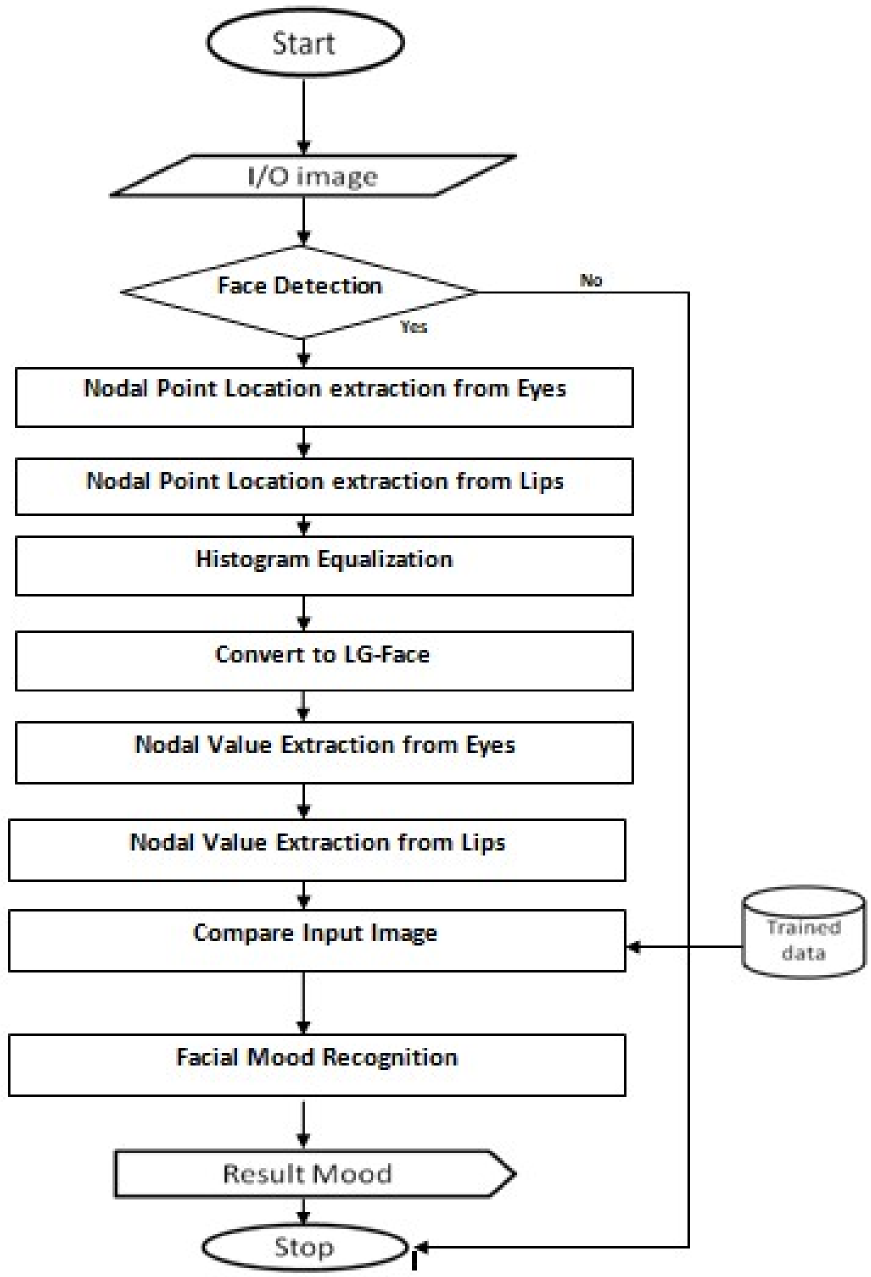


Fig 7: Logic Sequence

FLOW CHART FOR FACIAL MOOD RECOGNITION

The system works in a two step process which can be categorized into **Training the system** and later **testing the system**. The initial steps for both the processes are quite the same the only difference is since the system will recognize the expression via a neural network algorithm therefore it becomes absolutely necessary to train the system to differentiate between expressions which is implemented via clustering algorithm where the system is subjected to the input and the output and the system adjusts its synaptic weights to perform the proper clustering of the input sample.

1. **Start**

2. **I/O Image**: An input image is fed into the system via a image capturing device like a digital camera.

Fig 8: Input Image

3. **Face Detection**: On subjecting the image to these transformations we are left with an image which is illumination invariant from where the face detection is performed via face detection algorithms.

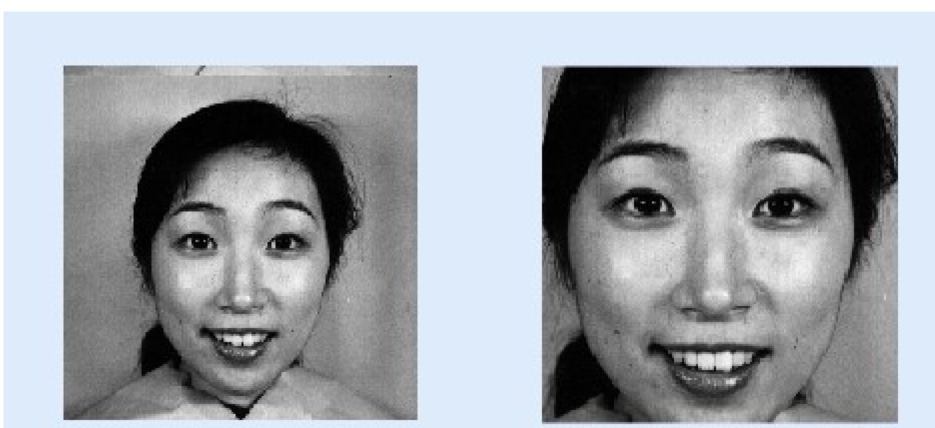


Fig 9: Face Detection

4. **Nodal Point Location Extraction from Eyes:** Nodal points locations are extracted using detect SURF features functionality available in MATLAB.

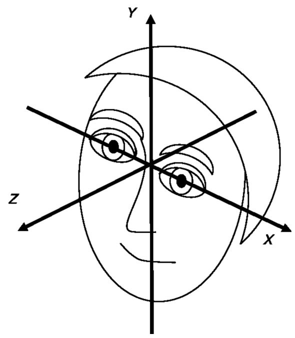


Fig 10: The feature point location of eyes

5. **Nodal Point Location Extraction from Lips:** Nodal points locations are extracted using detect SURF features functionality available in MATLAB.

Fig 11: The feature point location of binary image

Fig 12: The feature point location of lips

6. **Histogram Equalization:** This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

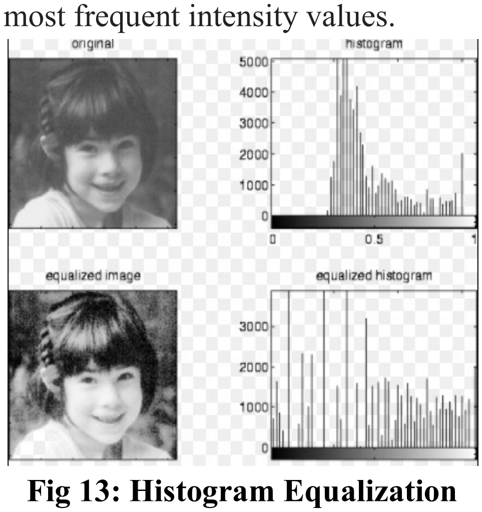


Fig 13: Histogram Equalization

7. **LG-face Conversion**: Then the face is transformed into a local gravity face. In astronomy the mass of a star can be calculated from its intensity of light. Hence forth the same algorithm is used to calculate the mass of individual pixels and the gravitational force of attraction on individual pixels from its adjacent neighbours.

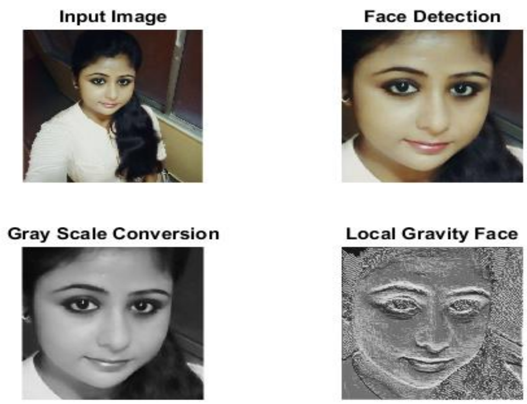


Fig 14: LG Face Conversion

8. **Nodal value extraction from eyes:** The point determine in the previous step are provided as input to the image array and the resulting Local Gravity Index values are determined for the image.

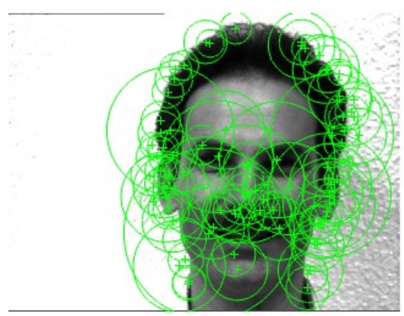


Fig 15: Nodal Point Extraction 1

9. **Nodal value extraction from lips:** The nodal point locations determined to the lips using detect SURF Features are provided as input to the lips section of the image the local gravity face index values for the lips are extracted for the lips which are then further utilized for comparison.

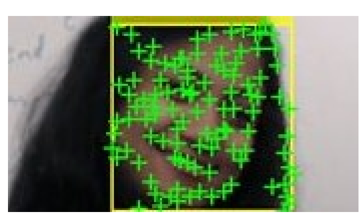


Fig 16: Nodal Point Extraction 2

10. **Trained Data:** The trained data comprises of all the sample inputs which are already mapped into clusters. Whenever an input image is provided it is mapped with all the images of all the clusters.

11. **Compare Input Image:** The unique vectors which are determined for the input image are correlated with the images stored in the database and each predetermined SURF point location are compared with that of the stored images in the database. The results of the correlation of the two images at the points are stored in an array which is later used in determined the best possible match of expression of the input image.

12. **Facial Mood Recognition:** The results of the correlation are used to analyse and find the best possible match for the input image with those of the database and the resulting expression is provided as output.

13. **Result Mood**: The result is obtained via a monitor who displays the current cluster the input sample is currently residing.

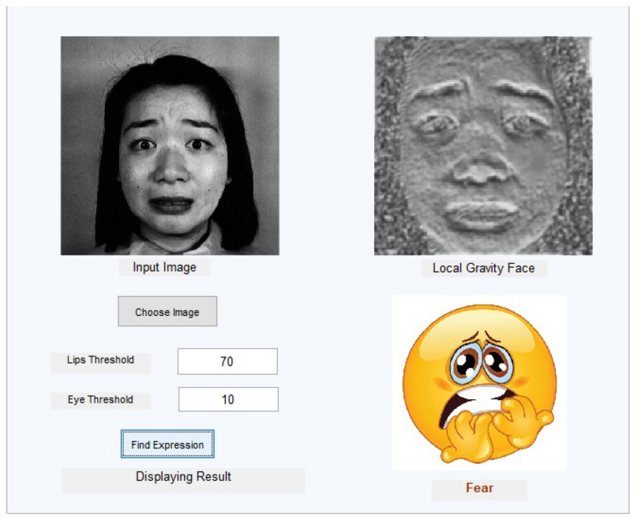


Fig 17. Final Result of the Facial Mood Recognition

14. **Stop**

USE CASE DIAGRAM:

The user has the capacity to determine the threshold levels for which successful detection of eyes and lips and other facial features are possible. On successful extraction the image is converted to an LG Face. The LGFA is the direction of the gravitational force that the center pixel exerts on the other pixels within a local neighborhood. A theoretical analysis shows that the LGFA is an illumination-invariant feature, considering only the reflectance part of the local texture effect of the neighboring pixels. It also preserves edge information.

Now using this illumination invariant image as a point of correlation we subject the system to various other images from random persons. When the system receives the image it detects the facial points of concerns which play a huge part in determination of the current emotional state of the person which are mainly the eyes and the lips. On detection of these parts we sample 50 distinct points on the image which can be used for correlation with the other images stored in the database. Then we compare these points of the input image to the ones stored in the database and the section with which the highest correlation coefficient is determined is provided as the output emotional expression of the input image.

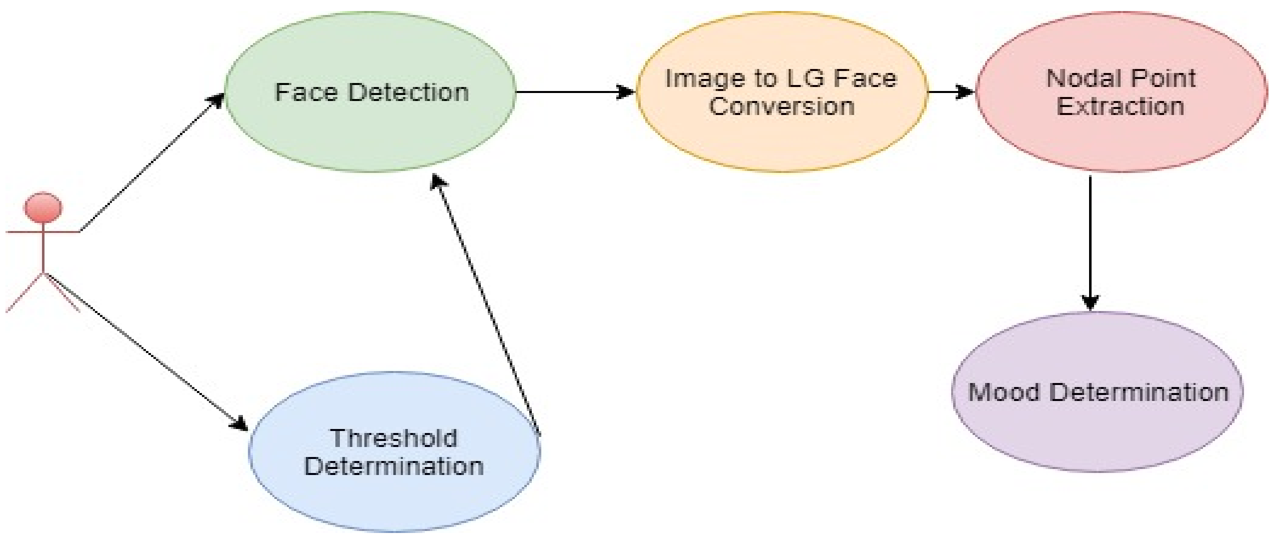


Fig 18. Use Case Diagram of the Facial Mood Recognition

RESULT AND DISCUSSION

PSEUDO CODE:

1. Input('Enter the image')
2. Input('Enter eye threshold')
3. Input('Enter lips threshold')
4. If(type(image) == RGB)
    a. Convert image to grayscale
5. Else
    a. imageFinal = image
6. detectLips(imageFinal);
7. detectEyes(imageFinal);
8. pointsLocation = extractFeaturePoints(imageFinalLips)
9. pointsLocationEyes = extractFeaturePoints(imageFinalEyes)
10. lgFace = convertImagetoLGFace(imageFinal)
11. pointValuesLG = lgFace[pointsLocation]
12. pointValuesEyesLG = lgFace[pointsLocationEyes]
13. happyIndex[] = findHappyIndex(pointValuesLG,pointValuesEyesLG)
14. sadIndex[] = findSadIndex(pointValuesLG,pointValuesEyesLG)
15. angryIndex[] = findangryIndex(pointValuesLG,pointValuesEyesLG)
16. neutralIndex[] = findNeutralIndex(pointValuesLG,pointValuesEyesLG)
17. dissapointedIndex[] = findDissapointedIndex(pointValuesLG,pointValuesEyesLG)
18. surprisedIndex[] = findHappyIndex(pointValuesLG,pointValuesEyesLG)
19. Loop 6 times
    a. EmotionIndexarray[counter] = <emotion_name>Index;
20. Endloop.
21. ultimateIndex = min(EmotionIndexArray)
22. display(imshow(ultimateIndex))

find <emotion>Index method:

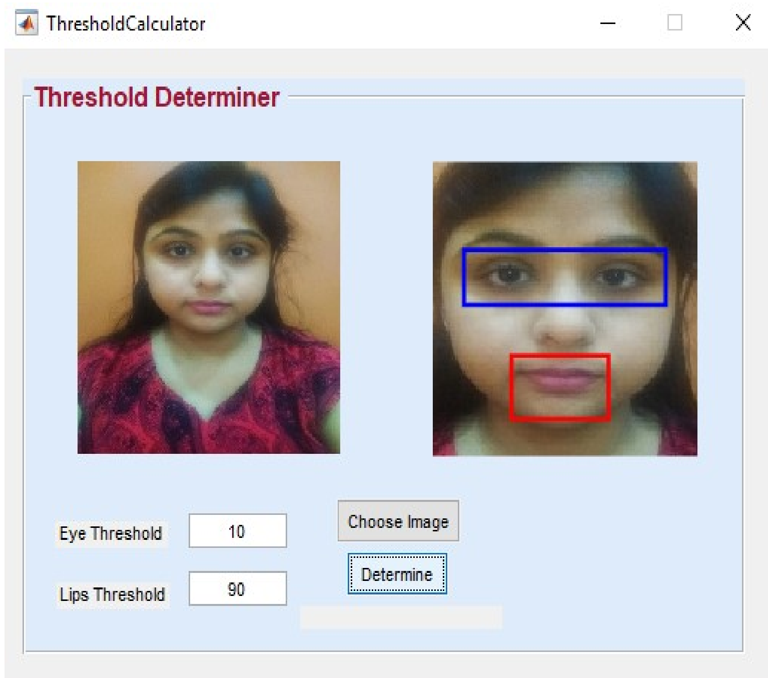
1. input(Image,ThresholdLips,ThresholdEyes)
2. lips = extractLips(image,ThresholdLIps)
3. eyes = extractEyes(image,ThresholdEyes)
4. pointLips = findFeaturePoints(lips)
5. pointEyes = findFeaturePoints(eyes)
6. lgFace = convertImagetoLG(Image)
7. pointLipsValues = (lgFace,pointLips)
8. pointEyesValues = (lgFace,pointEyes)
9. loop in database Images
    a. dbLGImage = convertImagetoLG(dbImage)
    b. pointLipsValuesDB = (dbLGImage,pointLips)
    c. pointEyesValuesDB = (dbLGImage,pointEyes)

d. eyeCor = correlate(pointLipsValues,pointLipsValuesDB)
e. lipsCor = correlate(pointEyesValues,pointEyesValuesDB)
f. arrayCorrelationEYE[<counter>] = eyeCor
g. arrayCorrelationLIPS[<counter>] = lipsCor

10. endloop
11. index = min(arrayCorrelationEYE)
12. indexLips = min(arrayCorrelationLIPS)

SNAPSHOTS

THRESHOLD DETERMINER



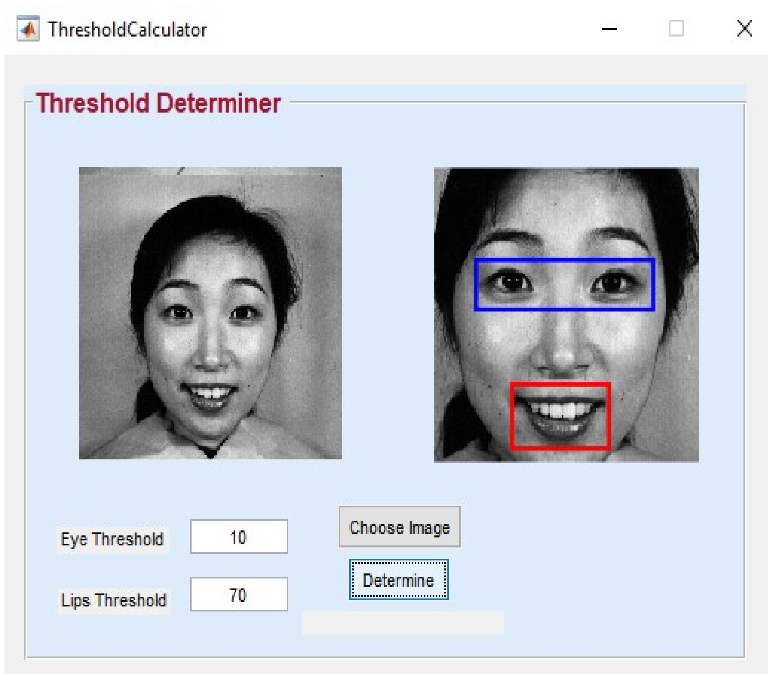


Fig 19. Threshold Determiner From Human Face

FINAL MOOD RECOGNITION

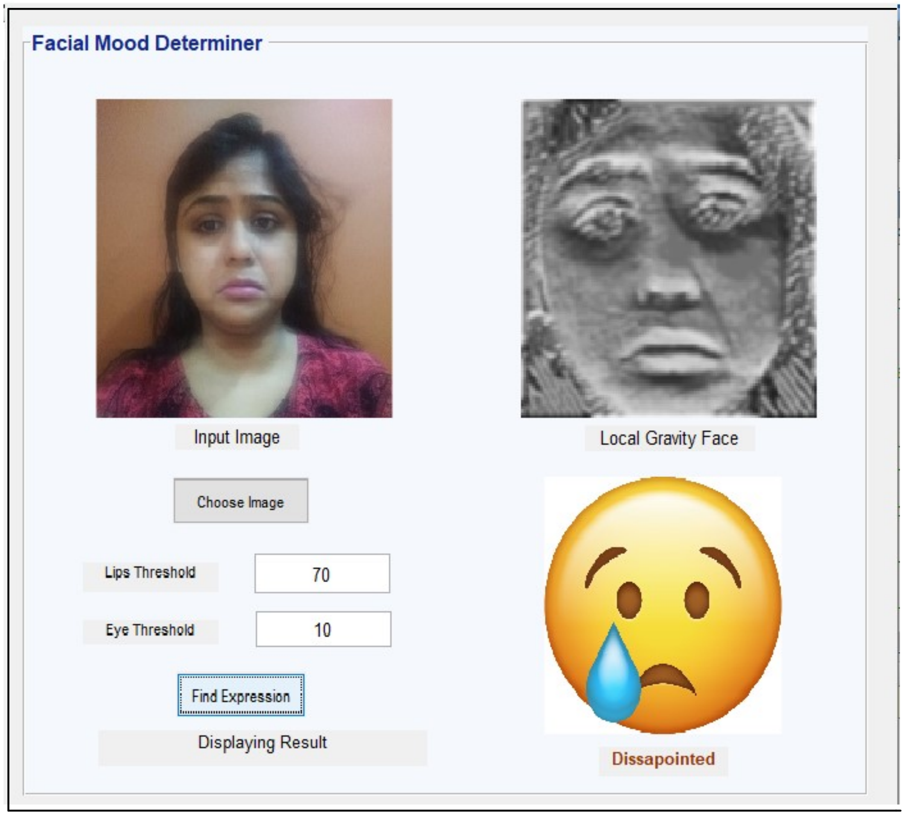


Fig 21. Final Mood – Disappointed

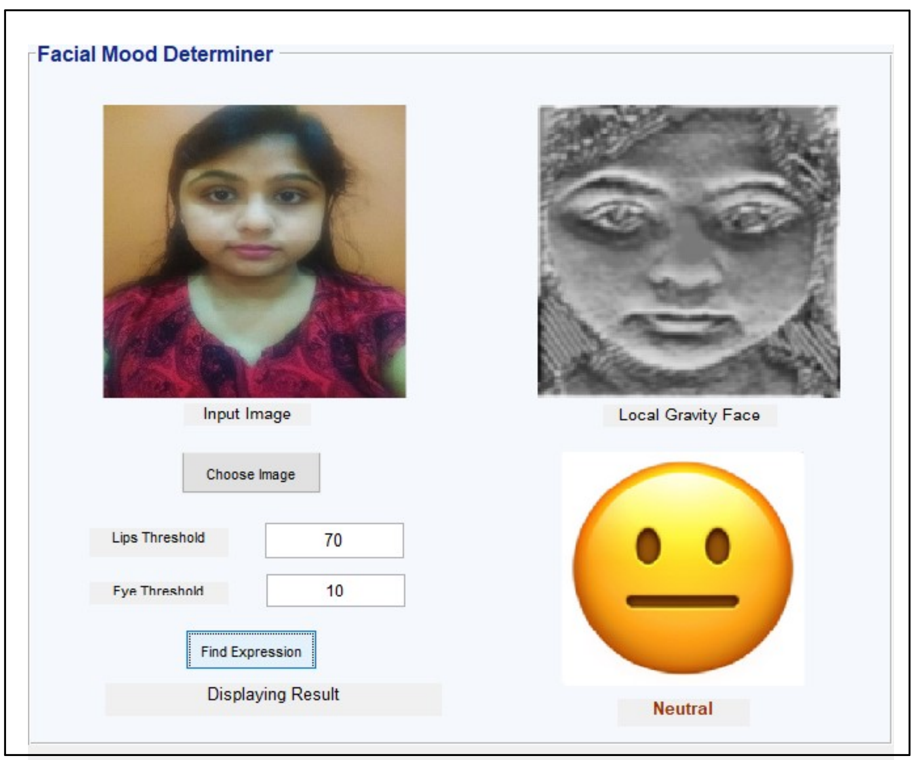


Fig 22. Final Mood – Neutral

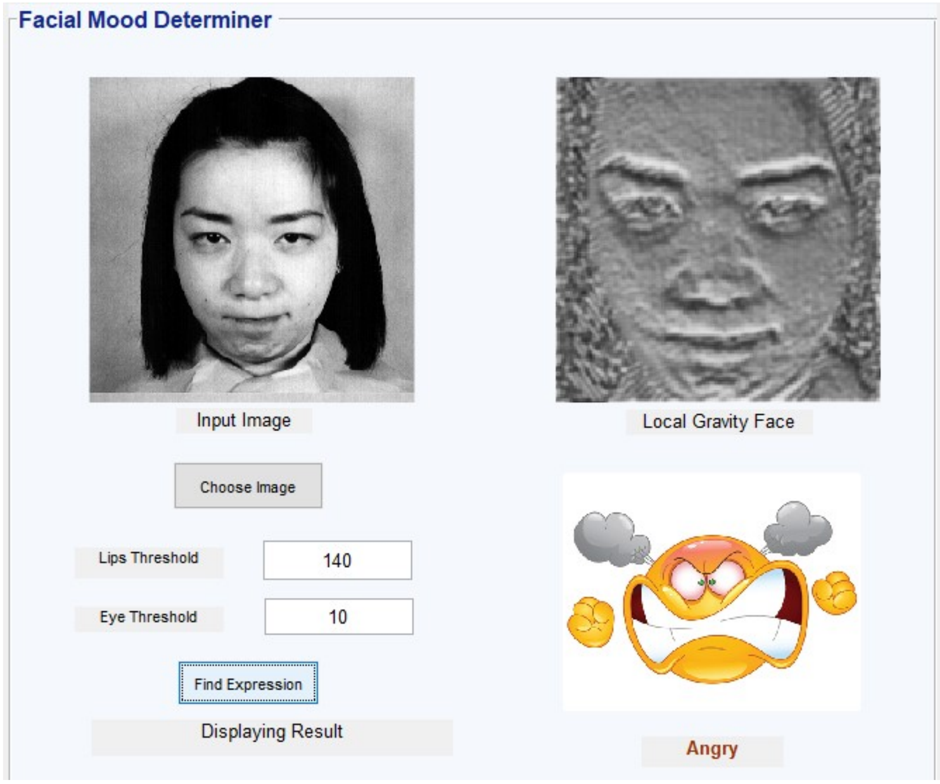


Fig 23. Final Mood – Angry

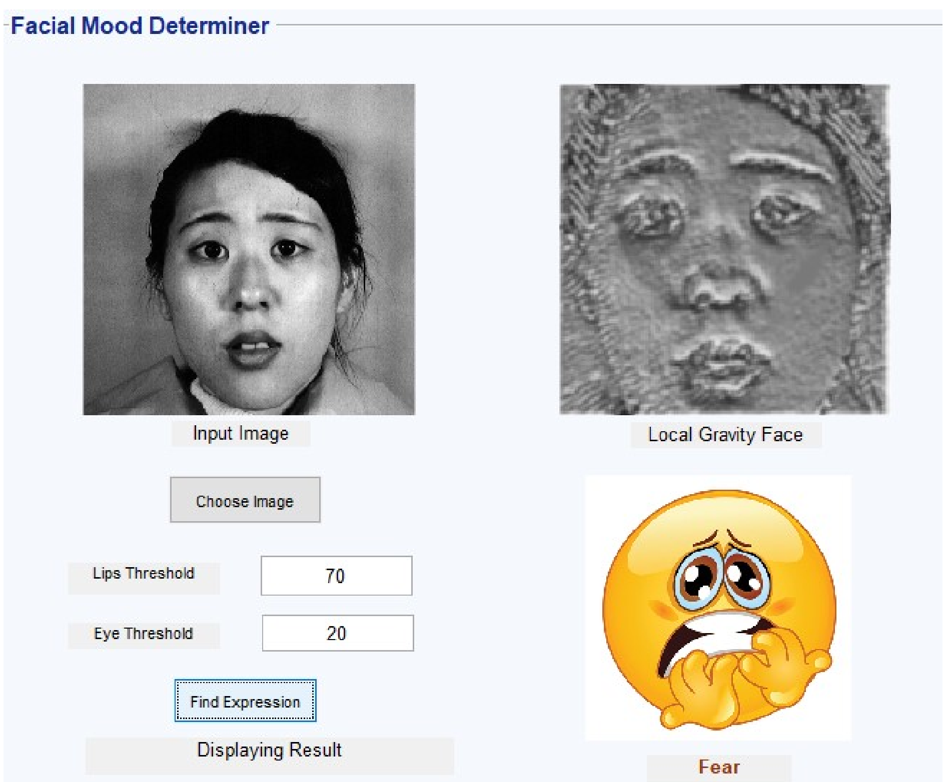


Fig 24. Final Mood – Fear

CONCLUSION

The sole aim of this project was to create an interface between man and machine which will serve in talking a step towards artificial intelligence.

During communication it is what is not said that means the real thing or in simpler terms non-verbal communication makes up for most of the essence of communication. We convey a lot more message by our body language and our facial expressions and this system is designed to detect those expressions.

This system uses neural networking to determine the expressions by the use of clustering algorithm.

The reason the neural network is employed is because of the fact that the machine has conceptual capacity far greater than that of the human mind and can be able to detect emotions and hidden expressions which remain imperceptible to the human eye.

This system has a wide range of applications where it can act as an artificial assistant with a consciousness which understands the user before acting to his or her decisions. It can be used as an enhancement to lie detector where the non-verbal communications are clearly grasped by the machine.

Actually whenever it comes to artificial intelligence the possibilities of its applications are infinite but one thing we can say for sure. Our efforts will bring advancement in the future and that future will be here faster than you can think.

FUTURE SCOPE

High correct recognition rate (CRR), significant performance improvements in our system. Promising result is obtained under face registration errors, fast processing time. System is fully automatic and has the capability to work with video feeds as well as images. It is able to recognize spontaneous expressions. Our system can be used in Digital Cameras where in the image is captured only when the person smiles, or if the person doesn't blink his eyes. In security systems which can identify a person, in any form of expression he presents himself. Rooms in homes can set the lights, television to a person state when they enter the room. Doctors can use the system to understand the intensity of pain or illness of a deaf patient.

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