Multilabel Facial Emotion Classification

A DISSERATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE AWARD OF THE DEGREE

OF

MASTER OF SCIENCE

IN

MATHEMATICS

Submitted by:

Mansi Bhardwaj

2K20/MSCMAT/18

Mansi Panchal

2k20/MSCMAT/19

Under the supervision of

Mrs. Trasha Gupta

DEPARTMENT OF APPLIED MATHEMATICS

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

MAY, 2022

M.Sc. Mathematics

Mansi Bhardwaj & Mansi Panchal

2022

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-1100042

CANDIDATE'S DECLARATION

We, Mansi Bhardwaj (2k20/MSCMAT/18) & Mansi Panchal (2k20 /MSCMAT/19) students of MSc. Mathematics , hereby declare that the project Dissertation titled '' Multilabel Facial Emotion Classification" which is submitted by us to the Department of Applied Mathematics, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Science, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place : Delhi **MANSI BHARDWAJ**

Date : **MANSI PANCHAL**

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-1100042

CERTIFICATE

I hereby certify that the Project Dissertation titled "Multilabel Facial Emotion Classification" which is submitted by Mansi Bhardwaj (2k20/MSCMAT/18) & Mansi Panchal (2k20/MSCMAT/19) Department of Applied Mathematics, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master Of Science, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place : Delhi

Date:

Mrs. TRASHA GUPTA

SUPERVISOR

ASSISTANT PROFESSOR

DEPARTMENT OF APPLIED MATHEMATICS

ABSTRACT

A Multi label emotion recognition system is an important field of research and also has lots of applications. Examples include classify physically disabled people (deaf, dumb, and bedridden) and Autism children's emotional expressions based on facial landmarks. Understanding different human emotions is of great relevance as to gain insights into human cognition and affect as well as for the design of computational models and perceptual interfaces. Us as human beings expresses our feelings through distinct emotions yet most part, research studies have been limited to six basic categories—happiness, surprise, sadness, anger, fear, and disgust which restricts us from the real world problems. Here, in this paper we classified an important group of expressions, which we call compound emotion categories. Compound emotions are that can be visualized as combination of basic component categories to create new ones. For instance, happily surprised and angrily surprised are two distinct compound emotion categories. The dataset used in this project is CFEE_Database_230. The work is categorized in 3 major parts, first step is to analyze the training dataset and extract the region of interest (ROI) which is the most active region on the face when a person changes its facial expressions. Second step is to detect multiple image features so system can differentiate the facial landmarks in different emotional state of a person’s face. And finally in the third step the main approach for multi- label classification of the sets of emotions is to compare the difference in the value set of the relevant features for different emotion class and then labelling them as a category in the compound emotions. At last we analyse the result by applying the different classifier and observe that we get 92.2% accuracy rate using MULAN classifier.

AKCNOWLEGEMENT

The satisfaction of successful completion of any task would be incomplete without mentioning the people who made it possible and whose constant guidance and encouragement crown all of my efforts with success. We express my deep sense of gratitude to our parents and our supervisor Mrs. Trasha Gupta, Assistant Professor, Department of Applied Mathematics, Delhi Technological University for her inspiration, constant assistance, valuable suggestions, sympathetic advice, fruitful conversation and unparalleled encouragement made throughout the course of study, without which this piece of work would not have taken its present shape.

MANSI BHARDWAJ

MANSI PANCHAL

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List of Abbreviations

(LBP)	Local Binary Pattern
(GLCM)	Gray Level Co-occurrence Matrix
(FOS)	First Order Statstics
(BPNN)	Back Propogation Neural Network
(BR Method)	Binary Relevance Method
(PCC)	Probablistic Classifier Chain
(MCC)	Classifier Chain with Monte Carlo optimization
(MULAN)	MULtiple method ANalysis
(CFEE)	Compound Facial Expression Emotion

CHAPTER 1: INTRODUCTION

FACES are keys to individual emotion, they play a major role in communication. The facial expressions of a person are the most important way we can speak. With 43 different muscles, our face is capable of making more than 10,000 speeches, many of which go back to our ancient roots. And although each facet has its own unique way of expressing emotions, there are a number of selected expressions that are always present, regardless of a person's age, race, language, or religion, which is the emotional category of word.

Mehrabian, a renowned psychologist, found in his research that the data of emotions that people classify as basic emotions are still being categorized. We have found that only 7% of the total sensory data are passed through language, and 38% are transported by our language resource, the Co-Editor who coordinates the review of this manuscript and authorizes it to be published by Rosalia Maglietta. which varies from culture to culture, such as rhythm, tone, tone, etc. To date, the highest percentage of facial data is 55%.

There is a significant amount of research on facial expressions in computer vision. Perhaps the most fundamental problem in this area is how to categorize the facial expressions to extract information about the underlying emotional states. In this paper we have considered the problem of classifying the different compound emotions on the basis of the relative change in people’s facial expressions. Mostly research is limited to these set of the 6 basic emotions ’Neutral’, ’Happy’, ’Sad’, ’Angry’, ’Surprised ’ ‘Fearful’.

In the present work, we demonstrate that the production and visual perception of compound emotion class that constitutes the combination of the given basic emotions. The problem of multilabel arises as the repertoire of facial expressions typically used by humans is better described using a rich set of basic and compound categories rather than a small set of basic elements. So the problem of multi -label emotion classification is of great relevance as human’s expresses there feeling s and emotions not just through the basic emotions instead in real world the human emotional can be expressed through several combinational emotions too.

The work is categorized in 3 major parts, first step is to analyze the training dataset and extract the region of interest (ROI) which is the most active region on the face when a person changes its facial expressions. Second step is to detect multiple image features so system can differentiate the facial landmarks in different emotional state of a person’s face. And finally in the third step the main approach for multi- label classification of the sets of emotions is to compare the difference in the value set of the relevant features for different emotion class and then labeling them as a category in the compound emotions.

In this paper we have used a machine learning algorithm to train the model to differentiate the emotional category. One of the most widely used techniques for reading machine-reading techniques is content classification, which is used in many cases such as saying that a given movie review is good or bad or that there is a cat or dog in the picture. This work may be divided into three domains, two subdivisions, multiple subdivisions, and multiple label divisions.

As our problem seeks to split emotions into a clearly integrated format it is a problem for many labels that businesses in the database can label multiple. For example if we talk about movie genre then a movie can be come under multiple genres as a movie can constitute drama, romance and comedy together.

Similarly we are supposed to classify the facial expressions as combinations of basic ones.

So we can label an emotion that may be a combination of 2 or may be 3 basic one emotions.

The dataset utilised is Compound Facial Expressions of Emotion(CFEE_database_230) is a facial expression database with around 6000 great divesre facial images constituting the mixed emotions images the class of compound emotions considered is : Happily Surprised, AngerSurprise, Fearfully Surprised, SadFear, SadAnger, SadSurprise, FearAnger.

These class of emotions are more realistic and we as humans expresses thse emotions very frequently in our day to day life,for instance Angrily surprised is a compound emotion classwe experience such emotion when a surprising event or action makes you angry for example, unexpectedly and without provocation, a friend insults you.

1.1 Basic Emotion

There are many different types of emotions that influence the way we live and interact with others. Psychologists have also tried to identify the different types of emotions that people experience.

Although there are differences of opinion among experts, most psychiatrists agree that there are at least six mainstream emotions listed here. Basic emotion category means different facial expressions: Neutrality, happiness, sadness, anger, fear, surprise

Figure 1 : Showing 6 Basic Emotions

Basic emotions	Facial movements
Neutral	face is relaxed and neutral No frowns or tension on face
Happy	The eye muscles tightened "Raven's feet" are wrinkles around the eyes cheeks raised the corners of the lips are raised diagonally

Sad	The inner corners of the eyebrows are raised eyelids the corners of the lips are pulled down
Anger	Eyebrows pulled down upper eyelids pull up lower eyelids pull up the edges of the folded lips lips can be tightened
Fear	Eyebrows pulled up and together upper eyelids pull up mouth stretched
Surprise	Entire eyebrow pulled up eyelids pulled up mouth hangs open pupils dilated

Table 1 : Basic Emotions and its Facial Movements

1.2 Compound Emotion

Integrated emotions are those that can be created by combining the components of the basic components to create new ones. For example, pleasant surprise and annoyance are two different categories of emotions combined.

Why are emotions included?

Joint emotions are expressed more often than basically just for example being threatened by someone emotionally close to you, or you are really disappointed when something scary makes you feel more than that emotion you may feel will be sad and scared about the event. . Such situations are very common in our lives so it is a big job for machines to be able to sense human emotions.

Figure2 : Showing 7 Compound Emotion

Compound emotions	Facial movements
Happily Surprised	(an emotion we feel when we receive good or joyful or unexpected news/outcomes) Mixed facial movement of happy and surprise
AngerSurprise	(An emotion we feel when surprising event or action makes you angry) Mixed facial movement of Anger and surprise
Fearfully Surprised	(An emotion we feel when a surprising event makes you fearful) Mixed facial movement of Fear and surprise
SadFear	(An emotion we feel when fearful event or action makes you sad) Mixed facial movement of Fear and sad

SadAnger	(An emotion we feel when event or action that makes you angry and leaves you disappointed or sad) Mixed facial movement of anger and sad
SadSurprise	(An emotion we feel when surprising event makes you sad) Mixed facial movement of Surprise and sad
FearAnger	(An emotion we feel when fearful event or action makes you angry) Mixed facial movement of Fear and Anger

Table 2 : Compound Emotion and its Facial Movements

1.3 MultiLabel Classification

Multilabel refers to the problem of classification, in which each element may belong to a few previously defined categories at once.

- In classifying multiple labels, a training set is made up of conditions associated with a set of labels, and the task is to predict event label sets that can be identified by analyzing training conditions with known label sets.
- For example, the division into several categories makes it possible to assume that each sample is assigned to only one label: the fruit can be orange or pear but not both at the same time. Although, an example of the division of many labels would be that a movie could be of any kind such as romance, comedy, drama or action at the same time.
- The difference between multiple categories and multiple labels

  The main difference is that in the problems of many classes the classes are different, and in the problems of many labels each label represents a different classification function, but the functions are related in some way..

The problem considered in this thesis is Multi label emotion recognition system.

The present work, we demonstrate that the production and visual perception of compound emotion class that constitutes the combination of the given basic emotions. The problem of multilabel arises as the repertoire of facial expressions typically used by humans is better described using a rich set of basic and compound categories rather than a small set of basic elements.

1.4 Applications

Human emotions are not limited to the six basic categories of emotions but rather an important category of mixed emotions that express clearly and informally about the attitude and personality that we constantly express ourselves as human beings and find that this category of emotions is broad. application list. An important application for the medical profession. Examples include classifying people with physical disabilities (deaf, mute, and bedridden) as well as children’s emotional states of Autism based on global facial features. So being able to read someone else's emotions can have a number of applications by psychologists as they are able to better understand their patient's attitude and feelings, especially in the case of those patients who are unable to express what they are feeling directly in words or actions. Along with the given problem of the detection of a combined category of emotions it increases the spectral of limited sensory acquisition.

CHAPTER 2: STUDY OF COMPUND EMOTION

2.1 Problem Statement

The scenario is about classifying different compound emotions that are combinations of the basics emotions into different classes. While previous research identified a facial condition associated with one label that are not enough to express the complete feeling of a person in this paper we have studied an important class of facial expressions observed the compound emotions.

For example the facial expression of a happy surprise when we feel incredibly happy, for example, at an amazing birthday party.. So here we have identified 7 classes of the compound emotions which are consistently produced across cultures, suggesting that the number of facial expressions is more in numbers than previously believe.
The hypothesis is that human emotions are not restricted to the class of the basic six emotions rather there exist an important class of compound emotions that are more expressive and informative about a person’s mental state and mood which we humans expresses almost regularly. It is of major use to detect such class of emotions. To date, most studies have focused on the study of the six most common emotions experienced in many lands — happiness, surprise, sadness, anger, fear, and neutrality while this paper explores the category of combined emotions.

2.2 Related Work

So recognition of multi label facial emotions is a challenging problem with many applications. . Previous work of the problem has typically focused by categorizing a set of such predetermined facial motions as in FACS (Facial Action Coding System), that is all visually distinguishable facial movements.

Ekman and Friesen [1] developed the Face Coding System (FACS) to explain subtle changes in facial expressions. FACS consists of 49 action units, including those of the head and eye. Thirty of these are related to body composition and the shortening of a particular set of facial muscles. Although there are only a small number of atomic action units, more than 7,000 active combinations have been detected. FACS provides the information needed to define facial expressions.

Another method used to solve the problem was proposed to divide the face into lower, middle, and upper levels [2]. At lower levels we take the regions corresponding to the face, mouth, eyebrows, and eyes and model the strongest and non-strongest of these regions using a set of parameter flow models. and unstable facial movements using a set of local models with optical flow parameters.

These approaches are bit complex as action units [3] is a difficult problem because there are no plural definitions and they come from complex combinations while in this paper, rather than using the prior method of action units to recognize any respective emotion we have approached the problem by a different procedure, here we firstly detected the facial landmarks which further differentiated the face into 8 facial regions which are the most sensitive areas when facial emotion changes thus are of greater relevance .The following 8 facial regions are mouth , inner mouth , right eye ,left eye ,right eyebrow ,left eyebrow, nose , Jaw. Then the respective features from each of the face regions are considered as the tools to classify the face emotions.

2.3 Methodology

This section explains the entire step-by-step approach employed in this work, which primarily consists of the following three phases: The initial step in the process is to identify the important facial landmarks that give key facial features or regions. The question now is why facial landmarks are so important in our case.

Face detection is a subset of the shape prediction problem. Shape forecast attempts to identify key points of interest in a given image (and usually a ROI describing an object of interest) [10]. Our goal in the context of global facial features is to use predictive methods to identify important facial features. [6].

2.4 Dataset

Compound Facial Expressions of Emotion(CFEE_database_230) a large face website with about 6000 different face downloads online. The mage on this site have significant variations in age of education, gender and race, shape, light conditions, closure, (e.g. glasses, facial hair or closure), post-processing activities (e.g. various filters and special effects), etc. CFEE_DB has a wide variety, large numbers, and rich annotations, including:

- 5972 number of real- world images
- two different subset sets: one subset with one label, comprising 6 categories of basic emotions; sub-set of two tabs, comprising 12 categories of integrated emotions,
- 6 classes of basic emotion include : Neutral, Happy, Sad, Fear, Surprise, Anger.
- 7 classes of compound emotion include : HappySurprise, AngerSurprise, FearSurprise, SadFear, SadAnger, SadSurprise, FearAnger.

2.5 Facial Landmark Detection

Face detection is a computer-aided operation where we want to detect and track key points on a person'sface.

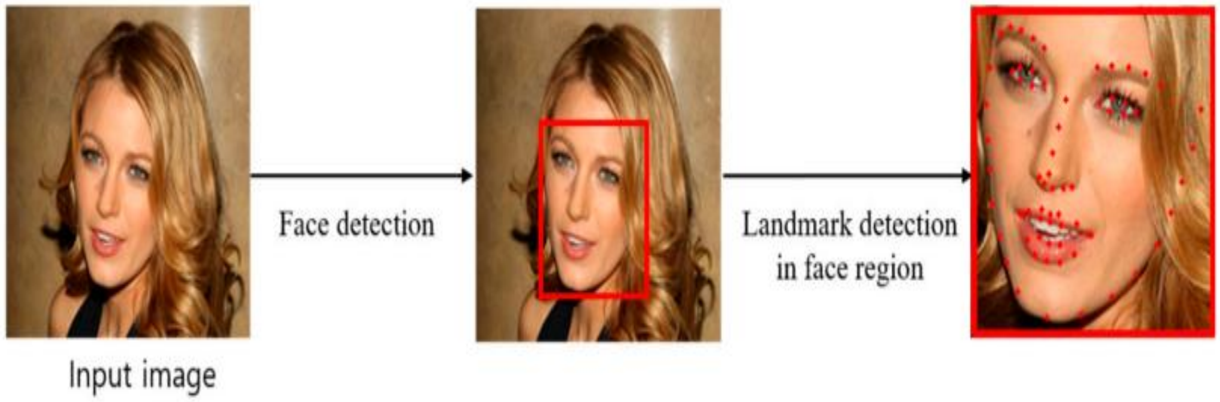

Figure3：Flowchart For Facial Landmark Detection

2.5.1 Applications of Facial Keypoint Detection

There are a few interesting apps for finding a key point in people's faces. A few of them are listed below:

- Facial feature detection improves face recognition.
- Head Pose Estimation
- Face Morphing
- Virtual Makeover
- Face Replacement

In this project, our goal in the context of global facial features is to use posture predictors to identify important facial features [6]. So finding facial features is a second step:

• **Identify the face in the photo.**

Face landmarking is the recognition and localisation of specific keypoints on the face, which is perhaps the most critical stage in the face processing process. The issue is to locate the location of a number of landmarks on a face based on a photograph of the face. The eye corners, nose tip, nostril corners, mouth corners, terminal points of the eyebrow arcs, jaw, and other landmarks are commonly employed. The dlib library's pre-trained facial landmark detector is used to estimate the location of 68 (x, y)-coordinates that correspond to facial structures.

• **On the face ROI, identify the important facial structures.**

Detecting the face's Region of Interest entails segmenting the face into the parts we're interested in, which are the most active on the face when a person alters their facial expressions. Both the shape and layout features rely on good segmentation techniques.

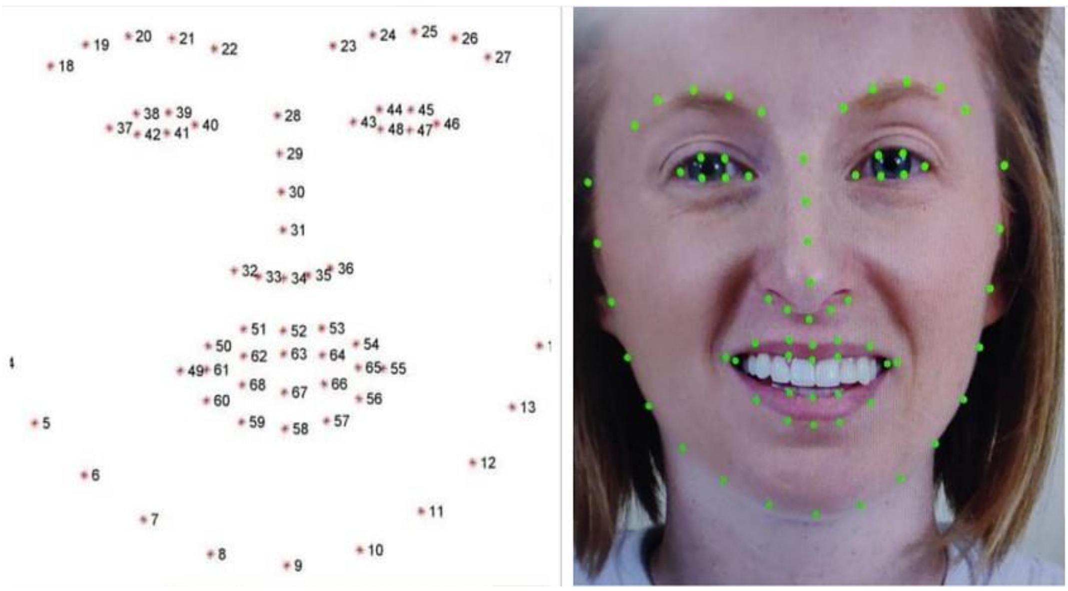

Figure 4 Detecting facial landmarks

2.6 Feature Extraction

Feature extraction is a technique for extracting the visual content of photographs so that they may be indexed and retrieved. Feature extraction is a term that refers to a piece of data that is useful in completing a computational task for a certain application.

The purpose is to turn the image into quantitative data that can be further processed for emotion labelling, classification, and recognition.

2.6.1 FOS :

First order feature extraction is a retrieval approach based on image histogram features. The Histogram depicts the likelihood of a given value of grayscale pixel degree occurring in a picture. Several first-order parameters can be derived from the numbers provided by the histogram, including mean, variance, skewness, kurtosis, and entropy.

We calculated following feature from in FOS : FOS_Mean, FOS_Variance, FOS_Median, FOS_Mode, FOS_Skewness, FOS_Kurtosis, FOS_Energy, FOS_Entropy, FOS_MinimalGrayLevel, FOS_MaximalGrayLevel, FOS_CoefficientOfVariation FOS_10Percentile, FOS_25Percentile,FOS_75Percentile, FOS_90Percentile, FOS_HistogramWidth

2.6.2 GLCM :

The GLCM functions calculate how many pairs of given pixels and the specified local relationships from an image, construct GLCM, and then subtract statistical measurements from this matrix to reflect the texture of the image [8]. After creating GLCMs with graycomatrix, we can use graycoprops to get more statistics from them. These figures provide information about the texture of the image. Statistics are listed in the table below. GLCM Contrast (Measuring spatial variability in gray matter matrix level), It measures the probability of a shared chance of stated pixel pairs.), GLCM Correlation (also known as angular second moment or homogeneity.) And so on.

We calculated following feature from in GLCM : ASM,GLCM_Contrast, Correlation, SumOfSquaresVariance, InverseDifferenceMoment, SumAverage, SumVariance, SumEntropy, Entropy, DifferenceVariance, DifferenceEntropy, Information1 ,Information2, MaximalCorrelationCoefficient.

2.6.3 Local Binary Pattern (LBP) :

Local Binary Pattern (LBP) is a basic but effective texture operator that labels pixels in an image by shortening the area of each pixel. This method is commonly used to investigate their local qualities and to discover the characteristics of specific image sections.

We calculated following feature from LBP : energy, entropy and mean feature

2.7 Multilabel Classifier

It is used when there are two or more categories and the data we want to classify may be one class or all at once, e.g. to distinguish what road signs are contained in the image or to classify the compound emotion on a human face which we are going to do in this project.

2.7.1 Back Propogation Neural Network (BPNN)

Backpropagation is the backbone of neural network training. It is a method of correcting the weights of a neural network based on the measure of errors found in the past (i.e., repetition). Proper weight planning allows you to reduce error rates and make the model more reliable by increasing its overall performance.

Spreading backpropagation in the neural network is a short form of "repeated distribution of errors." It is a common way to train artificial intelligence networks. This method helps to calculate the tendency for weight loss activity in relation to all weights in the network.

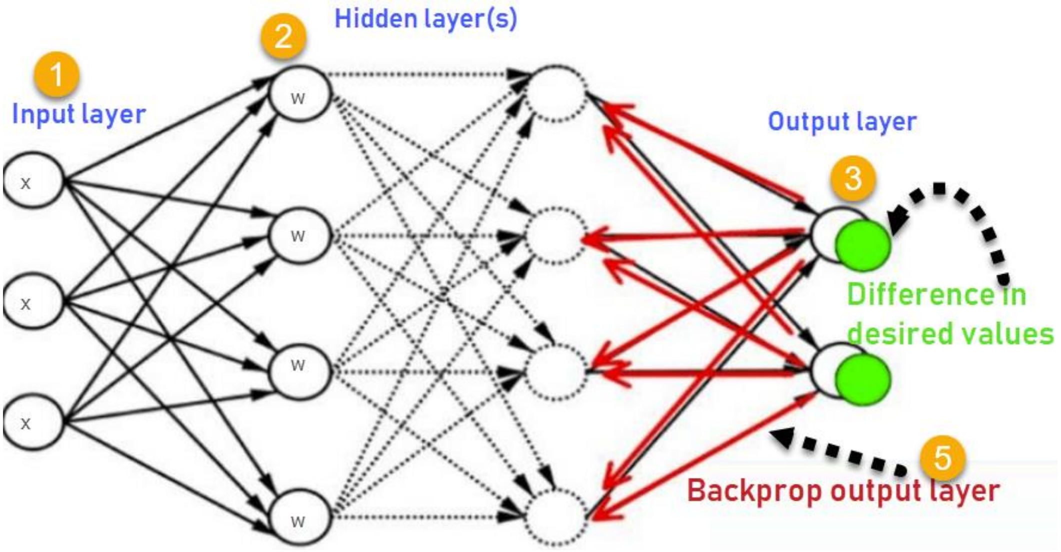

Figure 5 : Flowchart Of BPN Working

How BPNN works :

1. Input X, arrive via pre-connected
2. Model inputs using real weights W. Weights are often randomly selected.
3. Calculate the output of all neurons from the input layer, to the hidden layers, to the output layer.
4. Calculate error on the output

2.7.2 Binary Relevance Method (BR Method)

BR is a decay method based on the learning assumption that labels are independent. Therefore, each label is considered appropriate or unimportant according to the two categories studied on that label independently of other labels.

Converts multi-labeled L-label problem into L-label separation problem with the same label using the same base separator provided by the manufacturer. Output predictive union for all dividers per label.

2.7.3 Probablistic Classifier Chain (PCC)

The family of methods known collectively as the chains of separation has become a popular method of learning problems with multiple labels. This approach involves combining non-shelf binary class dividers into a target structure, such as the speculation of each label being the characteristics of other dividers. Such methods have been proven to be flexible and effective and have achieved modern technological performance across a wide range of data sets and metric testing metrics.

The segment chain chain connects binary segment dividers to a ‘chain’, so that the single-output output predictor is added as an additional element to the input of all subsequent dividers. This method is one of the many ways in which we want to model relationships between labels, thus gaining improved performance over the binary related method and considering the totally unrelated chains, and then finding a way to binary compatibility.

2.7.4 Classifier Chain with Monte Carlo Optimization (MCC)

Multiparty is a supervised learning problem where the model can be associated with multiple classes, rather than a single class such as a traditional binary problem or multi-sided divisions where the MCC is a modified version of the PCC separator we provide. better effect than PCC

2.7.5 MULtiple method Analysis (MULAN)

Mulan is a Java library for open source learning for databases with multiple labels. Multiple label data sets include training examples of targeted activity with a wide range of targeted binary options. This means that each database item with multiple labels can be a member of several categories or defined by multiple labels (classes). The library provides the following features:

- Feature selection. Simple basic methods are currently supported.
- Testing. Classes calculate a wide variety of test scores by checking for delays and counter-validation.

Mulan is a library as it is, providing only a structured API for library users.

CHAPTER 3: RESULT AND ANALYSIS

3.1 Result & Analysis

In this section, we tested multiple classifiers to see how accurate our experiment was. We utilised the free source machine learning framework "MEKA" for this. It helps with the creation, testing, and assessment of multi-label and multi-target classifiers.

A data instance can be connected with numerous labels in the multi-label problem. This is in contrast to the typical task of single-label classification (i.e., multi-class, or binary), which assigns a single class label to each instance. The multi-label context is gaining popularity, and it may be used to a wide range of domains, including text, music, photos, and video, as well as bioinformatics.

The result of our experiment with different classifier as follows :

Classifier Name	**Accuracy Rate (%)**
BPNN	73%
Binary Relevance Method (BR Method)	83.4%
Probabilistic Classifier Chain (PCC)	87%
MCC	87.1%
MULAN	92.2%

Table3 : Accuracy rate for different classifiers

It can be observed that to increase the accuracy of our experiment we have used four types of classifier and with MULAN [7] we get the higher accuracy.

Next, we have performed the above classifier taking cross validation as evaluation parameter and the result as follows :

Classifier Name	**Accuracy Rate (%)**
BPNN	75%
Binary Relevance Method (BR Method)	84.5%

Probabilistic Classifier Chain (PCC)	88%
MCC	88%
MULAN	92.2%

Table 4 : Accuracy rate with cross validation parameter

Again we can observed from Table 4 that using cross-validation as a evaluation parameter, there is a minimal increment of accuracy rate in all classifier except MULAN.

The results presented in this study reveal that, in the case of visual acuity, its features contain important information about emotions that cannot be extracted from visual information. This unwanted information is very important to improve the functioning of the emotional alert system. Most importantly the caption-based features have done wonders to read small details from facial areas whenever emotions are expressed through the facial emotions category..

3.2 Conclusion & Future Scope

To examine the class of compound emotions, this study looked at several parts of the face that make up the prominent features. Detecting face emotion is an intrinsically challenging problem due to individual variability in facial features, as well as ethnic and cultural differences. Detecting compound emotions is even more difficult because the distinction between dominant and complimentary emotions is often thin. The class of compound emotions is frequently misclassified, including by humans. However, the findings of this work suggest that a careful investigation of a face's region of interest (ROI) can clear up the majority of these misunderstandings.

This project analyzes the winner's approach- segmenting the face into the 8 crucial sub parts that are most effective regions when a person's facial emotion changes and detecting the image texture based features that can differentiate the facial details in a particular emotional state . The proposed method includes three major contributions :

- Spot the facial landmarks and deriving the suitable region of interest(ROI)
- Detecting the features for every sub region of face

- Analyzing the difference in the features and classifying and labeling the emotion class.

The results presented in this study suggest that it is possible to recognize a person's complexity emotional state rather than just the basic emotion class which is ineffective to express the true feelings of the person and catches limited information visually.

References

[1] P. Ekman and W.V. Friesen, Facial Action Coding System. Palo Alto, Calif.: Consulting Psychologists Press, Inc., 1978.

[2] Michael J. Black , Yaser Yacoob ―Tracking and Recognizing Rigid and Non-Rigid Facial Motions using Local Parametric Models of Image Motion‖ Proceedings of IEEE International Conference on Computer Vision June 1995

[3] Ying-li Tian , Takeo Kanade1 and Jeffrey F. Cohn ―Recognizing Lower Face Action Units for Facial Expression Analysis‖ IEEE Transactions on Pattern Analysis and Machine Intelligence, Feb. 2001

[4] Chirag Dalvi, Manish Rathod , Shruti Patil , Shilpa Gite AND Ketan Kotecha ―A Survey of AI-Based Facial Emotion Recognition: Features, ML & DL Techniques, Age-Wise Datasets and Future Directions‖ IEEE access November 30, 2021

[5] A. Mehrabian and S. R. Ferris, ‗‗Inference of attitudes from nonverbal communication in two channels,‘‘ J. Consulting Psychol., vol. 31, no. 3, pp. 248–252, 1967, doi: 10.1037/h0024648.

[6] G. M. BEUMER, , QIAN TAO, M. BAZEN, VELDHUIS‖ A LANDMARK PAPER IN FACE RECOGNITION.Seventh IEEE International Conference on Automatic Face and Gesture Recognition (FG 2006), 10-12 April 2006.

[7] Grigorios Tsoumakas, Eleftherios SpyromitrosXioufi, Jozef Vilcek "MULAN: A Java library for multi-label learning" July 2011 Journal of Machine Learning Research.

[8] P. Mohanaiah, P. Sathyanarayana, L. GuruKumar "Image Texture Feature Extraction Using GLCM Approach" International Journal of Scientific and Research Publications, Volume 3, Issue 5, May 2013.

[9] M. M, A. M (2021) Facial geometric feature extraction based emotional expression classification using machine learning algorithms. PLoS ONE 16(2): e0247131.

[10] Priya Sahaa, Debotosh Bhattacharjeeb, Barin Kumar Dec, Mita Nasipurib "An Approach to Detect the Region of Interest of Expressive FaceImages " International Conference on Information and Communication Technologies (ICICT 2014).