DETECTION OF BIPOLAR PATIENT'S FACIAL EXPRESSION USING CNN ALGORITHM

A PROJECT REPORT

Submitted by

S.ALAGUPANDIYARAJ 710517205002

N.ANBHAZHAGAN 710517205003

S.JAYASREE 710517205007

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COIMBATORE-641 109

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ANNA UNIVERSITY: CHENNAI 600 025

BONAFIDE CERTIFICATE

Certified that this project report "DETECTION OF BIPOLAR PATIENT'S FACIAL EXPRESSION USING CNN ALGORITHM" is the bonafide work of **"S.ALAGUPANDIYARAJ (710517205002), N.ANBAZHAGAN (710517205003), S.JAYASREE (710517205007) "** who carried out the project work under my supervision.

SIGNATURE	SIGNATURE
Dr.K.PUSHPALATHA M.E.,Ph.D.,	**Dr.K.PUSHPALATHA M.E.,Ph.D.,**
HEAD OF THE DEPARTMENT	**SUPERVISOR**
	Associate Professor
Department of Information and	Department of Information and
Technology	Technology
Coimbatore Institute of	Coimbatore Institute of
Engineering and Technology	Engineering and Technology
Coimbatore – 641109.	Coimbatore – 641109**.**

Submitted for the university examination held on...........................

INTERNAL EXAMINER	**EXTERNAL EXAMINER**

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ABSTRACT

Facial expression recognition (FER) has received significant interest from computer scientists and psychologists over recent decades, as it holds promise to an abundance of applications, such as human-computer interaction, affect analysis, and mental health assessment. Although many facial expression recognition systems have been proposed and implemented, majority of them are built on images captured in controlled environment, such as CK+ [96], MMI [97], Oulu-CASIA [98], and other lab-collected datasets. The controlled faces are frontal and without any occlusion. The FER systems that perform perfectly on the lab-collected datasets are probable to perform poorly when recognizing human expressions under natural and un-controlled conditions. , we propose a Convolution Neural Network with attention mechanism (ACNN), mimicing the way that human recognize the facial expression. Intuitively, human recognizes the facial expressions based on certain patches of the face. To avoid the complex process of explicit feature extraction in traditional facial expression recognition, a face expression recognition method based on a convolutional neural network (CNN) and image edge detection is proposed. Firstly, the facial expression image is normalized, and the edge of each layer of the image is extracted in the convolution process. The extracted edge information is superimposed on each feature image to preserve the edge structure information of the texture image. Then, the dimensionality reduction of the extracted implicit features is processed by the maximum pooling method. Finally, the expression of the test sample image is classified and recognized by using a sigmoid classifier.

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LIST OF ABBREVIATIONS

ANN	ARTIFICIAL NEURAL NETWORK
BD	BIPOLAR DISORDER
CNN	CONVOLUTION NEURAL NETWORK
ECG	ELECTRO CARDIOLOGY
FER	FACIAL EXPRESSION RECOGNITION
FMRI	FUNCTIONAL MAGNETIC RESONANCE IMAGE
MLP	MULTILAYER PRECEPTION
NLP	NATURAL LANGUAGE PROCESSING

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO EMOTIONS

Emotions are biological process associated with all the nervous system brought on by neuro physiological changes variously associated with thoughts, feelings, behavioural responses, and a degree of pleasure or displeasure.

1.2 LIST OF EMOTIONS

Emotion is one type of affect, other types being mood, temperament and sensation (for example, pain). Emotions can be understood as either states or as processes. When understood as a state(like being angry or afraid), an emotion is a type of mental state that interacts with other mental states and causes certain behaviors. Understood as a process, it is useful to divide emotion into two parts. The early part of the emotion process is interval between the perception of the stimulus and the triggering of the bodily response.The later part of the emotion process is a bodily response, for example, changes in heart rate, skin conductance, and facial expression. This description is sufficient to begin an analysis of the emotions, although it does leave out some aspects of the process such as the subjective awareness of the emotion and behavior that is often part of the emotion response.

The early part of the process is typicaly taken to include an evaluation of the stimulus,whichmeansthat the occurrence of an emotion depends on how the individual understandsor"sees" the stimulus. For example, one person may respond to being laid- off from a job with anger, while another person responds with joy— it depends on how theindividual evaluates this event. Having this evaluative component in the process means that an emotion is not a simple and direct response to a stimulus. In this way, emotions differ from reflexes such as the startle response or the eye-blink response, which are direct responses to certain kinds of stimuli. The folowing are some of the features that distinguish emotion from moods. An emotion is a response to a specific stimulus that can be internal ,like a belief or a memory. It is also generlly agreed that emotions have intentional content, which is to say that they are about something, often the stimulus itself. Moods, on the other hand, are typicaly not about anything, and at least some of the time do not appear to be caused by a specific stimulus. Emotions also have a relatively brief duration—on the order of seconds or minutes whereas moods last much longer. Most theories agree about these features of the emotions. There is much less agreement, however, about most of these other features that the emotions may (or may not) have.

1.3 EVOLUTIONARY THEORIES

The evolutionary approach focuses on the historical setting in which emotions developed. Typically, the goal is to explain why emotions arepresent in humans today by referring to natural selection that occurred some time in the past. However, a trait can enhance fitness without being an adaptation. One example, noted by Darwin in The Origin of Species, is the skull sutures in newborns: The sutures in the skulls of young mammals have been advanced as a beautiful adaptation for aiding parturition [that is, live birth], and no doubt they facilitate, or may be indispensable for this act; but as sutures occur in the skulls of young birds and reptiles, which have only to escape from a broken egg, we may infer that this structure has arisen from the laws of growth, and has been taken advantage of in the parturition of the higher animals In this case, the evidence from non- mammals indicates that this trait was not selected because it aids psychological traits because there is no fossil record to examine. Hence, live birth, although it later became useful for this task. This is especially true for establishing that an emotion is an adaptation presents some difficult challenges.

Nevertheless, this has not prevented the development of theories that explain emotions as adaptations. The attractiveness of this approach is easy to see. Since all humans have emotions and most non- human animals display emotion-like responses, it is likely that emotions(or emotion-like behaviors) were present in a common ancestor. Moreover, emotions appear to serve an important function, which has led many to think that the certain emotions have been sections. The first is based on the claim that emotions are the result of natural selection that occurred in early hominids. The second also claims that emotions are adaptations, but suggests that the selection occurred much earlier. Finally, the third position suggests that emotions are historical, but does not rely on emotions being adaptations.

1.4 THEORIES OF THE EMOTION PROCESS

The third category of theories contains those that attempt to describe the emotion process itself. Generally speaking, the emotion process begins with the perception of a stimulus, although in some cases the “stimulus” may be internal, for example ,a thought or a memory. The early part of the emotion process is the activity between the perception and the triggering of the bodily response (that is, the emotion response), and the later part of the emotion process is the bodily response: changes in heart rate, blood pressure, facial expression, skin conductivity, and soforth.

Most of the theories that will be considered in this section focus on the early part of the emotion process because according to these theories the specific emotion that occurs is determine during this part of the process. There is, however, disagreement about how simple or complex the early part of the emotion process might be, which has lead to competing cognitive and non-cognitive theories.

1.5 DIGITALIMAGE PROCESSING

The identification of objects in an image. This process would probably start with image processing techniques such as noise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures. The clever bit is to interpret collections of these shapes as single objects, e.g., cars on a road, boxes on a conveyor belt or cancerous cells on a microscope slide. One reason this is an AI problem is that an object can appear very different when viewed from differentangles orunder different lighting. Another problem is deciding what features belong to what object and which are background or shadows etc. The human visual system performs these tasks mostly unconsciously but a computer requires skillful programming lots of processing power to approach human performance. Manipulating data in the form of an image through several possible techniques. An image is usually interpreted as a two-dimensional array of brightness values, and is most familiarly represented by such patterns as those of a photographicprint, slide, television screen, or movie screen.

1.6 IMAGE PROCESSING

Digital image processing, the manipulation of images by computer, is relatively recent development in terms of man's ancient fascination with visual stimuli. In its short history, it has been applied to practically every type of images with varying degree of success.

The inherent subjective appeal of pictorial displays attracts perhaps a disproportionate amount of attention from the scientists and also from the layman. Digital image processing like other glamour fields, suffers from myths, mis-connections, mis- understandings and mis-information.It is vast umbrella under which fall diverse aspect of optics, electronics, mathematics, photography graphics and computer technology. It is truly multidisciplinary endeavor ploughed with imprecise jargon. Several factors combine to indicate a lively future for digital image processing. A major factor is the declining cost of computer equipment. Several new technological trends promise to further promote digital image processing. These include parallel processing mode practical by low-cost microprocessors, and the use of charge coupled devices(CCDs) for digitizing, storage during processing and display and large low cost of image storage arrays.

1.7 CLASSIFICATION OF IMAGES

There are 3 types of images used in Digital Image Processing. They are

- Binary image
- Gray scale image
- Color image

1.7.1 Binary Image

A binary image is a digital image that has only two possible values for each pixel. Typically the two colors used for a binary image are black and white though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color. Binary images are also called bi-level or two-level.

This means that each pixel is stored as a single bit (0 or 1).This name black and white, monochrome or monochromatic are often used for this concept, but may also designate any images that have only one sample per pixel, such as gray scale images.

Binary images often arise in digital image processing as masks or as the result of certain operations such as Segmentation, thresholding, and dithering. Some input/output devices, such as laser printers, fax machines, and bi-level computer displays, can only handle bi-level images.

1.7.2 Gray Scale Image

A grayscale Image is digital image is an image in which the value of each pixelis a single sample, thatis, It carries only intensity information. Images of this sort, also known as black-and- white, are composed exclusively of shades of gray (0-255), varying from black (0) at the weakest intensity to white (255) at the strongest. Grayscale images are distinct from one-bit black-and-white images,which in thecontext of computer imaging are images with only the two colors, black, and white (also called bi- level or binary images). Grayscale images have many shades of gray in between. Gray scale images are also called monochromatic, denoting the absence of any chromatic variation. Gray scale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g., infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured. But also, they can be synthesized from a full color image; see the section about converting to grayscale.

1.7.3 Color Image

A (digital) color image is a digital image that includes color information for each pixel. Each pixel has a particular value which determines its appearing color. This value is qualified by three numbers giving the decomposition of the color in the three primary colors Red, Green and Blue. Any color visible to human eye can be represented this way. The decomposition of a color in the three primary colors is quantified by a number between 0 and255.

For example, white will be coded as R = 255, G = 255, B = 255; black will be known as (R, G, B) = (0,0,0); and say, bright pink wil be:(255,0,255).In other words, an image is an enormous two-dimensional array of color values, pixels, each of them coded on 3 bytes, representing the three primary colors.

This alows the image to contain a total of 256 x 256 x 256 = 16.8 milion different colors. This technique is also known as RGB encoding, and is specifically adapted to human vision.

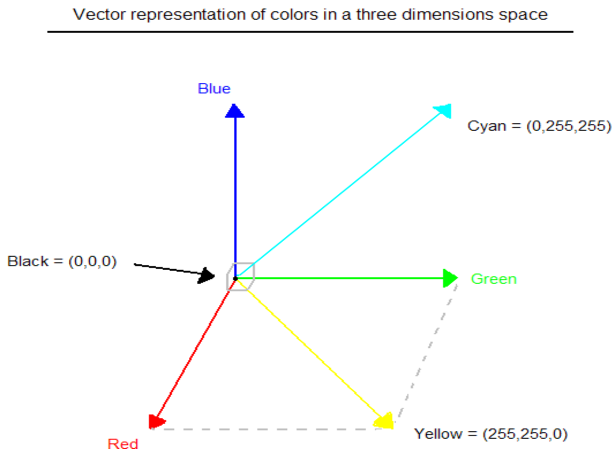


Fig.1.1 Vector representation of colors in three dimensions space.

From the above figure1.1 Vector representation of colors in three dimensions space, colors are coded on three bytes representing their decomposition on the three primary colors. It sounds obvious to a mathematician to immediately interpret colors as vectors in a three-dimension space where each axis stands for one of the primary colors.
Therefore, we wil benefit of most of the geometric mathematical concepts to deal with our colors, such as norms, scalar product, projection, rotation or distance.

1.8 BASIC OF IMAGE PROCESSINGIMAGE

An image is a two-dimensional picture, which has a similar appearance to some subject usualy a physical object or a person. Image is a two-dimensional, such as a photograph, screen display, and as well as a three-dimensional, such as a statue. They may be captured by optical devices—objects and phenomena, such as the human eye or water surfaces. The such as cameras, mirrors, lenses, telescopes, microscopes, etc. and natural word image is also used in the broader sense of any two-dimensional figure such as a map, a graph,a pie chart,or an abstract painting .In this wider sense, images can also be rendered manualy, such as by drawing, painting, carving, rendered automaticaly by printing or computer graphics technology as shown in fig1.2, or developed by a combination of methods, especially in a pseudo-photograph.

Fig 1.2 Training images

An image is a rectangular grid of pixels. It has a definite height and a definite width counted in pixels. Each pixel is square and has a fixed size on a given display. However different computer monitors may use different sized pixels. The pixels that constitute an image are ordered as a grid(columns and rows); each pixel consists of numbers representing magnitudes of brightness and color.

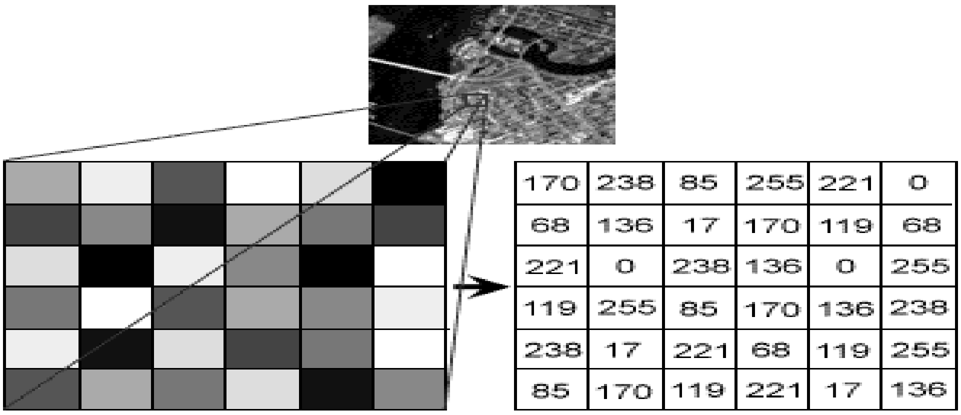


Fig 1.3 Pixel Representation

Each pixel has a color. The color is a 32-bit integer. As shown in figure1.4 Bit Representation the first eight bits determine the redness of the pixel, the next eight bits the greenness, the next eight bits the blueness, and the remaining eight bits the transparency of thepixel.

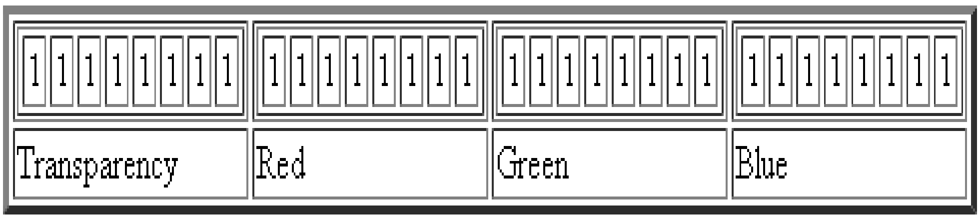


Fig 1.4 Bit Representation

1.8.1 Image File Sizes

Image file size is expressed as the number of bytes that increases with the number of pixels composing an image, and the color depth of the pixels. The greater the number of rows and columns, the greater the image resolution, and the larger the file. Also, each pixel of an image increases in size when its color depth increases, an 8-bit pixel (1 byte)stores256 colors, a 24-bit pixel (3 bytes) stores 16 milion colors ,the latter known as true color. Image compression uses algorithms to decrease the size of a file. High resolution cameras produce large image files, ranging from hundreds of kilobytes to megabytes, per the camera's resolution and the image- storage format capacity. High resolution digital cameras record12- megapixel(1MP = 1,000,000 pixels / 1 milion) images, or more, in true color. For example, an image recorded by a 12 MP camera since each pixel uses 3 bytes to record true color, the uncompressed image would occupy 36,000,000 bytes of memory, a great amount of digital storage for one image, given that cameras must record and store many images to be practical. Faced with large filesizes,bothwithinthecamera and a storage disc, image file formats were developed to store such largeimages.

1.8.2 Image File Formats

Image file formats are standardized means of organizing and storing images. This entry is about digital image formats used to store photographic and other images.

Image files are composed of either pixel or vector (geometric) data that are rasterized as shown in fig 1.5 to pixels when displayed (with few exceptions) in a vector graphic display. Including proprietary types, there are hundreds of image file types. The PNG, JPEG, and GIF formats are most often used to display images on the Internet.

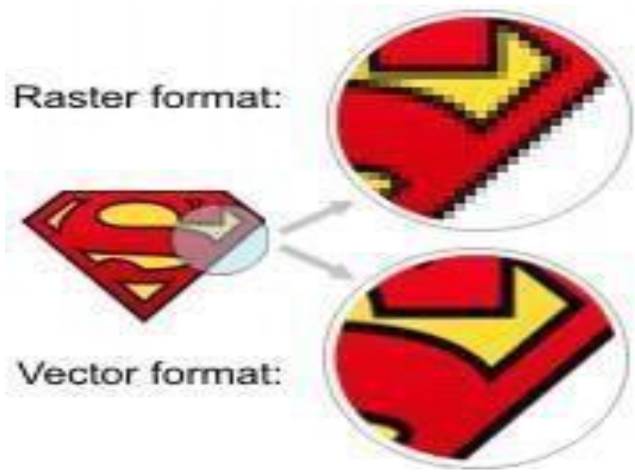


Fig 1.5 Raster and Vector Format of images

In addition to straight image formats, Metafile formats are portable formats which can include both raster and vector information. The metafile format is an intermediate format. Most Windows applications open Metafiles and then save the min their own native format.

CHAPTER 2

LITERATURE SURVEY

New technologies have recently been used for monitoring signs and symptoms of mental health illnesses and particularly have been test the outcomes in bipolar disorders. Web-based psycho educational programs for bipolar disorders have also been implemented. This paper aims to identify periods of depression using convolution neural network to study the individuals with bipolar disorder.

2.1 A Survey On Bipolar Disorder Classification Methodologies Using Machine Learning

This paper focuses on a scenario based Bipolar disorder (BD) classification methodology. The methodology currently used for the identification of disorder using functional magnetic resonance imaging (FMRI) data analysis requires specialists in the field and the process is generaly time consuming. The present breakthroughs on the prediction using retinal vasculature, where the brain and retinal share the same biomarker structure, machine learning and deep learning, which remains as the most used approach for classification. This paper reviews feature selection and various methodologies used on BP classification and identifies the best methodology.

2.2 Self-Monitoring And Psycho Education In Bipolar Patients With A Smart-Phone Application

The project wil be carried out in three complementary phases, which wil include a feasibility study (first phase), a qualitative study (second phase) and a randomized controlled trial (third phase) comparing the Smartphone application (SIMPLe) on top of treatment as usual with treatment as usual alone. During the first phase, feasibility and satisfaction wil be assessed with the application usage log data and with an electronic survey. Focus groups wil be conducted and technical improvements wil be incorporated at the second phase. Finaly, at the third phase, survival analysis with multivariate data analysis wil be performed and relationships between socio-demographic, clinical variables and assessments scores with relapses in each group will be explored.

ADVANTAGES

One of the advantages of new technologies ,and specifically smart phones, is that it is possible to overcome these difficulties in a cost-efficient way through them.

DRAWBACKS

There are some potential risks and limitations of this project: The facTthat the patient will interact with a device instead of a therapist could decrease the level of compromise with the program.

2.3 Detecting Bipolar Depression From Geographic Location Data

Detecting Bipolar Depression From Geographic Location Data is proposed. This paper aims to identify periods of depression using geo location movements recorded from mobile phones in a prospective community study of individuals with bipolar disorder (BD). Recorded location data were pre-processed by detecting and removing imprecise data pointsand features were extracted to assess the level and regularity of geographic movements of the participant. A subset of features were selected using a wrapper feature selection method and presented to a linear regression model and a quadratic generalized linear model with a logistic link function for questionnaire score estimation and a quadratic discriminant analysis classifier for depression detection in BD participants based on their questionnaire responses

ADVANTAGES

This is the first study of the utility of using geolocation data to detect depressive symptoms in a community sample of bipolar pati ents.

The findings suggest that features of geolocation may be a useful proxy for mood states.

DRAWBACKS

They need to be extended to explore mood changes within individuals but may prove to be useful tools in the early identification of depressive episodes and in guiding self-management.

2.4 Predicting Mood Changes in Bipolar Disorder through Heartbeat Non l inear Dynamics

It is a methodology predicting mood changes in BD using heartbeat nonlinear dynamics exclusively, derived from the ECG. Mood changes are here intended as transitioning between two mental states: euthymic state i.e., the good affective balance, and Non-euthymic state. Heart Rate Variability(HRV)series from 14 bipolar spectrum patients (age: 33.439.76, age range: 23-54; 6 females) involved in the European project PSYCHE, under going whole night ECG monitoring were analyzed. Data were gathered from a wearable system comprised of a comfortable t-shirt with integrated fabric electrode sand sensors able to acquire ECGs. Each patient was monitored twice a week, for 14 weeks, being able to perform normal (unstructured) activities. From each acquisition, the longest artifact- free segment of heartbeat dynamics was selected for further analyses. Sub-segments of 5 minutes of this segment were used to estimate trends of HRV linear and non linear dynamics.

ADVANTAGES

considering the results of accuracy, sensitivity and specificity, we can state that the proposed methodology is able to predict the next mood state with acceptable reliability

DRAWBACKS

Machine learning systems able to discriminate a so high number of classes are very challenging and require a very huge amount of data.the investigation of which feature would provide major information in forecasting the next mood state.

2.5 Early Detection Application of Bipolar Disorders Using Back propagation Algorithm

The back propagation algorithm that has been done to find out the results, obtained accuracy and the highest results of training, the highest results obtained with the total test data correct or suitable is 249 and the wrong data is 1 of 250 test data. If it is calculated by a formula, the resulting accuracy rate is 99.6%. And it can be concluded broadly that the greatest influence of the accuracy of the back propagation algorithm is based on momentum. Because in testing momentum the highest accuracy can be produced compared to the results of other analyzes.

ADVANTAGES

The greatest influence on the level of accuracy is based on momentum. Because in testing momentum the highest accuracy can be produced compared to the results of other analyzes.

DRAWBACKS

Irregular changes in all results of this analysis are caused by the initial weight randomly entered

2.6 DETECTION OF BIPOLAR PATIENT'S FACIAL EXPRESSION USING ANN

2.6.1 ARTIFICIALNEURAL NETWORK

Implementing Artificial Neural Network training processing Python. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired the brain. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning largely involves adjustments to the synaptic connections that exist between neurons.

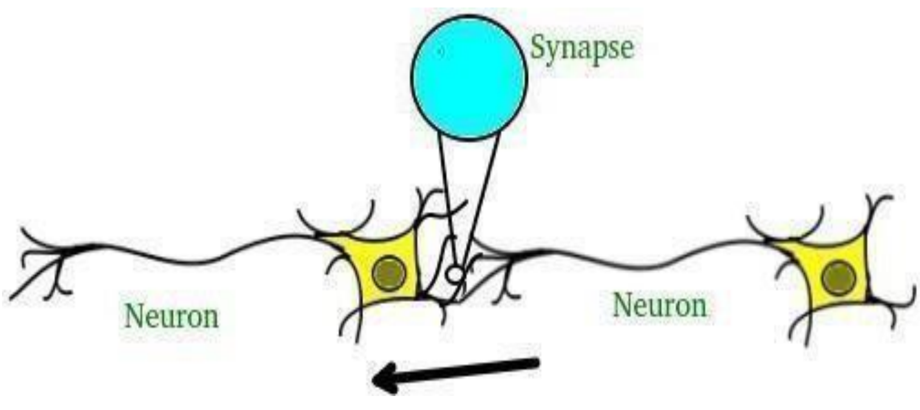


Fig4.1 Structure of Neuron

The brain consists of hundreds of bilions of cells caled neurons. These neurons are connected together by synapses as shown in fig 4.1 structure of Neuron which are nothing.But the connections across which a neuron can send an impulse to another neuron. When a neuron sends an excitatory signal to anotherneuron, then this signal wil be added to all of the other inputs of that neuron. If it exceeds a given threshold then it wil cause the target neuron to fire an action signal forward this is how the thinking process works internaly .Artificial Neural Network (ANN)models have proven to be a very interesting tool, and there are many relevant and interesting contributions using ANN models, with different purposes, but somehow related to real- time estimation of asset reliability and energy generation.

This document provides a precise review of the literature related to the use of ANN when predicting behaviors in energy production for the referred renewable energy sources. Special attention is paid to describe the scope of the different case studies, the specific approaches that were used over time, and the main variables that were considered. Al contributions, this paper highlights those incorporating intelligence to anticipate reliability problems and to develop ad-hoc advanced maintenance policies. The purpose is to offer the readers an overall picture per energy source, estimating the significance that this tool has a c h i e v over the last years, and identifying the potential of these techniques for future depend ability analysis.

2.6.2 DRAWBACKS OF EXISTING SYSTEM

- ✓ Difficult to get accurate results.
- ✓ Possibilities of misclassification images are also high using ANN Algorithm.
- ✓ Image Accuracy is minimized.

2.6.3 PROBLEMCONSIDERATION

The first thing to be aware of in our consideration of employing the ANNs is the nature of the problem we are trying to solve: does the problem require a supervised or an unsupervised approach. The supervised problem means that the chemist has already a set of experiments with known outcomes for specific inputs at hand, while the unsupervised problem means that one deals with a set of experimental data which have no specific associated answers (or supplemental information)attached. Typically, unsupervised problems arise when the chemist has to explore the experimental data collected during pollution monitoring, or always he or she is faced with the measured data at the first time or if one must find a good method to display the data in a most appropriate way.

Usualy, first problems associated with handling data require unsupervised methods. Only further after we became more familiar with the measurement space (the measurement regions) of input and output.

Variables and with the behaviors of the responses, we can select sets of data on which the supervised methods (modeling for example) can be carried on. The basic types of goals or problems in analytical chemistry for solution of which the ANNs can be used are the following:

Selection of samples from a large quantity of the existing ones for further handling, classification of an unknown sample Into a class out of several pre- defined (known in advance) number of existing classes.

Clustering of objects, i.e., finding the inner structure of the measurement space to which the samples belong, and making direct and inverse models for predicting behaviors or effects of unknown samples in a quantitative manner. Once we have decided which type of the problem we have, we can look for the best strategy or method to solve it. Of, course in any of the above aspects we can employ one or more different ANN architectures and different ANN learning strategies.

2.7 EXSISTING METHOLOGY

Despite the notable success of traditional facial recognition methods through the extracted of handcrafted features, over the past decade researchers have directed to the deep learning approach due to its high automatic recognition capacity. In this context, we will present some recent studies in FER, which show proposed methods of deep learning in order to obtain better detection. Train and test on several static or sequential databases.

2.1 Popular databases for measuring intensity of emotions

Database	Database Description	Emotion Description Intensity	Type
Cohn-Kanade (CK) [62]	100 multi-ethnic subjects, 69% female, 31% male (age: 18–50) with frontal and 30∘ view	23 series of facial display, available, AU-coded face database	P

Database	Database Description	Emotion Description Intensity	Type
		(single and combination)	
Extended CK (CK+) [63]	123 multi-ethnic subjects, extension of CK	66/123 subjects considered, spontaneous smiles, onset to peak coded	SP
JAFFE [64]	Japanese Female Facial Expression, Grayscale images with 10 subjects	6 basic emotions + neutral, 2–4 samples per expression, available	P
Bosphorus	105 subject, 44 female, 61 male	2D/3D AU-coded, pose, and illumination variations, available	P
BU-3DFE [65]	Binghamton University 3D Facial Expression, multi-ethnic, 56 female and 44 male (age: 18–70), 2500 samples	4 intensity levels, 6 basic emotions + neutral, available	P
RU-FACS	Rochester/UCSD Facial Action Coding System, 100 subjects	AU-FACS coded, private database with 33 AUs, unavailable	SP
NVIE	Natural Visible and Infrared (IR) facial Expression, Visible and IR imaging, 215 students (age: 17–31)	temporal analysis for face data, basic 6 expressions, available	SP
MMI	25 multi-ethnic subjects, 12 female, 13 male (age: 20–32)	Onset, offset, apex temporal analysis, single + combined AUs, available	SP
DISFA [60,66,67]	Denver Intensity of Spontaneous Facial Actions, 12 female, 15 male, 130,000 video frames	Intensity of 12 AUs coded, available	S
Belfast Induced Emotion	Three set of tasks, lab-based emotion induction tasks	Intensity plus emotion, trace style rating of intensity and valence	S
PAINFUL DATA	UNBC-McMaster Shoulder Pain Expression Archive Database, 200 video sequences, 66 female, 63 male	Pain related AUs coded, available	S

(Type: P: Only Posed, S: Only Spontaneous, SP: Spontaneous and Posed).

2.2 Comparative study of accuracy achieved for intensity of emotions.

Work	Technique	Database	Accuracy	Drawbacks
[69]	Iterated Closest Point (ICP), PCA	355 images	92.00%	Low accuracy *
[70]	Geometric-based approach, Haar feature selection technique (HFST)	FRGC v2	97.00%	Unsuitable for real-time applications
[71]	K-means clustering with back-propagation	CK	98%	Unsuitable for real-time applications
[72]	AAM, Lucas-Kanade, BPNN	BU-3DFE	83.80%	Low accuracy
[73]	Feature Distribution Entropy, Euclidean distances between 83 3D facial feature points, Adaboost	BU-3DFE	95.1%	Unsuitable for real-time applications
[74]	Distance vectors, neural network	BU-3DFE	91.30%	Low accuracy
[75]	Principal Component Analysis	FRGC v1	95%	—
[42]	Stochastic Neighbor Embedding, Gabor wavelet, SVM	JAFFE	58.70%	Low accuracy, small database
[76]	Local Binary Patterns (LBP)	10 Volunteers	89.60%	Low accuracy, small database
[77]	Gradient-based ternary texture patterns, SVM	CK	97.10%	—
[78]	Gaussian curvature, Gabor wavelets, shape index, SVM	Bosphorus, (2902 images)	63.10%	Only 25 AUs from still images considered
[79]	Facial data generator, Hercules engine	Webcam data	89.60%	Low accuracy, slow
[80]	Spectral regression, SVM	18 min-video	92%	Limited data
[81]	Dynamic Bayesian Network (DBN), Adaboost (ADB)	DISFA	72.77% (DBN), 69.31%	Low accuracy, AU extraction and intensity inference

Work	Technique	Database	Accuracy	Drawbacks
			(ADB)	phases independent
[82]	Conditional random Field Model	DISFA, FERA2015	70% (DISFA), 50% (FERA)	Limited data, low accuracy

* Low accuracy indicates it is low for real-world applications.

2.8 RESEARCH METHODOLOGY

2.8.1 Introduction To Deep Learning

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

Deep-learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

2.8.2 Machine Learning vs. Deep Learning

In practical terms, deep learning is just a subset of machine learning. In fact, deep learning technically *is* machine learning and functions in a similar way (hence why the terms are sometimes loosely interchanged). However, its capabilities are different.

While basic machine learning models do become progressively better at whatever their function is, they still need some guidance. If an AI algorithm returns an inaccurate prediction, then an engineer has to step in and make adjustments. With a deep learning model, an algorithm can determine on its own if a prediction is accurate or not through its own neural network

- ✓ Machine learning uses algorithms to parse data, learn from that data, and make informed decisions based on what it has learned.
- ✓ Deep learning structures algorithms in layers to create an "artificial neural network" that can learn and make intelligent decisions on its own
- ✓ Deep learning is a subfield of machine learning. While both fall under the broad category of artificial intelligence, deep learning is what powers the most human-like artificial intelligence

CHAPTER 3

SYSTEM DESIGN

3.1 PROPOSED METHEDOLOGIES

3.1.1 Convolutional Neural Network

Convolutional neural network (CNN) is the most popular way of analyzing images. CNN is different from a multi-layer perceptron (MLP) as they have hidden layers, called convolutional layers.

3.1.2 Basics Of CNN

Existing facial expression classifiers have been almost perfect on analyzing constrained frontal faces , they fail to perform wellon partially occluded faces that are common in the wild. In proposed work, Convolution Neutral Network (CNN) has high accuracy.

Convolution Neutral Network with attention mechanism (CNN) that can perceive the occlusion regions of the face and focus on the most discriminative unconcluded regions. It combines the multiple representations from facial regions of interest. Each representation is weighed via a proposed Gate Unit that computes an adaptive weight from the region itself according to the unobstructedness and importance. Facial expression to analysis tasks, occlusion is one of the inherent challenges in the real-world facial expression recognition and other facial analysis tasks, e.g., facial recognition, age estimate, gender classification. Previous approaches that address facial occlusions can be classified into two categories: holistic - based or part-based methods. Holistic-based approaches treat the face as a whole and do not explicitly divide the face into sub –regions.

The deep learning technology shows remarkable performance in various computer vision tasks such as image classification. This use the Convolutional Neural Network (CNN) which has shown better prediction results for the emotion classification compared to the model that uses a shallow network such as the linear model.

The CNN has a big impact especially in the image classification, and it is an effective network model for learning filters that capture the shapes that repeatedly appear in images. The learning process for the image emotion prediction should be different from that of image classification.

In addition, one of the main issues in the emotion recognition is the affective gap. The affective gap is the lack of coincidence between the measurable signal properties, commonly referred to as features, and the expected affective state in which the user is brought by perceiving the signal. To narrow this affective gap, several works proposed emotion classification systems based on the psychology and art theory based high level features such as harmony, movement, rule of third. While those features help to improve the emotion recognition, a better set of features are still necessary. The effective features among various features are also important.

3.2 SYSTEM SPECIFICATION

3.2.1 HARDWARE SPECIFICATION

1. Processor Ram - Intel(R)Core(TM)i5CPUM480@2.67
2. Ram - 4GB
3. System Type - 64 bit Operating System

3.2.2 SOFTWARE SPECIFICATION

1. OS - Windows7
2. IDE - Python3.6

CHAPTER 4

DETECTION OF BIPOLAR PATIENT'S FACIAL EXPRESSION USING CNN ALGORITHM

4.1 INTRODUCTION

The main objective is to classify the imbalanced datasets by using convolutional neural network to improve the accuracy of data. CNNs have wide applications in image andvideo recognition, recommender systems and natural language processing. In this article, the example that I will take is related to Computer Vision. Convolutional Neural Networks (CNNs) are designed to map image data (or 2D multi-dimensional data) to an output variable (1 dimensional data). They have proven so effective that they are the ready to use method for any type of prediction problem involving image data as an input. The benefit of using CNNs is their ability to develop an internal representation of a two-dimensional image.This allows the model to learn position and scale in variant structures in the data that is important in workingwith images.

4.2 REASON FOR CONVOLUTIONALNEURAL NETWORK

CNNs is image classification, It is used for understanding in Natural Language Processing (NLP) and speech recognition. A CNN can also be implemented as a U-Net architecture, essentially two almost mirrored CNNs resulting in a CNN architecture can be presented in a U shape. U-nets are used on the output needs to be of similar size to the input such as segmentation and image improvement

4.3 TOOLS FOR IMPLEMENTING CNN

Table 4.1 Tools used for implementing CNN

Tool	Developed	Supported Operating Systems	Programming Language	GPU Support
Sklearn	David Cournapeau	Linux, Windows,mac OS	Python,Cython,C and C++	Yes
Tensor Flow	Google	Mac OS, Linux (32 or 64-bit)	python, c, c++	Yes
Keras	Google	Windows, Linux, Mac OS (32 or 64-bit)	python	Yes

4.4 CNN ARCHITECTURE

CNN consist of the input layer and the output layer and also multiple hidden layers. The hidden layers of a CNN typically consist of convolution layers, pooling layers, fully connected layers. It is made up of neurons with learnable weights and biases. Each neuron receives several inputs, takes a weighted sum over them, pass it through an activation function and responds with an output. The below figure shows the architecture of CNN.

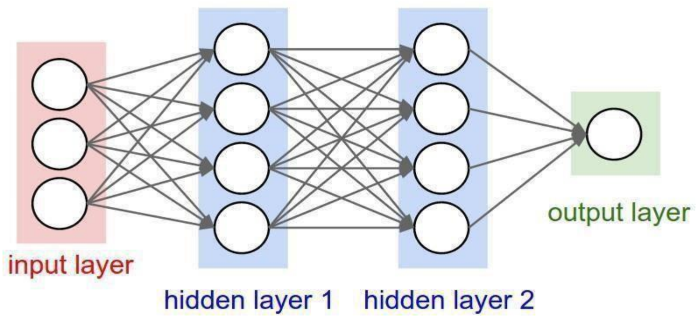


Figure 4.1 CNN ARCHITECTURE

4.4.1 Layers of CNN

A simple ConvNet is a sequence of layers, and every layer of a ConvNet transforms one volume of activations to an other through a differentiable function. The three main types of layers to build ConvNet architectures: Convolutional Layer, Pooling Layer, and Fully-Connected Layer (exactly as seen in regular Neural Networks).Stacking all layers to form a full ConvNet architecture. Convolutional Layer

The convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), that have a small receptive field, but extend through the full depth of the input volume. This layer applies a convolution operation to the input, passing result to the next layer. The convolution emulates the response of an individual neuron.

4.4.2 Pooling Layer

Pooling layers reduce the dimensions of the data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer. Local pooling combines small clusters, typically 2 x 2. Global pooling acts on all the neurons of the convolution layer. Max pooling uses the maximum value from the cluster of neuron, average pooling uses the average values from the cluster of neuron.

4.4.3 Fully Connected Layer

The layer connects every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional MLP. The flattened matrix values used.

The following steps are followed in the classification

Step 1: The sentence represented as n*k format.

Step 2: Convolution layer with multiple filters widths and feature maps.

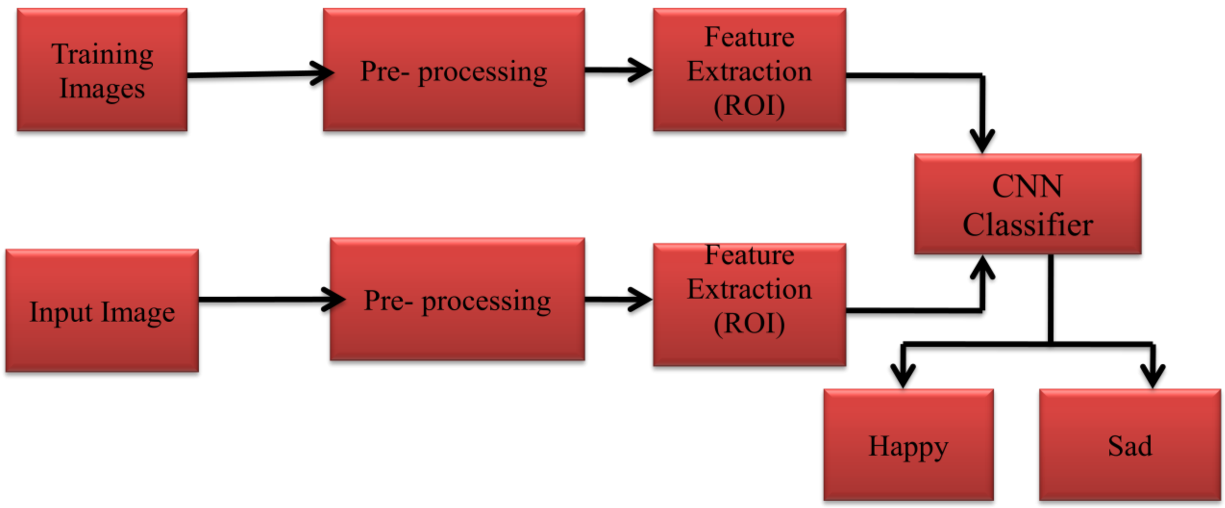
Step 3: Perform max over time pooling with the output of the Convolution Layer

Step 4: Fully connected layer with dropout and output.

4.5 ADVANTAGES OF CNN

- ✓ Detection using CNN is rugged to distortions such as change in shape due to camera lens, different lighting conditions, horizontal and vertical etc., However CNN are shift invariant since the same weight configurations is used across the space.
- ✓ In a CNN number of parameters is drastically reduced, training time is also reduced and also memory space is reduced.
- ✓ In practical mining standard neural network equivalent to CNN would have more parameters , that would lead to more noise addition during the training process.

4.6 SYSTEM FLOW DIAGRAMS



4.7 LIST OFMODULES

The three modules are,

- Module 1 – Training Images
- Module 2 –Classification
- Module 3 – Real time detection of facial expression

4.7.1 Module-1Training Images

The training of Convolution Neural Network requires maximum number of images as their training dataset. The following images as fig 4.1 are collected from various online source and research dataset of available works. Images are accumulated, shuffled and converted to Numpy array .Numpy array is considered as input

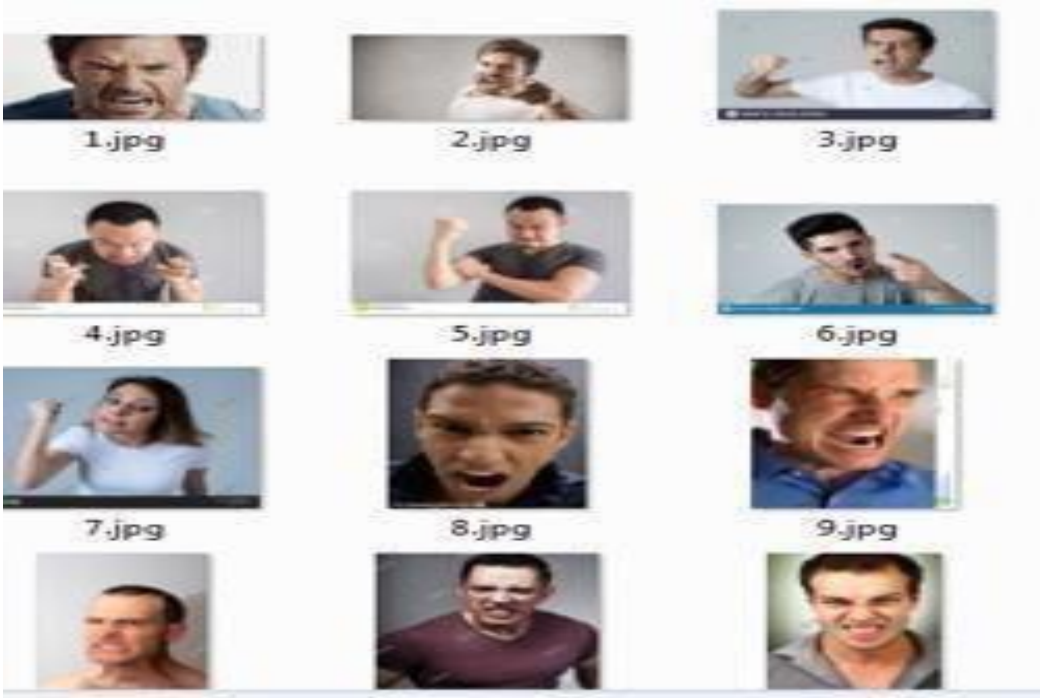


Fig 4.2 Training set

for Convolution Neural Network

4.6.2 Pre-Processing

In proposed work the performance of preprocessing methods are compared namely Contrast adjustment, Intensity adjustment, histogram equalization, binarization, morphological operation and resizing the input images. The original images in a dataset may have inconsistent size and contains redundant information. The expression is mainly reflected by the eyes, nose, and mouth area, whereas the surrounding area is basically useless. Therefore ,it is unnecessary to extract features from the whole image, and the processing of redundant information will only increase the workload of the system. Thus, image preprocessing is necessary. Normalization and Equalization were performed on the

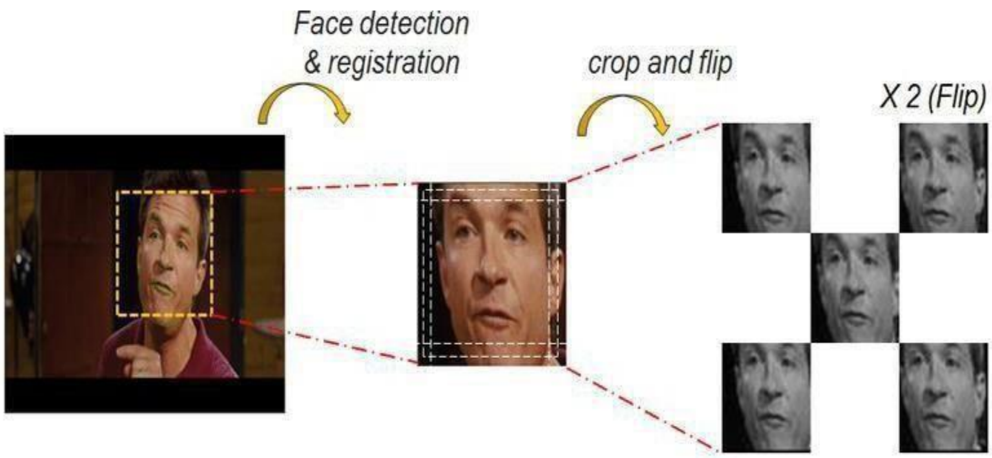


Fig 4.3 Face Detection and Registration

original images The facial images were detected and all images were normalized to a gray-level image of size 64x64 pixels.

4.6.3 Module 2 – Classification

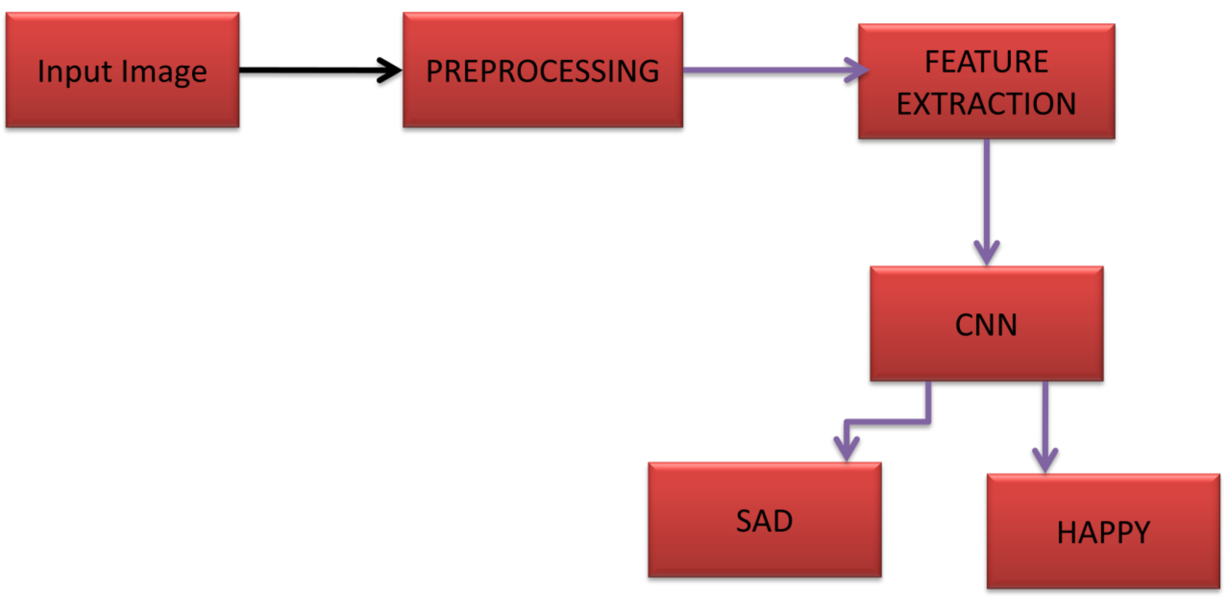
We proposed a system which automatically recognizes the emotion represented on a face. Thus a neural network based solution combined with image processing is used in classifying the universal emotions: Happiness, Sadness, Anger, Disgust, Surprise and Fear. Colored frontal face images are given as input to the prototype system. After the face is detected, image processing based feature point extraction method is used to extract a set of selected feature points. Finally, a set of values obtained after processing those extracted feature points are given as input to the neural network to recognize the emotion contained.

4.6.4 Module 3: Real time detection of facial expression

We have developed a convolution neural network for classifying human emotions from dynamic facial expressions in real time. We use transfer learning on the fully connected layers of an existing convolution neural network which was pertained for human emotion classification. A variety of datasets, as wel as our own unique image dataset, is used to train the model. An overall training accuracy of 90.7% and test accuracy of 57.1% is achieved.

Finally, a live video stream connected to a face detector feeds images to the neural network. The network subsequently classifies an arbitrary number of faces per image simultaneously in real time, where inappropriate emotions are predicted with accuracy.

The system automatically detects frontal faces in the video stream and codes them with respect to 7 dimensions in real time: neutral, anger, disgust, fear, crying, sadness, surprise. Rise. The system presented here differs from previous work in that it is fully automatic and operates in real-time at a high level of accuracy (93% generalization to new subjects on a 7-alternative forced choices. The results demonstrate the feasibility of implementing neural networks in real time to detect human emotion.



CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

The technological improvements in information and communication technologies, a highly anticipated key contributor to improve the patient's experience analytics, such as to evaluate the patient's emotions over the life time of the patients. In Proposed system first the database is trained using convolution neural network. Using visual emotion recognition system patient's emotion is detected then classification parts were implemented on it. The seven emotions (happy, angry, sad, crying, surprise, neutral and fear are detected from video data which are mapped and classified.

5.2 FUTURE WORK

In this projects deep learning issued for image classification, the future enhancement may be voice regoconization using Natural Language Processing.

Appendix I

Source Code:

```
from keras.preprocessing.image import img_to_array
from keras.models import load_model
import numpy as np
import imutils
import pickle
import cv2
import os
from playsound import playsound


image = cv2.imread("examples/1.jpg")
output = imutils.resize(image,width=400)
print (output)
image = cv2.resize(image, (96, 96))
image = image.astype("float") / 255.0
image = img_to_array(image)
image = np.expand_dims(image, axis=0)
print("[INFO] loading network...")
model = load_model("Facial expression")
mlb = pickle.loads(open("mlb.pickle", "rb").read())
print("[INFO] classifying image...")
proba = model.predict(image)[0]
print(proba)
idxs = np.argsort(proba)[::-1][:1]
for (i, j) in enumerate(idxs):
	label = "{}: {:.2f}%".format(mlb.classes_[j], proba[j] * 100)
	a= proba[j] * 100
	cv2.putText(output, label, (10, (i * 30) + 25),
		cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 255, 0), 2)
cv2.imshow("Output", output)
cv2.waitKey(0)

print(label)
label = label.split(':')
if label[0]=="SADNESS":
  playsound('1.mpeg')
elif label[0] == "HAPPY":
```

```
   playsound('2.mpeg')
elif label[0] == "FEAR":
    playsound('3.mpeg')
elif label[0] == "NEUTRAL":
    playsound('4.mpeg')
elif label[0] == "ANGRY":
    playsound('5.mpeg')
elif label[0] == "SURPRICES":
    playsound('6.mpeg')
elif label[0] == "CRYING":
    playsound('7.mpeg')
```

classification

```
        # set the matplotlib backend so figures can be saved in the background
import matplotlib
matplotlib.use("Agg")
# import the necessary packages
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam
from keras.preprocessing.image import img_to_array
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.model_selection import train_test_split
from pyimagesearch.smallervggnet import SmallerVGGNet
import matplotlib.pyplot as plt
from imutils import paths
import numpy as np
import random
import pickle
import cv2
import os
EPOCHS = 44
INIT_LR = 1e-3
BS = 32
IMAGE_DIMS = (96, 96, 3)
print("[INFO] loading images...")
imagePaths = sorted(list(paths.list_images("dataset")))
random.seed(42)
random.shuffle(imagePaths)
data = []
labels = []
for imagePath in imagePaths:
        image = cv2.imread(imagePath)
        image = cv2.resize(image,(IMAGE_DIMS[1],IMAGE_DIMS[0]))
        image = img_to_array(image)
        data.append(image)
```

```
        l = label = imagePath.split(os.path.sep)[-2].split("_")
        labels.append(l)
data = np.array(data, dtype="float") / 255.0
labels = np.array(labels)
print("[INFO] data matrix: {} images ({:.2f}MB)".format(
        len(imagePaths), data.nbytes / (1024 * 1000.0)))
print("[INFO] class labels:")
mlb = MultiLabelBinarizer()
labels = mlb.fit_transform(labels)
for (i, label) in enumerate(mlb.classes_):
        print("{}. {}".format(i + 1, label))
(trainX, testX, trainY, testY) = train_test_split(data,
        labels, test_size=0.2, random_state=42)
aug = ImageDataGenerator(rotation_range=25, width_shift_range=0.1,
        height_shift_range=0.1, shear_range=0.2, zoom_range=0.2,
        horizontal_flip=True, fill_mode="nearest")
print("[INFO] compiling model...")
model = SmallerVGGNet.build(
        width=IMAGE_DIMS[1], height=IMAGE_DIMS[0],
        depth=IMAGE_DIMS[2], classes=len(mlb.classes_),
        finalAct="sigmoid")
opt = Adam(lr=INIT_LR, decay=INIT_LR / EPOCHS)
model.compile(loss="binary_crossentropy", optimizer=opt,
        metrics=["accuracy"])
print("[INFO] training network...")
H = model.fit_generator(
        aug.flow(trainX, trainY, batch_size=BS),
        validation_data=(testX, testY),
        steps_per_epoch=len(trainX) // BS,
        epochs=EPOCHS, verbose=1)
print("[INFO] serializing network...")
model.save("Facial expression")
print("[INFO] serializing label binarizer...")
f = open("mlb.pickle", "wb")
f.write(pickle.dumps(mlb))
f.close()
print("Training done")
```

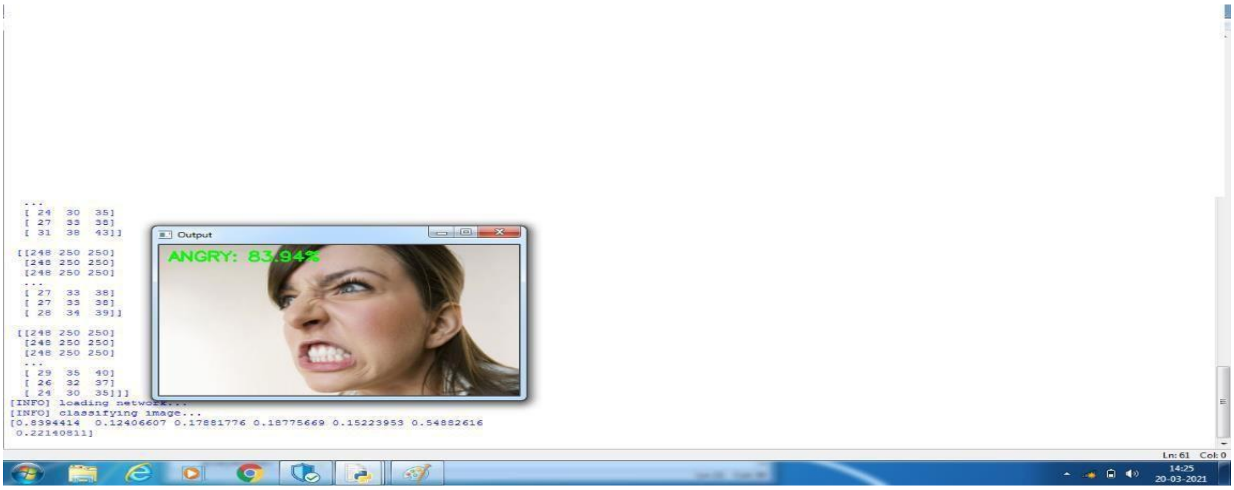
APPENDIX II

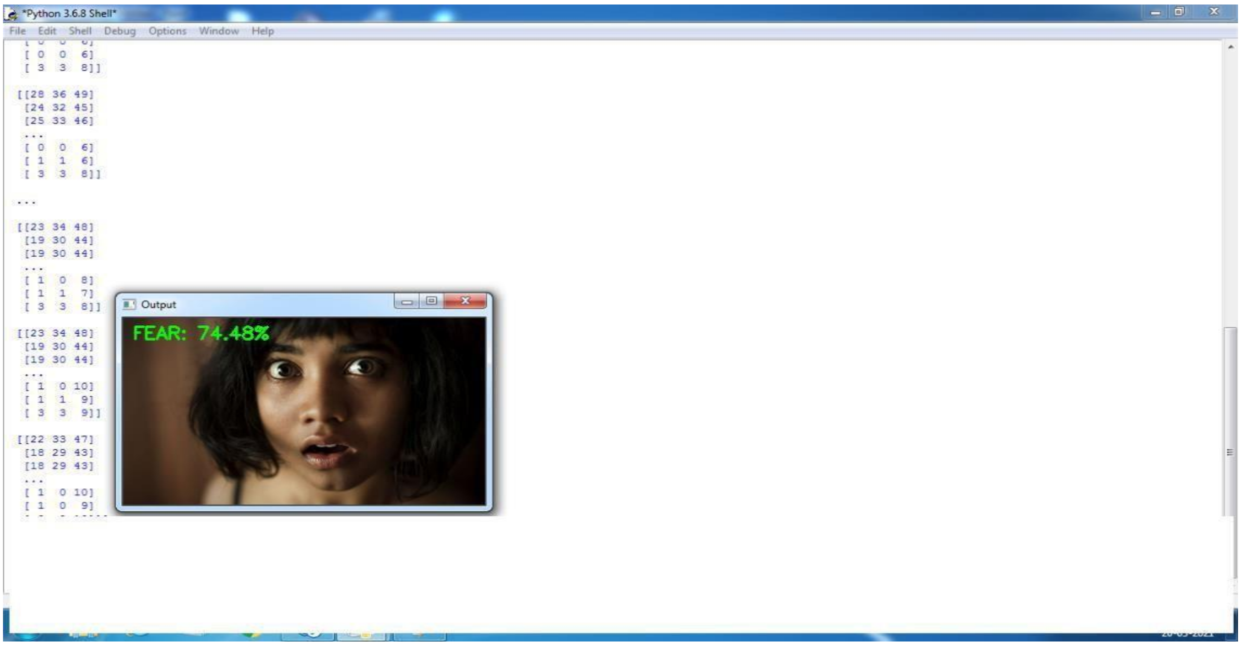
```
[INFO] loading images...
[INFO] data matrix: 102 images (22.03MB)
[INFO] class labels:
1. ANGRY
2. CRYING
3. FEAR
4. HAPPY
5. NEUTRAL
6. SADNESS
7. SURPRICES
[INFO] compiling model...
[INFO] training network...
Epoch 1/44
1/2 [=============>..............] - ETA: 5s - loss: 1.1725 - acc: 0.4118 2/2 [==========
==================] - 18s 9s/step - loss: 1.1334 - acc: 0.4382 - val_loss: 1.6104 - val_acc: 0.2993
Epoch 2/44
1/2 [=============>..............] - ETA: 7s - loss: 1.0489 - acc: 0.5268 2/2 [==========
==================] - 17s 8s/step - loss: 1.0159 - acc: 0.5424 - val_loss: 1.4767 - val_acc: 0.4830
Epoch 3/44
1/2 [=============>..............] - ETA: 7s - loss: 1.1233 - acc: 0.5312 2/2.[==========
==================] - 15s 7s/step - loss: 0.9948 - acc: 0.5644 - val_loss: 1.4151 - val_acc: 0.4082
```

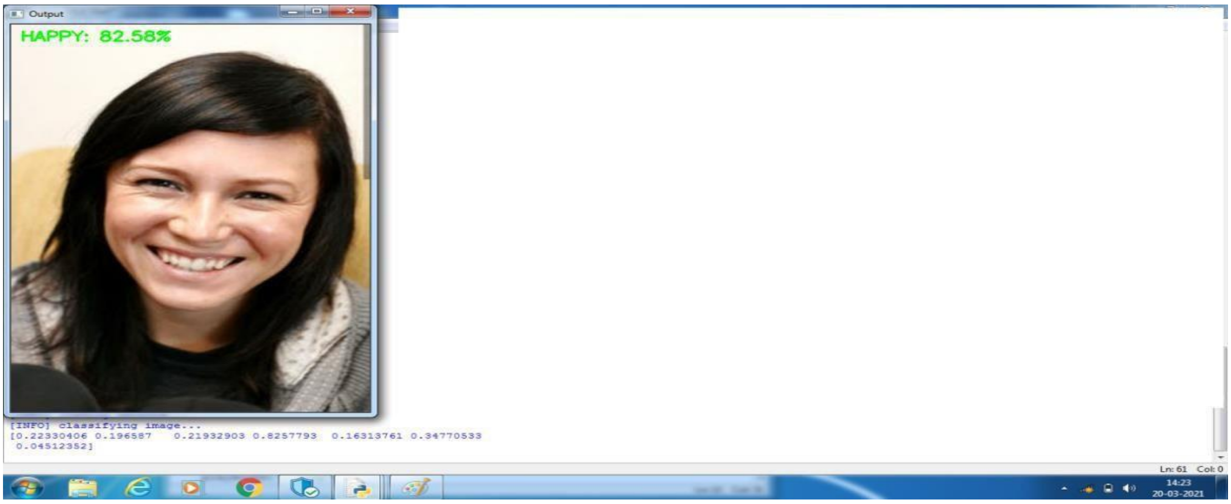
```
Epoch 41/44
1/2 [=============>..............] - ETA: 5s - loss: 0.2978 - acc: 0.8616 2/2 [==========
===================] - 10s 5s/step - loss: 0.3126 - acc: 0.8634 - val_loss: 0.5794 - val_acc: 0.7619
Epoch 42/44
1/2 [=============>..............] - ETA: 5s - loss: 0.3533 - acc: 0.8438 2/2 [==========
===================] - 13s 6s/step - loss: 0.3430 - acc: 0.8527 - val_loss: 0.6671 - val_acc: 0.7551
Epoch 43/44
1/2 [=============>..............] - ETA: 3s - loss: 0.3528 - acc: 0.8906 2/2 [==========
===================] - 10s 5s/step - loss: 0.3458 - acc: 0.8870 - val_loss: 0.6155 - val_acc: 0.7687
Epoch 44/44
1/2 [=============>..............] - ETA: 7s - loss: 0.3119 - acc: 0.8616 2/2 [==========
===================] - 14s 7s/step - loss: 0.3488 - acc: 0.8594 - val_loss: 0.6058 - val_acc: 0.7687
[INFO] serializing network...
[INFO] serializing label binarizer...
Training done
```

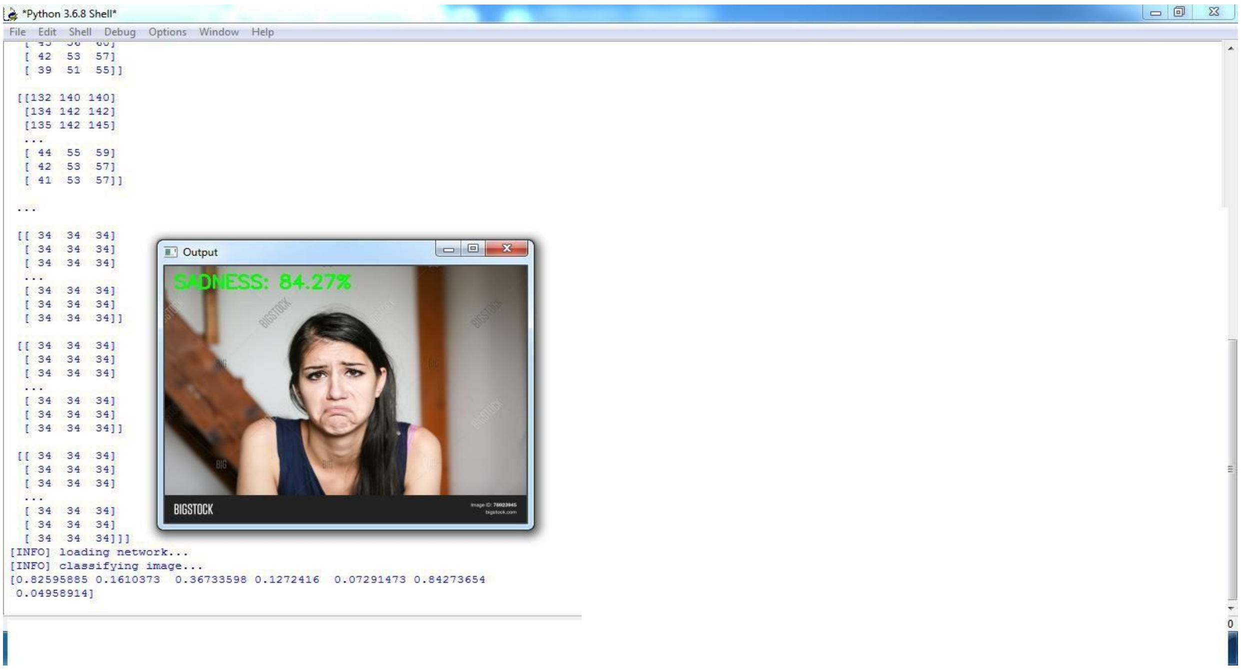
The above image represented that the model is trained well with the sample images and emotions are classified in major 7 categories.

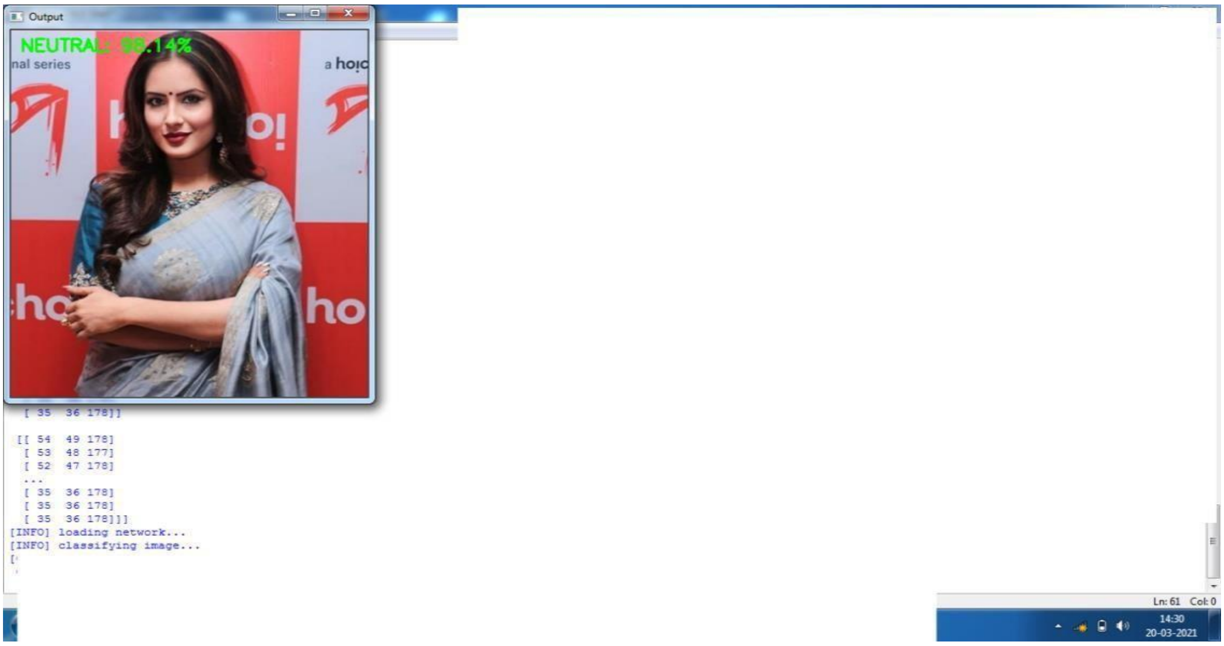

```
[INFO] loading network...
[INFO] classifying image...
[0.06123714 0.99596465 0.12803209 0.10355534 0.15099992 0.09299295
 0.31134108]
```

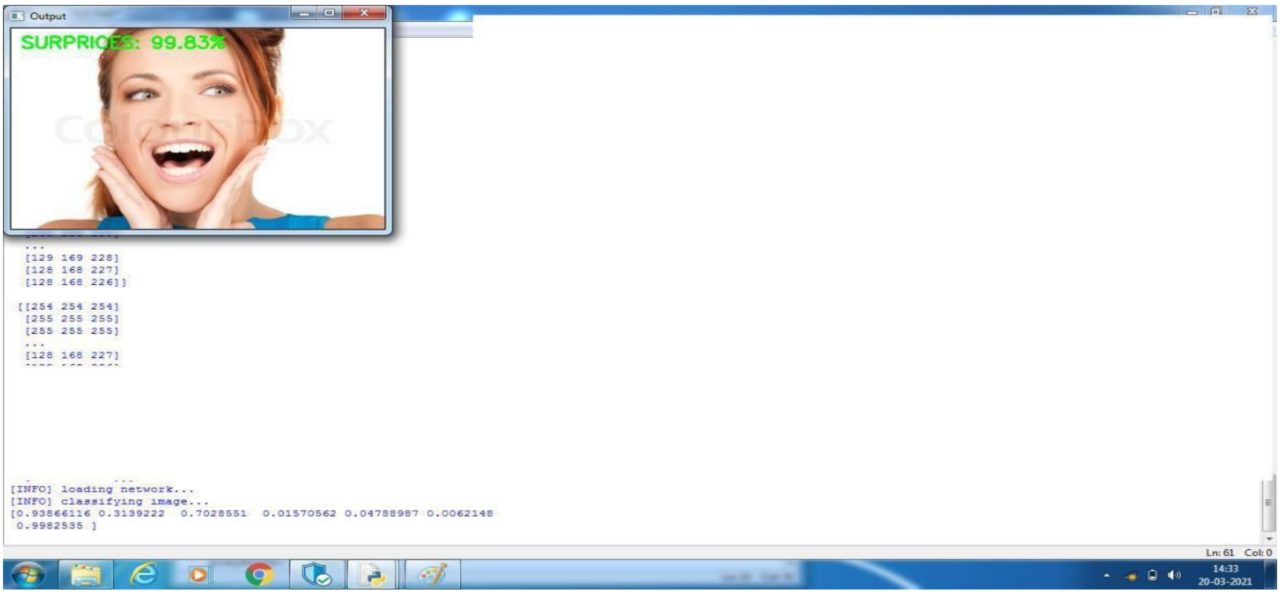

Output
ANGRY: 83.94%
[INFO] loading network...
[INFO] classifying image...


Python 3.6.8 Shell
File Edit Shell Debug Options Window Help
Output
FEAR: 74.48%


Output
HAPPY: 82.58%
[INFO] classifying image...
[0.22330406 0.196587 0.21932903 0.8257793 0.16313761 0.34770533
0.04512352]
Ln: 61 Col: 0
14:23
20-03-2021


Python 3.6.8 Shell
File Edit Shell Debug Options Window Help
[42 53 57]
[39 51 55]]
[[132 140 140]
[134 142 142]
[135 142 145]
...
[44 55 59]
[42 53 57]
[41 53 57]]
...
Output
SADNESS: 84.27%
BIGSTOCK
[INFO] loading network...
[INFO] classifying image...
[0.82595885 0.1610373 0.36733598 0.1272416 0.07291473 0.84273654
0.04958914]


Output
NEUTRAL: 98.14%
[[54 49 178]
[53 48 177]
[52 47 178]
...
[35 36 178]
[35 36 178]
[35 36 178]]]
[INFO] loading network...
[INFO] classifying image...
Ln: 61 Col: 0
14:30
20-03-2021


Output
SURPRICES: 99.83%
[129 169 228]
[128 168 227]
[128 168 226]]
[[254 254 254]
[255 255 255]
[255 255 255]
...
[128 168 227]
[INFO] loading network...
[INFO] classifying image...
[0.93866116 0.3139222 0.7028551 0.01570562 0.04788987 0.0062148
0.9982535]
Ln: 61 Col: 0
14:33
20-03-2021

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