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PHYSIOLOGICAL EMOTION RECOGNITION BY MEANS OF MACHINE LEARNING DEMONSTRATION

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ABSTRACT:

The objective of Emotion Recognition is to identify the emotions of humans which can be captured either from face or from verbal communication. In this project, we focus on identifying human emotions from facial expressions. Facial expressions are important when we communicate, this will enable us to develop and decipher impressions of people around us. We make use of Image Processing Techniques such as Computer Vision Technique to recognize faces in both images and video streams and also Convolution Neural Networks from Deep Learning Technique has been used for better results and also to classify the image followed by feature extraction from the image. Using the extracted feature, the system is trained to classify a facial expression as happy, sad, disguised, neutral, pain or angry. This system works upon the human face for as we know that the face reflects the human brain activities or emotions. Hence, we impart intelligence to the computer in recognizing the human emotions by which we can easily identify the emotion of other humans without much effort. These specialized systems can be further developed and used for a set of research scenarios of emotion recognition applications in the following domains: software engineering, website customization, gaming, monitoring, security, treating patients in the medical field, marketing research , E-learningetc.;

1. INTRODUCTION

Emotion classification requires a study of various factors and variables including common sense emotions of happiness or anger with varying degrees. These qualities and intensities are second nature to humankind and their detection by facial recognition software has proven to be difficult and costly [1].Emotion is omnipresent and an indispensable aspect of human existence [2]. A subject's behavior can heavily influence their way of communication, and in turn affect their daily activities. Emotions also perform a vital role in everyday communication. Simply saying 'ok' can have a different meaning depending on context which could convey remorse, sadness, anger, happiness, or even disgust; however, the full meaning can be understood using facial expressions, hand gestures, and other non-verbal communications[3 -5]. Emotions perform an essential role in human cognition, particularly in rational decision-making, perception, human interaction, and human intelligence. Affective computing has appeared to satiate the gap in emotion, specifically in HCI, by gathering technology and emotions into HCI [6]. HCI measures the emotional status of a user by capturing emotional interactions between a human and a computer. Emotion recognition is the method of knowing a human's emotional status.

Fig 1: Physiological Emotion Recognition by Machine Learning Technique

Analysis of Emotion Recognition profits from the progress of psychology, modern neuroscience, cognitive science, and computer science [7]. In computer science, Emotion Recognition by computer systems aims to enhance human–machine interaction over a broad range of application areas, including clinical, industrial, military, and gaming [8]. Different approaches have been suggested for Emotion Recognition and can be split into two types: first, using the characteristics of emotional behavior, such as facial expression, tone of voice, and body gestures, to identify a particular emotion; second, using signals to identify emotions. The physiological activities can be registered by noninvasive sensors, often as electrical signals. These models involve skin conductivity, electrocardiogram, and EEG [9-13]. Emotion evaluation techniques may consist of subjective and/or objective measurements. Subjective measures can be instruments for self-reporting, such as questionnaires, adjective checklists, and pictorial tools. Objective measures can apply physiological signals such as blood pressure responses, skin responses, pupillary responses, brain waves, and heart responses. Subjective and objective methods can be used jointly to improve the accuracy and reliability of emotional state determination [14].

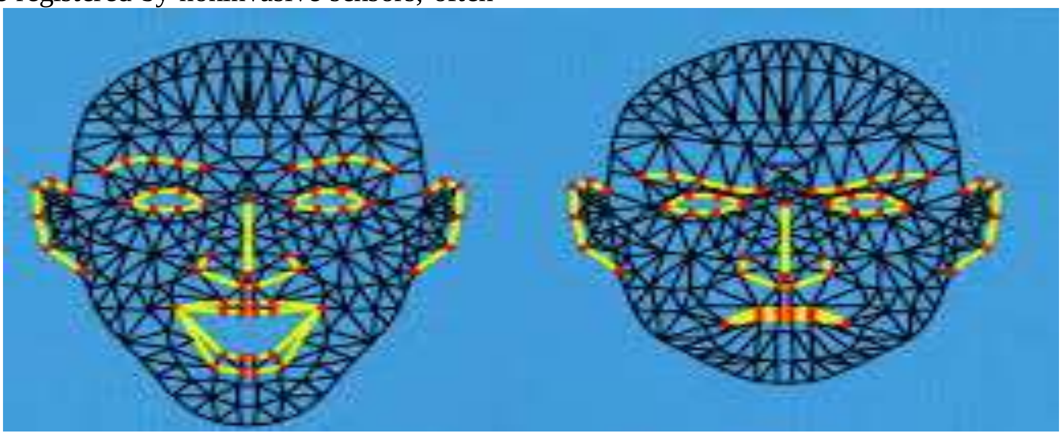

Fig 2: Human emotion

Emotion models were divided into two types: dimensional and discrete. The dimensional model describes the permanence of an emotional state. Most dimensional models combine valence and arousal. The discrete model of emotions assumes more emotions according to a particular number of emotions. Valence regards the level of pleasantness related to emotion. The range of valence represents an unpleasant state to a pleasant state. Arousal indicates the force of experience by emotion. This arousal happens along a continuous sequence and ranges from inactive (e.g., bored) to active (e.g., excited). The following points define the valence, arousal, and dominance emotion categories [15]: • Valence: positive, happy emotions affecting a higher frontal consistency in alpha signals, and higher right parietal beta signal power, a contrast to negative emotion. • Arousal: excitation displaying a higher beta signal power and consistency in the parietal lobe, and lower alpha signal activity. • Dominance: the force of emotion, which is usually shown in the EEG as an addition to the beta/alpha signal activity proportion in the frontal lobe, and an increment in beta activity at the parietal lobe. Plutchik [16] illustrates eight essential emotions: anger, fear, sadness, disgust, surprise, anticipation, acceptance, and joy. All other emotions can be created by these essential ones; for example, disappointment is a combination of surprise and sadness. Emotions can also be classified as negative, positive, and neutral emotions. The basic positive emotions care and happiness are necessary for survival, development, and evolution. Basic negative emotions, including sadness, anger, disgust, and fear, usually operate automatically and within a short period. However, the neutral emotional show policy is not based on scientific theory or research; it is more of a theory or prescriptive model of negotiations [17-18]. Figure 1 shows another classification of emotions, ranging from negative to positive in the case of valence and from high to low in the case of arousal. For example, depressed, as an emotion, lies in the category of low arousal and negative valence.

2. SYSTEM ANALYSIS AND METHODS:

EXISTING METHOD:

This system is built with a multi-modal physiological emotion database, which collects four model physiological signals, i.e., electroencephalogram (EEG), galvanic skin response, respiration, and electrocardiogram (ECG). To alleviate the influence of culture dependent elicitation materials and evoke desired human emotions, an emotion elicitation material database is collected specifically, and then selected from more than 1500 video clips.28 samples are chosen for validating the system with accuracy. The physiological signals of participants were synchronously recorded when they watched these standardized video clips that described six discrete emotions and neutral emotion [18 - 21].

With three types of classification protocols, different feature extraction methods and classifiers (support vector machine and k-Nearest Neighbor) were used to recognize the physiological responses of different emotions, which presented the baseline results. Simultaneously, a novel attention-long short-term memory (A-LSTM) is presented, which strengthens the effectiveness of useful sequences to extract more discriminative features (Fig. 3).

Fig 3: Different Physiological emotionexpressionin human beings

In addition, correlations between the EEG signals and the participants' ratings are investigated. The database has been made publicly available to encourage other researchers to use it to evaluate their own emotion estimation methods [22-24].

PROPOSED METHOD:

In this system, we make use of OpenCV with some 'face recognizer' classes that are capable of recognizing the images using different techniques. Hence this system predicts the phases in an image or video that is processed. After phase detection, we make use of convolution neural networks to classify the image followed by feature extraction. Such extracted features are trained to classify the facial expression as happy, sad, disguised, neutral, pain orangry.

BENEFITS:

- These systems could be deployed for the processing of real-time videosfor monitoring video feeds or automating video analytics, thus saving cost with better user satisfaction.
- This system is cost effective since it does not include anyexpensive hardware or any other sensor attachment.
- One of the major advantages of this system is its ease of access and minimal economicrequirement.

FEASIBILITYSTUDY:

The achievability of the project is analysed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the people. For the ability analysis, some understanding of the majorrequirements for the system is essential.

TECHNICALFEASIBILITY:

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demand on the available technical resources.

ECONOMICALFEASIBILITY:

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. Thus, the developed system is well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to bepurchased.

SOCIALFEASIBILITY:

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must use it with ease.

SYSTEM DESIGN:

ARCHITECTURE DIAGRAM:

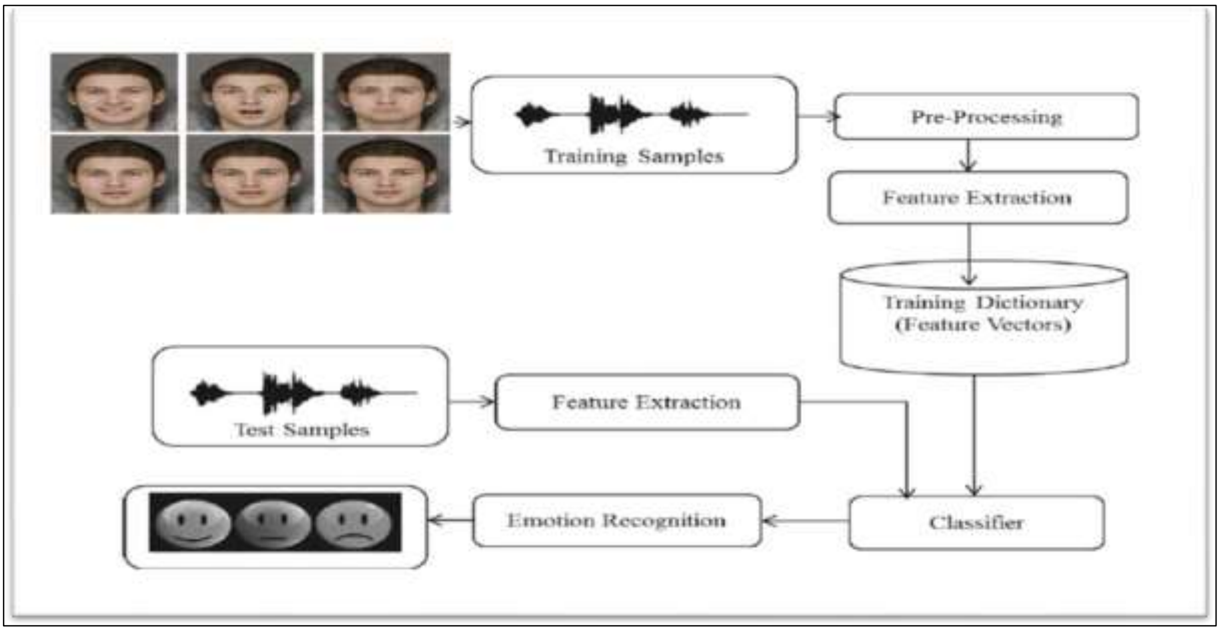

Fig 4: Architecture Diagram

Organizing the dataset remains as the initial phase of the system. The source files are included in our currently working directory. The source file consists of a dataset with around 35,888 images for training, testing and validation. The images are stored in CSV file (Comma Separated Value) as pixel values within which they are classified with appropriate emotions labels(“happy”, “neutral”, “angry”)for training and validation. The neural network which initially learnt nothing is trained using the image dataset. The image will be pre-processed followed by the extraction of the features from the images. The algorithm will be trained at this step. The next step is to extract the features from the test samples so as to classify them as happy, sad, angry, disgust, neutral, scared or with thehelp of the mentioned attributes. Based on this trained classifier, the test sample will be classified as one the trained emotions (Fig 4).

The system architecture of the proposed scheme comprises of three modules:

- Loading theDataset
- Training theModel
- Detection of Emotions

LOADING THEDATASET.

We make use of certain packages for importing and making use of dataset. Some of the major packages are Pandas, NumPy and Computer Vision. The entire data is stored in a directory and its location is defined. Here, the dataset is as a CSV File. Using Pandas, we import and read the CSV file. Once done, we obtain the pixel values of that particular image and resize the image to a standard size that is, height and width to be 48*48 respectively. We initialize the face= [], so as to perform face recognition using the image pixels. We obtain the sequence of images as splits with in data type and assign it to face. NumPy is a package intended to perform certain array manipulation and scientific calculations. We obtain the array of pixel values from the reshaped input image. Since we make use of NumPy array, we display the images using computer vision methods such as imshow(), where we can also pass the wait key functions as an argument in milliseconds as a delay for the window to close. This methodology facilitates various functionalities like Image filtering, Geometric Image Transformations, Miscellaneous Image Transformations, Drawing functions, Histograms and Color Space Conversions. After these steps, the preprocessed image is sent as an input to the emotion detection module or the trainingmodule.

TRAINING THEMODEL

We import necessary packages to perform several operations such as rotation, transformation, scaling, shearing and flipping. The functions forthe processing of images are imported. We initialize the batch size to be 32 which denotes the subset size of the training sample which will be used to train the neural network during the training phase and the number of epochs to be 10,000 which is good for medium sized dataset. Verbose is used to get the information of the system in the form of words. The input shape is declared to be 64*64 with the number of classes to be7. The image data generator is declared with the various arguments such as feature wise center, feature wise standard normalization to be false and the horizontal flip to be true. The convolution neural network needs to be initialized with the input shape and adding some additional information so as to solve an ill-posed problem or to prevent overfitting. Conv2D is initialized with the number of filters and the size of receptive fields to be 3*3.The learned filter is applied to the input image so as to create a feature map that summarizes the existence of features within the given input image. In case of maximum pooling, the maximum value for all patches of the feature map is calculated. The above functionalities are applied in many other subsequent modules so as to get the neural network trainedcompletely.

DETECTION OFEMOTIONS

In this module, the images will be imported as an array alongside the allocation of respective directories and appropriate names, accessing it. The images are applied to the cascade classifier, which do have many numbers of classifiers within it. The classifiers are complex by themselves and are built using any of the boosting algorithms. The simplest classifier is decision tree classifier which consists of weights, which acts as the threshold weight so as to pass on to the subsequent layers of classification. The model will be updated whenever an image is given as an input to it. We declare the various classifications of emotions to be determined at this step. The input shall be in the form of video file or default web camera (The default web camera is accessed using the default port number 0). The frames are read from the captured video. Using the Imutlis package,we make use of it tools that facilitate the image processing. Here the image needs to be resized to specific size (i.e: width of size is set to 800). The image is then converted into 8-bit grayscale so that the image consists only of monochromatic shades from black to white, removing all the colours information of the image leaving only the luminance of each pixel. The facial key point of the face is extracted from the grayscale image; resized to a fixed 64*64 pixels which is said to be the pre-trained model shape. The facial classification is made using the convolution neural networks. The classifier then identifies the type of emotion being exhibited and then it encloses the face within a bounding box followed by labeling of the emotion. Once the processing of image is complete, the computer vision library is used to view the emotion being identified by the system.

3. RESULT AND DISCUSSION

The evolution in the creation of sensors and signal record devices, as well as the development of signal handling and feature extraction techniques, has increased opportunities for using signals extracted from human organs, such as brain signals or heart signals, to identify a person's condition, and thus detect psychological or pathological conditions in humans. This made the task of classifying signals required for improving the productivity of performance in the categorization of cases based on signals. Categorizing emotions based on EEG signals could be one of the most complex applications with regard to analyzing human actions. This type of application can be defined as determining a person's emotional state, which could reflect particular problems (Fig 5).

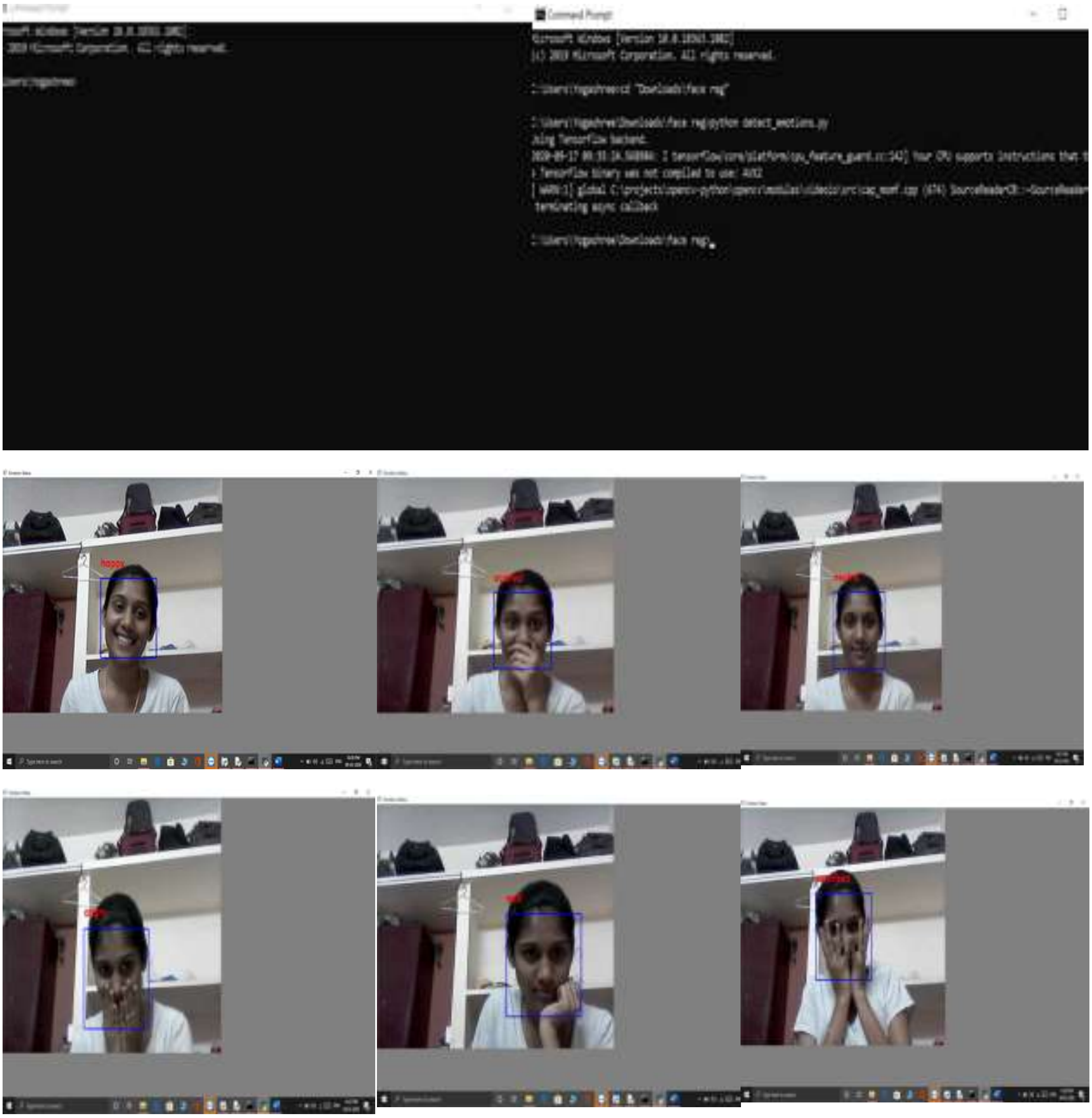

Fig 5: Experiment identification of different Physiological emotion expression

4. CONCLUSION:

There is increasing integration of computers and computer interfaces in our lives. Facial Emotion Recognition System is still in a developing stage whose predominant aim is torecognize emotionsof human face which is obviously a complex task even for humans because exact recognition of facial emotion depends on context from where the emotion originates and expressed. As the facial expression recognition systems are becoming robust and effective in communications, many other innovative applications and uses are yet to be seen.

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CONFLICTS OF INTEREST:

The authors declare that there is no conflict of interest

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