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Machine learning based model to predict Human Emotions using facial features

Akshat Singhal
Computer Science and Engineering
Chandigarh University
Ajitgarh, India
singhalakshat0109@gmail.com

Vanshita Bhardwaj
Computer Science and Engineering
Chandigarh University
Ajitgarh, India
Vanshitabhardwaj6@gmail.com

***Abstract*— This paper focuses on Emotion Recognition using facial expressions. It aims to detect facial expressions accurately and efficiently. Here, we have used facial expressions as the criteria wherein the lips, eyebrow movement, eyes, etc. are the factors that help us detect various emotions. The purpose of this paper is to serve various fields where emotion recognition will be viable and can be helpful for better outcomes. Spectrums like video gaming, psychology, medical fields, etc. can use Emotion Recognition System in a very positive way. Convolutional Neural Network has developed to help in recognizing emotions through facial expressions and classify them into seven basic categories which are: happy, sad, neutral, surprise, fear, disgust, and angry. So, Convolutional Neural Network is implemented to extract relevant features of the input images and classify them into seven categories. For evaluating the proposed model, Facial Emotion Recognition 2013 dataset is used so that the model achieves the best accuracy rate.**

Keywords—Convolutional Neural Network (CNN), Facial Emotion Recognition 2013 (FER 2013), Extended Cohn-Kanade (CK+), Japanese Female Facial Expressions (JAFFE), Emotional Facial Action Coding System (EMFACs), Action Units (AUs).

I. INTRODUCTION

An easy way to detect a person's emotions is his or her face as [1] facial expressions determine how that person is affected. This paper focuses on [2] seven different categories of emotions: happiness, neutrality, surprise, sadness, anger, disgust, and fear. Emotions are desires that play a vital role in the lives of mortals. Every mortal responds to the environment around them. It allows people to create multiple effects such as self-awareness and interaction with others. Most importantly, emotions have a major role to play in people's learning and behaviour. There are many kinds of emotions you may want to have such as love, joy, inspiration, or pride. On the other hand, there are negative emotions such as loneliness, or sadness that you would like to avoid or overcome. You may feel satisfied after a good night's sleep, panic before the test, or get angry when you hit your toe. Emotions play a major role in affecting our moods. Life would be miserable without such pleasures as joy and sorrow, love and fear, breakdown and disappointment. Emotions add colour and spice to life. Emotions such as happiness, disappointment, and grief often have both physical and [3] mental beginnings affecting the gesture. The word emotion is derived from the Latin word 'Emover' which means to move or entertain. Emotions can be defined as the state of being mentally or emotionally disturbed. Emotions are based on two things Awakening and [4] Valence where valence is a positive or negative effect while happiness measures how comforting or motivating information is.

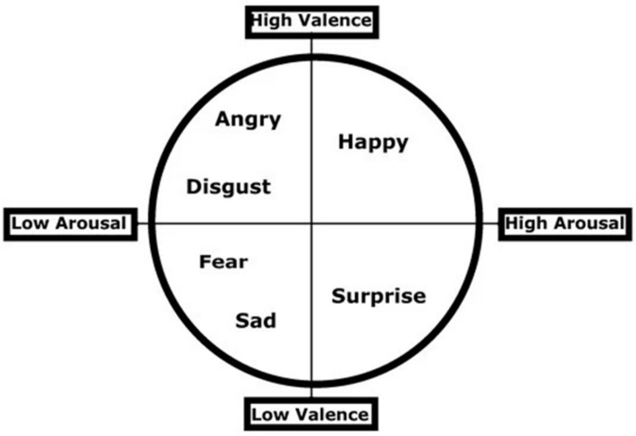

Fig-1: Valence Arousal Model

With the rapid growth of the use of [5] intelligent technology in society and its development, the need for technology that can fulfill the needs of everyone and select the best results from it is increasing exponentially. Automatic emotional testing is important in areas such as [6] marketing, [7] education, [8] robotics, and entertainment. The function is used to perform colorful simulations:

(i) to robots to design interactive or service robots to communicate with humans;

(ii) advertising for the production of technical announcements, based on the client's emotional state;

(iii) in education used to perfect learning processes, knowledge transfer, and cognitive processes;

(iv) on active entertainment to promote the most appropriate entertainment for targeted fans.

In scientific literature, many attempts are made to distinguish emotions and to distinguish between emotions, and affections. According to the last bracket, keywords are defined as follows:

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(i) “emotions” are the [9] biological response to a particular stimulus (person, situation, or event). Often, violence, for a short time, and one is often scared about it;

(ii) “touch” is the result of an emotionally charged effect and includes their dynamic trade;

(iii) “feeling” is always tolerated by something that one is afraid of; its length depends on the length of time that the representation of the object remains active in the human mind;

(iv) “Attitude” is usually subtle, long-lasting, low-tempered, and more aggressive in the background, but may affect a person’s behaviour positively or negatively.

As with any advancing technology, emotional recognition is incomplete and has its limitations and challenges. One of the difficult situations is that data sets are divisive by people, and different people can read and interpret emotions in unusual ways. Additionally, other visible signs such as raised eyebrows may convey other emotions besides anger, and different symptoms may be widespread expressions of anger, though they are no longer visible. Another problem facing this generation is the emotional response to people of different colours. Some models get angrier with black people. This means that educational settings need to be more diverse, and professionals are already doing everything possible to recoup this. It might pose a challenge in the beginning but if rectified it can be a game-changer in the longer run. Colour should just not be a matter of concern and all the focus should hence be on the features individually. Accuracy is key which can be achieved only through a focussed approach, colour is not a part of a person’s emotions and hence shouldn’t be considered and must be rectified if it poses to be a problem. Emotions can be combined to form different emotions. The same can be said of how we can combine the colours of one colour to form special shades of the sun. The main emotions mentioned above serve as building blocks. Combined emotions create complex emotions. For example, the basic emotions involved in acceptance as truth and happiness can be combined to create greater feelings and love.

Fig [2] shows two types of models of human emotions classified based on discrete emotions and valence-arousal. These two classifications were proposed by [10] Ekman and James Lang respectively.

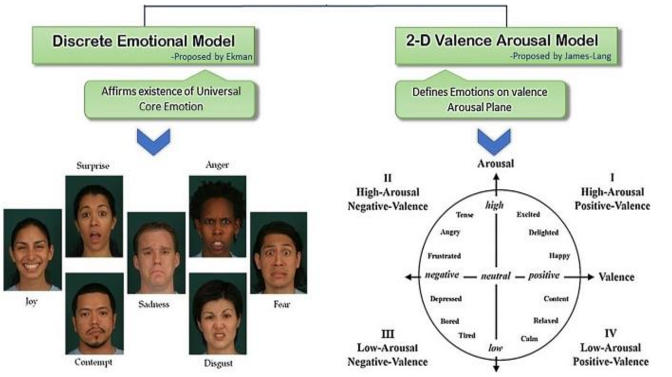

Fig-2. Two different Models of Human Emotions

Now let’s take a closer look at some of the simplest emotions and try to see how they affect a person's behavior:

1) Happiness: Happiness is a state of well-being, and it is characterized by a feeling of well-being, satisfaction, contentment, satisfaction, and well-being. The big smile on his face shows that.

2) Grief: It is usually manifested by feelings of sadness, shame, apathy, hopelessness, and a depressed mood and can be seen when a person sees a drooping face.

3) Fear: People pass by on a plane or in response to a fight when faced with some form of fear. Your heart is pounding, your muscles are tight, and your mind is alert. Facial expressions such as lowering the chin or widening the eyes and body reactions such as an increase in heart rate.

4) Anger: This is a very strong feeling, and is characterized by feelings of agitation, hatred, opposition, and frustration with others. The frowning face shows it.

5) Surprise: This is one of the basic types of human emotions. It is usually short, and we can express surprise as a reaction to the shock of the unexpected.

Fig-3: Different Emotional States of Human

Emotional experiences have three components: self-response, physical response, and behavioral or expressive response. The actual expression of emotion is part of the moral responsibility of the emotional response. Smiling, irritability, laughter, or moaning are examples of behavior, which vary according to the values and personality of the community. Although ample evidence indicates that many facial expressions are present throughout the world, such as sadness, our moral responses are influenced by social and cultural values and by the way we are raised. For example, love is expressed in a different way depending on the individual and the community. Emotions are far more than a mental state, as evidenced by the physical and moral responses associated with them. Our entire personality and health are influenced by emotions. In addition, our emotional intelligence is greatly influenced by our ability to understand the moral responses of others.Although there have been many studies and in-depth research on emotions, the discipline of emotional recognition has a bright future. The fact that [11] Artificial Intelligence can detect a person's emotions is so intriguing.

II. RELATED WORKS

[12] stated the machine learning approach for recognizing emotions using facial expressions. [12] had implemented the depth channel approach using depth data. Microsoft Kinetic Sensor had been used which works on the algorithm that uses local movements detection within the face area to recognize actual facial expressions. This approach had been validated on the Facial Expressions and Emotions Database using 169 recordings of 25 persons. According to the evaluated system's performance had given an overall successful detection rate of 78.8%. had presented a fuzzy logic-based emotion recognition system. The fuzzy logic-based system emphasizes Action Units and relevant facial features. [13] had first processed two images to extract relevant facial features. The differences in the position of the different feature points were then fuzzified to obtain the strength of exhibited AU's. The strengths were then fed through fuzzy rule sets and defuzzied to obtain the exhibited strength of the emotions. had proposed the method of using the empirical mode decomposition (EMD) technique for detecting facial emotion recognition. The EMD algorithm can decompose any nonlinear and non-stationary signal into several intrinsic mode functions (IMFs). Facial feature extraction through pre-processing of the image is a crucial process in emotion recognition so it had been implemented at first so that only intrinsic features were selected for the classification of the emotions. [14] had proposed the decision tree method for recognizing emotions through facial expressions. Relevant facial features had been extracted using a geometric approach and an automatic supervised learning method called decision tree had been applied. [15] Viola-Jones algorithm had been applied to detect the face, basically to distinguish faces from non-faces. A machine learning approach, called Classification and Regression Tree had been used to classify facial expressions into seven different emotions. [16] had proposed VGGNet CNN architecture for emotion recognition. FER 2013 dataset had been used to train the images and six different algorithms had been implemented for classification to achieve the accuracy rate of 73.2%.

Table-1: Comparing related works

S.No	Author	Year	Technique Used	Accuracy	Classifier
[9]	Wei-Long Zheng et al.	2014	Power Spectral density using physiological signals and eye -tracking	73.59%	SVM
[12]	Mariusz Szwoch et al.	2015	Depth Channel	50%	SVM
[13]	Austin Nicolai et al.	2015	Fuzzy System	78.8%	Fuzzy Classifier
[15]	P.M Ashok Kumar et al.	2021	Deep Learning	93%	SVM, CNN
[16]	Yousif Khaireddin et al.	2021	Neural Network	90%	CNN
[33]	Shervin Minaee et al.	2021	Deep Learning	99.3%	CNN, SVM
[34]	Luan Pham et al.	2021	Residual Masking Network	65.94%	CNN

III. METHODOLOGY

A. *Pre-processing*

To recognize seven basic emotions, the relevant facial feature must first be extracted from the images. As this system focuses on the recognition and classification of different types of images so here extraction feature is used. A basic thresholding method is also implemented. It is because there is sufficient change in contrast between the subject's skin tone and that of the eyes, eyebrows, and mouth. This is accomplished using image processing and computer vision tools. The first step is to find all relevant facial features of interest, such as eyes, eyebrows, and mouth. First, it detects the subject's face or recognized an image. After normalizing the size of the original image, the subject's face is placed in a bounding box with all relevant features.

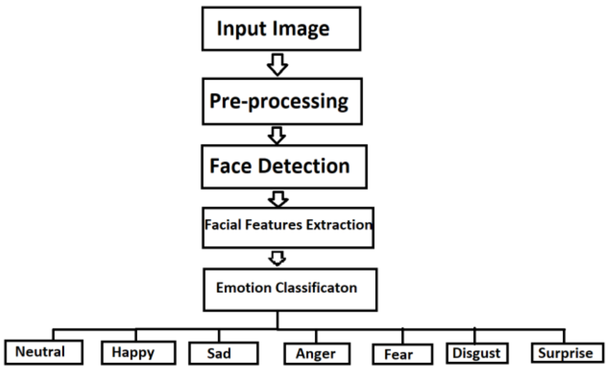

Fig-4: Flowchart Depicting Image Pre-processing

OpenCV, an open-source library, is used, which is very useful for computer vision applications. It plays an important role in real-time operation as it helps in image processing by reading images and isolating regions of interest. It also helps to recognize emotions with high accuracy by analyzing images by rotating them from different angles.

As an image is just a function of two variables if it is gray-scaled. If in case of colors are present, then it will be a 3-D image. So we have implemented the NumPy library also as it is best suitable for handling matrices to process the image for further classification and recognizing emotions. The Cascade classifier is also implemented at the time of pre-processing the image. Haar cascade is the popular algorithm for recognizing emotions through facial expressions. It is a method for combining the more complex classifiers in a cascade which allows negative inputs such as non-face features to be quickly discarded while spending more computation time on promising or positive face-like regions. It significantly decreases the computation time and makes the process more efficient.

B. *Dataset Collection*

The database for images used for measuring the performance of the system was the FER2013. It contains approximately 30,000 different facial RGB images with different expressions of size restricted to 48x48. The whole dataset is comprised of seven different expressions. These seven expressions include Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. For each subject, there are approximately 900 images present depicting each classified emotion.

Fig-5. Multiple Happiness images for same label

The dataset consists of 48x48 pixel grayscale images of faces. The faces have been registered automatically registered so that the face occupies the same amount of space in each image as it is more or less centered. The training set consists of 28,709 instances and the public test consists of 3,589 instances. Fig [5] depicts multiple happiness images for the same label. Fig [6] depicts seven different emotional states which are present in the dataset used in this proposed model.

Fig-6: Different emotion images of dataset

IV. EXPERIMENT WORK AND ANALYSIS

A. *Convolution Neural Network*

CNN is very effective for learning features and modelling a high level of abstraction as comes back in 1998. It is a deep learning algorithm that is specially designed for working with images and videos. It takes the normalized image as input, extracts and learns the features of the image, and classifies them based on the learned features. It has various filters which extract some information from the images such as edges, and different kinds of shapes, and then all these are combined to identify the image and its relevant features. [35] CNN includes six components which are: Convolutional layer, sub-sampling layer, Rectified linear unit (ReLU), Fully connected layer, an output layer, and SoftMax layer.

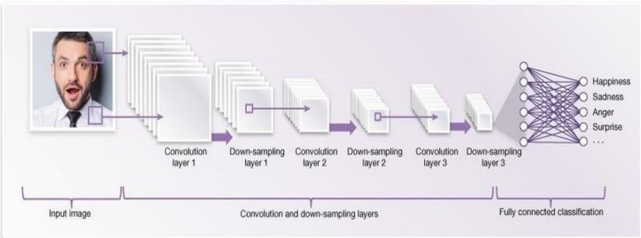

Fig-7: Working of CNN model

- Convolution Layer: These layers are determined by the number of generated maps and the kernel's size. As the kernel is moved over the valid area of the given image and performs a convolution for generating the map. If fk is a filter with a kernel size a x b and is supposed to be applied to the given image y.
- Sub-sampling layers: Sub-sampling reduces the map size of previous layers to increase the invariance of kernels. Sub-sampling includes two types of pooling which are: average pooling and maximum pooling. Input value gets reduced when the maximum function of Max-pooling is applied.
- Fully connecter layer: These layers are just similar to neurons in the general neural network where each neuron is fully attached to every neuron in a prior layer.
- Output Layer: This layer represents the class of the input image whose size is equal to the number of classes.
- Softmax Layer: The error of the network is propagated back through this layer.

B. *Proposed Framework*

This model works in two steps:

1. Feature Extraction
2. Classification

A typical CNN model which we have used in our project looks like this:

- Input layer: Here normalization of our input takes place. Every image is made up of pixels that range from 0 to 255. So we normalize them i.e. convert them to the range between 0 to 1 before passing it to the model. Fig [6] shows the input image of size 4x4 and has three channels i.e. RGB and pixel values.

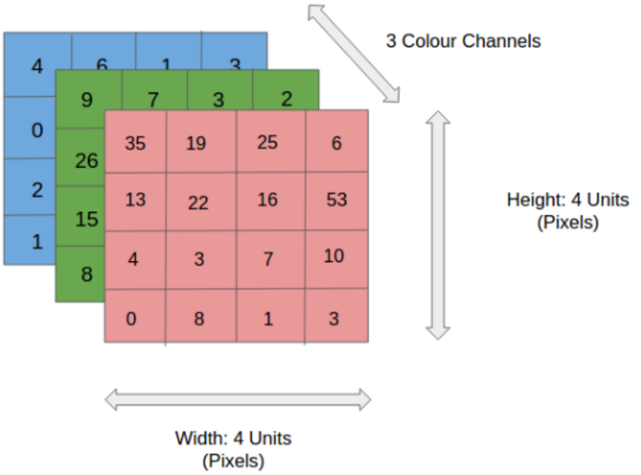

Fig-8: Depicting Input Layer

- Convolution layer + Activation function: Here the filter is applied to our input image to extract or detect its features. A filter is applied to the image multiple times and creates a feature map which helps in classifying the input image.

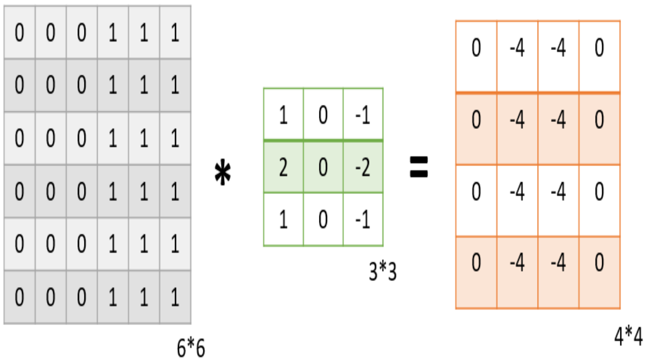

Fig-9: Filter applied to the input

- In Fig[9], we have an input image of size 6x6 and applied a filter of 3x3 on it to detect some features. It is indicating only one filter but many such filters are applied to extract relevant information from the image.

  Now, get a Feature Map of 4x4 which has some information about the input image as a result of applying the filter to the image. Many such Feature Maps are generated.

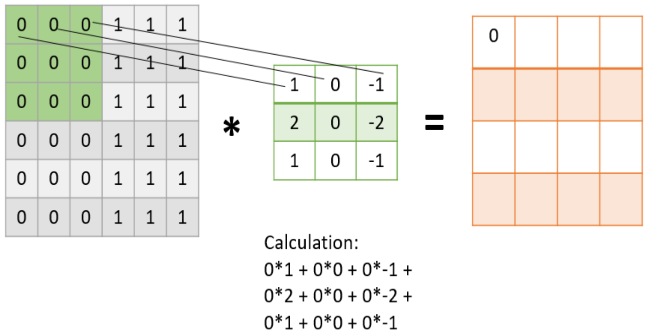

Fig-10: Depicting the process of filtration

As the filter is applied as the first step to the image, the pixel values of the image are multiplied by the values of the filter and then summed up to get the final value. After that, the filter is shifted by one column. This jump to the next column or row is known as a stride. Fig [8] shows the working of the filter as it shifts by one column each time to cover the whole image. Similarly, the filter passes over the entire image to obtain the final feature map.

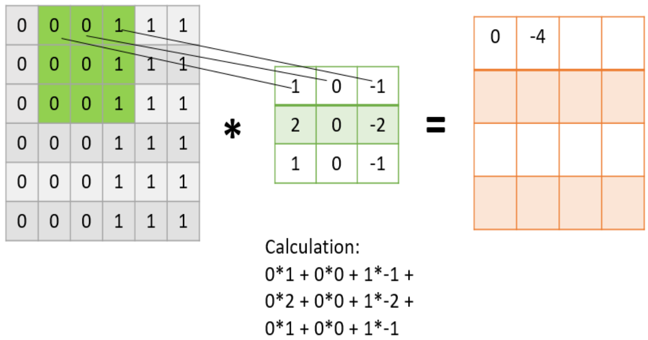

Fig-11: Shifting of filter by one column

The [36] feature Map we get here is smaller than the size of the image. As we increase the value of stride, the size of the Feature Map decreases.

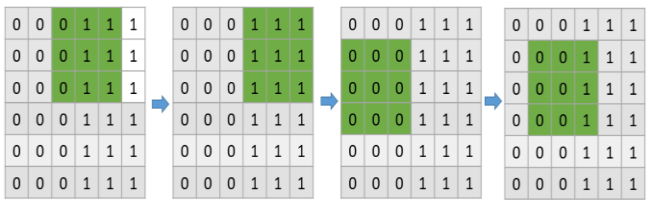

Fig-12: Depicting Feature Map

- Pooling layer: This layer is applied after the convolutional layer. It is used to reduce the dimensions of the feature map which helps in featuring and preserving the important information and features of the input image and reduces the computation time.

  Using pooling, a lower resolution version of input is created that still contains the large or important elements of the input image.

  The most common types of pooling are [37] Max Pooling and Average Pooling. Here is an example depicting the use of a pooling layer of 2x2 with a stride of 2.

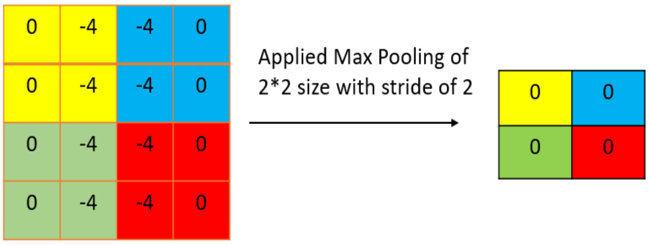

Fig-13: Max Pooling on the Feature Map

- Fully connected layer: Now the classification part begins. The fully connected layer is used for classifying the input image into a label. This layer connects the information extracted from the previous process to the output layer and eventually classifies the input into desired seven labels which are: neutral, anger, fear, surprise, disgust, happy, and sad.

V. CONCLUSION

This paper exhibited an emotion recognition system using an approach of deep learning. A CNN is implemented for relevant and optimal feature extraction and detecting seven different expressed emotions. The experiment results proved that the CNNs can learn characteristics of facial expressions and detect different emotions accurately. It also increases the facial emotion recognition accuracy up to 92%.

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