



AUTOMATED HUMAN EMOTION RECOGNITION WITH MODIFIED CONVOLUTIONAL NEURAL NETWORK

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Article history:	Abstract:
Received: 1 st September 2021 Accepted: 2 nd October 2021 Published: 26 th November 2021	Human emotional detection is very useful in human-robot interaction, technical equipment domain. This paper covers a method how a Modified Convolutional Neural Network (MCNN) works to detect an emotion. The steps start with face detection followed by the emotion. The method of face and eyes detection was published in Web of Scientist: International Scientific Research Journal ISSN: 2776-0979 (Volume 2, Issue 5, May, 2021) which is one of our research results. The proposed algorithm can identify from basic emotions classification to complex one with copious emotions. It depends on the emotion model introduced as training set to define the number of emotion classes. To develop this approach, we open this paper with introduction then the method and close with conclusion

Keywords: Human emotions, Modified Convolutional Neural Network.

INTRODUCTION

With the rapid increase in the use of smart technologies in society and the development of the industry, the need for technologies capable to assess the needs of a potential customer and choose the most appropriate solution for them is increasing dramatically. Automated emotion evaluation (AEE) is particularly important in areas such as: robotics, marketing, education, and the entertainment industry [4]. The application of AEE is used to achieve various goals:

- in robotics: to design smart collaborative or service robots which can interact with humans;
- in marketing: to create specialized adverts, based on the emotional state of the potential customer;
- in education: used for improving learning processes, knowledge transfer, and perception methodologies
- in entertainment industries: to propose the most appropriate entertainment for the target audience.

In the scientific literature are presented numerous attempts to classify the emotions and set boundaries between emotions, affect, and mood. From the prospective of automated emotion recognition and evaluation, the most convenient classification is presented in. According to the latter classification, main terms defined as follows:

- "emotion" is a response of the organism to a particular stimulus (person, situation or event). Usually it is an intense, short duration experience and the person is typically well aware of it;
- "affect" is a result of the effect caused by emotion and includes their dynamic interaction;
- "feeling" is always experienced in relation to a particular object of which the person is aware; its duration depends on the length of time that the representation of the object remains active in the person's mind;
- "mood" tends to be subtler, longer lasting, less intensive, more in the background, but it can affect affective state of a person to positive or negative direction.

In our case, we separate human face from images and treat it separately to detect the emotion

1. PROPOSED APPROACH

The method doesn't depend on image input format. In case of image color, the conversion to grayscale type is required. We have two steps to follow: face detection, then eyes detection. The following figure presents shortly the chart of our algorithm (Fig. 1) with test result (Fig.2) [2].

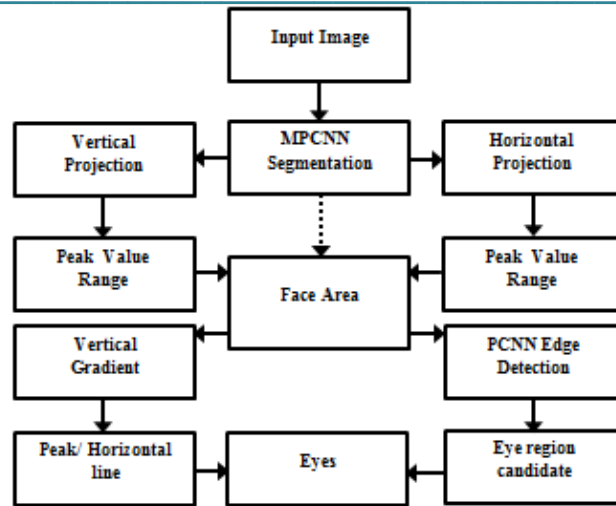


Fig. 1 Face/Eyes detection method



Fig. 2 Face detections

Once we get an area face, a Modified Pulse Couple Neural Networks (MPCNN) is in charge of segmentation and edge detection for image feature extraction. To reduce the volume of data to be processed, we introduce the notion of:

- **Entropy**

Entropy is a kind of representation of the image statistical feature, which reflects the amount of information contained in the image. Similarly, the entropy of output binary images is a one-dimension entropy series, as shown in equation (01), where E is the information entropy of binary image; P_1 is the probability of 1's in a binary image, and P_0 is that of 0's in the binary image [1].

$$E = -P_1 \log_2(P_1) - P_0 \log_2(P_0) \tag{01}$$

- **Another parameters**

Some derived feature extraction methods based on entropy are presented, including energy entropy (EE), logarithm (L) and energy logarithm (EL) as shown in equation (02) – (04) [1].

$$EE = -P_1^2 \log_2 P_1^2 - P_0^2 \log_2 P_0^2 \tag{02}$$

$$L = -\log_2 P_1 - \log_2 P_0 \tag{03}$$

$$EL = -\log_2 P_1^2 - \log_2 P_0^2 \tag{04}$$

Now, we have the image signature and the fully neural network will take care of emotion classification [3]. The process is described in Fig.3.

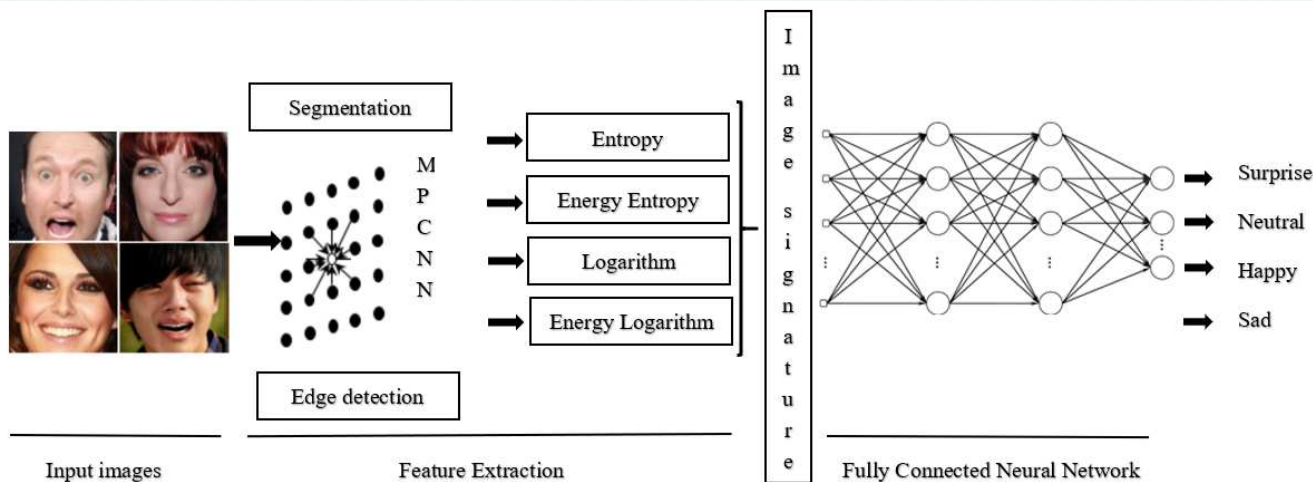


Fig. 3 Emotion classification

2. Experience Result

According to the research performed by Feidakis, Daradoumis and Cabella where the classification of emotions based on fundamental models is presented, exist 66 emotions which can be divided into two groups: ten basic emotions (anger, anticipation, distrust, fear, happiness, joy, love, sadness, surprise, trust) and 56 secondary emotions. To evaluate such a huge amount of emotions, it is extremely difficult, especially if automated recognition and evaluation is required. Moreover, similar emotions can have overlapping parameters, which are measured. To handle this issue, the majority of studies of emotion evaluation focuses on other classifications, which include dimensions of emotions, in most cases valence (activation - negative/positive) and arousal (high/low), and analyses only basic emotions which can be defined more easily. A majority of researches use variations of Russel’s circumplex model of emotions (Fig. 4) which provides a distribution of basic emotions in two-dimensional space in respect of valence and arousal. Such an approach allows for the definition of a desired emotion and evaluating its intensity just analyzing two dimensions [4].

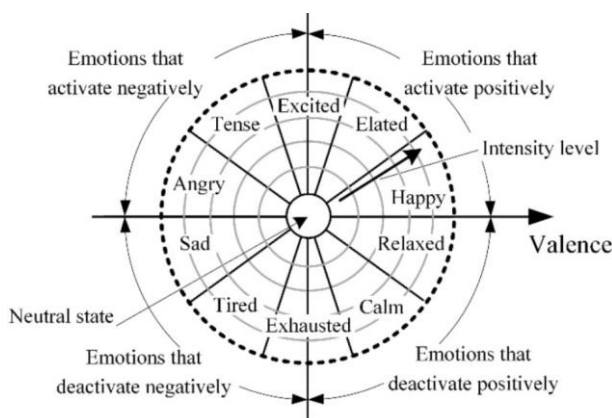


Fig. 4 Russel’s circumplex model of emotions

As told in beginning, this approach is able to solve a problem of human emotion detection with many different classes such as Russel’s circumplex model of emotions. To prove this capacity, we apply directly with familiar followings datasets. 60% is dedicated for apprenticeship and 40% for testing purpose.

- **AffectNet**

AffectNet is one of the popular datasets for detecting facial emotions. The dataset contains around one million facial images. They were collected from search engines with a thousand two hundred and fifty keywords from six languages altogether. Around four-hundred and fifty thousand images were manually annotated by 12 experts.

- **Extended Cohn-Kanade Dataset (CK+)**

The Extended Cohn-Kanade Dataset (CK+) is used as a test-beds for many algorithms and it is widely used. The dataset contains 5,876 images of a hundred and twenty-three people. These images are labeled with seven emotions. All the images were taken with a constant background.

- **FER-2013**

The FER-2013 is a widely used emotion dataset. The images are labeled with seven emotions: neutral, happy, surprise, sad, fear, disgust, and anger. The dataset contains 28,000 of training data, 3,500 of validation data, and 3,500 of test data. The images were collected from google. The images were collected in a way that they vary in the pose, age, and occlusion.

- **EMOTIC**

EMOTIC database of images of people taken from the real environments, and annotated with their apparent emotions. They are labeled with 26 categories of emotion. They were labeled using Amazon Mechanical Turk (AMT) platform. The dataset contains 18,313 images and 23,788 annotated people. Some images were collected from Google as well.

- **Google Facial Expression Comparison Dataset**

Google Facial Expression Comparison Dataset is an emotion dataset that is used on a large scale. The dataset contains triplet images with labels. Each triplet is labeled by the top six raters. Here, the dataset helps in identifying which of the two faces are similar in emotions. The dataset is used mainly for summarizing albums, classifying emotions, etc.

The below table resumes the accuracy obtained for each data sets.

Table 1: Performance measurement

Data Set	AffectNet	CK+	FER-2013	EMOTIC	Google
Accuracy (%)	98.08	97.91	97.82	98.93	98.03

3. CONCLUSION

Emotion recognitions is a powerful and very useful technique for the evaluation of human emotional states and predicting their behavior in order to provide the most suitable advertising material in the field of marketing or education. In addition, emotion recognition and evaluation is very useful in the development process of various human machine interaction systems [4]. The combination of MPCNN and MCNN give a powerful tool in recognition domain. This article demonstrates the same by detecting human recognition and the overall accuracy is around 98.15% which can be classified as good performance. This combination may be applied in different domain such as fingerprint recognition, etc.

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