

# Deep Learning based Emotion Recognition through Biosensor Observations

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## Abstract

Emotion is the conscious experience which can be characterized by functional mental activity and by the degree of contentment and discontentment. In this paper, we have studied physiological changes to infer emotions from biosensor observations. We have considered four basic emotions i.e. Joy, Sad, Surprise and Disgust. The emotions are stimulated through video stimuli. The Likert scale is used to collect subject's aerosol and valence level to determine the ground truth emotions of the user while watching and listening video stimuli. The wearable ECG, GSR and BVP sensor observations are collected from human subject to infer the emotion which is internally exposed through video stimuli. The convolutional neural network (CNN) of deep learning architecture is used to infer emotions from biosensor's signal features. The simulation results show higher accuracy of the proposed CNN based emotion recognition approach.

## 1. Introduction

The Geneva Emotion Wheel [1] of social science study represents 40 emotions, where valence and aerosol levels are considered as the axes of 2D representation. However, it is difficult to classify each of the 40 emotions through modern artificial intelligent (AI) and therefore four or six basic emotions are studied in activity recognition and image processing domain. The new trend is analyzing emotions through physiological observations. Video stimuli based emotion recognition through bio-sensor observations is the primary goal of this research where we considered the four basic emotions i.e. Joy, Sadness, Surprise and Disgust as shown in Fig. 1. We applied convolutional neural network (CNN)[5] to classify those basic emotions.

## 2. Existing works

Facial expression based emotion recognition is studied in [2], where the authors' used maximum entropy Markov model (MEMM)[4] to recognize six basic emotions. Koelstra S. et al.[3] proposed physiological signal based emotion analysis where the authors used 40 channels of physiological and peripheral sensors including EEG, ECG and EMG signals [3]. The work used the naive Bayes classifier to classify valence and aerosol levels. They achieved 65.1% and 61.8% accuracy in aerosol and valence level classification respectively. However, in this paper we proposed CNN [5] based emotion recognition

method, where the wearable and light weight Electroencephalogram (ECG), Galvanic skin response (GSR) and Blood volume pressure (BVP) sensors are used.

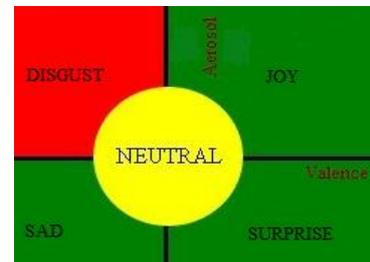


Fig. 1. Emotion Wheel based on the Geneva Emotion Wheel [1]

## 3. CNN based Emotion Classification

In algorithm 1, we need the training dataset [3] of subject's sensor observations  $O_{s_i}$  and the ground truths of subjects' emotion class. The goal of this algorithm is to learn weights  $w$  of CNN. At first we initialize the CNN with random weights and we also initialize learning rate  $\eta$  to 0.7. For each subject's sensor observations  $o_{s_i}$ , Firstly, the algorithm predicts the emotion class  $p_{s_i}$  of each of the subjects based on the input sensor observations of training dataset and the initialized weights. Secondly, the algorithm extracts the actual emotions  $e_{s_i}$  of all the subjects from the ground truths. Thirdly, the algorithm determines the error between the CNN output and ground truths. Fourthly, the algorithm computes the gradient of all the weights of hidden layer to output layer. Then, the algorithm computes the gradient of all weights from input layer to hidden layer.

**Algorithm 1: CNN\_Training()**

**Input:** Training dataset of subjects' sensor observations  $O_{s_i}$ , ground truths of subjects emotion class  $e_{s_i}$

**Output:** CNN weights ( $w$ )

**Initialization:** CNN weights  $w$  and learning rate  $\eta$

- 1) Repeat
  - 2) For each subjects sensor observations  $O_{s_i}$ 
    - 3) Predict emotion  $p_{s_i} = \text{neural-net-output-emotion-class}(\text{network}, O_{s_i})$
    - 4) Extract actual emotion  $e_{s_i} = \text{ground-truth-emotion-class}(O_{s_i})$
    - 5) Determine  $error_{global} = (p_{s_i} - e_{s_i})$
    - 6) Compute  $\Delta w_h$  for all weights from hidden layer to output layer
    - 7) Compute  $\Delta w_i$  for all weights from input layer to hidden layer
    - 8) Update CNN weights through  $w = w - \eta \Delta w_h$
  - 9) Until ( $error_{global} < error_{threshold}$ )

Afterwards, the algorithm updates the weights by subtracting gradient times learning rate from the former weights. The algorithm iterates the above mentioned weights until it can classify all the emotion classes or until it reaches at the error threshold.

**4. Performance Evaluation**

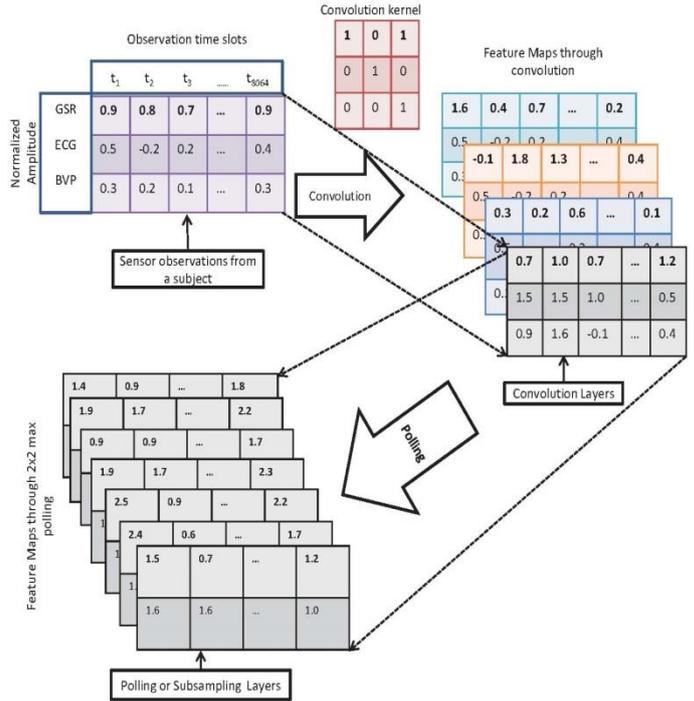
We used DEAP dataset [3] for training and testing the proposed CNN based emotion recognition method. The DEAP dataset consists of 32 subjects and 40 different video stimuli. Fig. 2 shows the convolution and pooling steps and used kernels of 1<sup>st</sup> cycle convolution. The confusion matrix is shown in Table 1, which shows the average classification accuracy of 4 emotion class is 81.17%.

**Table 1:** Confusion Matrix of Emotion Classification

	Joy	Disgust	Sad	Surprise
Joy	437	33	28	35
Disgust	20	230	19	16
Sad	8	11	155	13
Surprise	23	19	16	217
<b>Average=(437+230+155+217)/1280=0.81171875</b>				

**5. Conclusion**

Emotion analysis through CNN ensures higher accuracy while reducing the extensive feature extraction overheads. The physiological sensors data are continuous and sequential; therefore the use of recurrence neural network (RNN) may enhance the classification accuracy.



**Fig. 2** Convolution and pooling steps, where 3x3 kernels are used in convolution phase and 2X2 kernel in polling phase.

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