
A Systematic Review on Emotion Recognition System Using Physiological Measures

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Abstract.

Emotion detection is the process of identifying and classifying different types of emotions. The systems can understand, recognize, identify and display emotions with the help of affective computation. The type of emotion expressed by a person is recognized via affect recognition. The Artificial Intelligence (AI) and Human-Computer Interaction (HCI) fields are realized effectively in emotional computing. The on-going research is in place to reveal an effective emotion recognition model through identifying the correlation of physiological signals and their highest contribution with other modalities like audio, video, and eyeball movement. The survey on this domain is conducted through following Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA), which acts as a standard guideline for conducting a qualitative review and meta-analyses. This study discloses 35 relevant documents over 513 articles on the web of sciences. Now a day, machine learning techniques are widely used to improve the classification result as well prediction. A brief assessment of the building emotion models with modern technologies like deep learning, its advantages, limitations, and future scope is discussed with a case study addressing the effective emotion model of interest..

Keywords. Affective computing, human computer interaction, emotion recognition, physiological signals, deep learning.

1. INTRODUCTION

Although computers do not have emotions, in human- computer relationship, they frequently communicate their emotions, to be as natural as possible when people connect with computers; the computers do not recognize them. Human emotions are organized using two methods based on conscious response and unconscious response in conscious response identify the emotions using PANAS (Positive and Negative Affect Schedule) which is the self-questionnaire that can estimate both positive and negative affects. In unconscious response, their emotions are identified from physic measures like electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG) activity, skin temperature, blood pressure, respiration rate, and facial expressions. The non-physiological signals are not able to reflect the innermost mental states of humans [1]. Emotion recognition has its application towards various sectors from education, marketing, healthcare, and ensuring human safety while engaged in driving and so on [2].

The remaining part of the paper follows the structure as outlined as below In section 2, an exhaustive survey is carried out to ascertain the necessary facts about emotion recognition, its input modalities, and technologies that help in evaluating accurate emotions. The survey is conducted in strict adherence to the guidelines of PRISMA [3-5]. Section 3 discusses the knowledge inferred from the related literal work of resultant documents out of the qualitative analysis driven through PRISMA. Section 4 concludes the work and the scope for enhancement.

2. MATERIALS AND METHODS

The entire process flow of the systematic survey is captured in this section. This section addresses the research questions that initiate the study, the sources of documents, search keywords, and the final list of relevant documents using inclusion criteria in detail.

2.1. Research Questions

The key research goal of the study is to reveal the facts on emotion recognition, machine learning practices in predicting exact emotions and to analyse the real-time challenges associated with emotion models. The research questions are formulated in addressing the issues in the emotion model which in turn presents the gap to be addressed by the researcher in the future and listed as below.

Q1: What are the types of emotion models?

Q2: What are the input modalities of the emotion model? Q3: Are there any unimodal promises of better efficiency?

Q4: How machine learning can be integrated with emotion recognition?

Q5: What is the level of exploitation of machine learning algorithms and their efficiency?

2.2 Search Strategy

In order to select the documents of study, a search is devoted to three major electronic data sources (EDS) like IEEE Xplore, WoS, and Scopus. The articles which are published from 2010 through 2021 are accounted for selection. The keywords are refined according to the research questions. The major keywords of choices are Emotion Recognition, Physiological Signals, Facial Expressions, Multimodal, Machine Learning, and Deep Learning. These keywords are exercised with Boolean operators like “AND” and “OR” to formulate a query that in turn retrieves the document from the sources of interest. Furthermore, the scope of new sources is investigated, and to portray the market trend in emotion recognition, trusted website content is added with.

2.3 Criteria for Selection

The document selection is executed using the exclusion criteria listed below to extract the more relevant articles for the inclusion of the study.

EC1: Short summary research papers

EC2: Articles beyond the reputed publishers

EC3: No wider contribution on emotion recognition

The entire process of article selection process for the study aligned with updated PRISMA guidelines is depicted in Figure 2.1. Further, the quality assessment of extracted documents is scrutinized by manual investigation through analysing their content

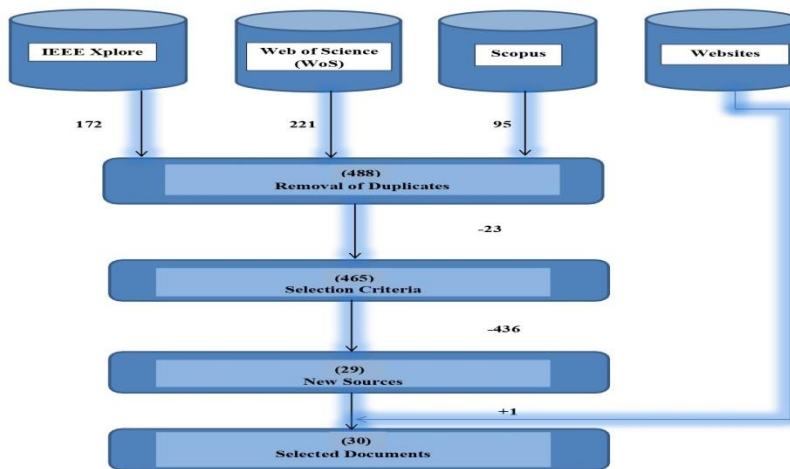


Figure 2.1. Selection Process of Systematic Study on Emotion Recognition

3. RESULTS AND DISCUSSIONS

The summary of the study based on the research questions is elaborated here. Further, a novel design for emotion recognition incorporating a deep learning algorithm is discussed.

3.1 Emotion Models

Human emotions are categorized into two types in emotional space namely discrete emotion model and dimension emotional model.

Mathura Prakash et al. [6] contributed an emotion recognition system that detects different emotions of the face and obtains the average emotional state during a particular event and assessed the same via the audience feedback system. The resultant of the assessment process is illustrated in Figure 3.2. The bar graph shows the number of times the occurrence of a particular emotion, and the pie chart describes the percentage of having a gathered emotion.

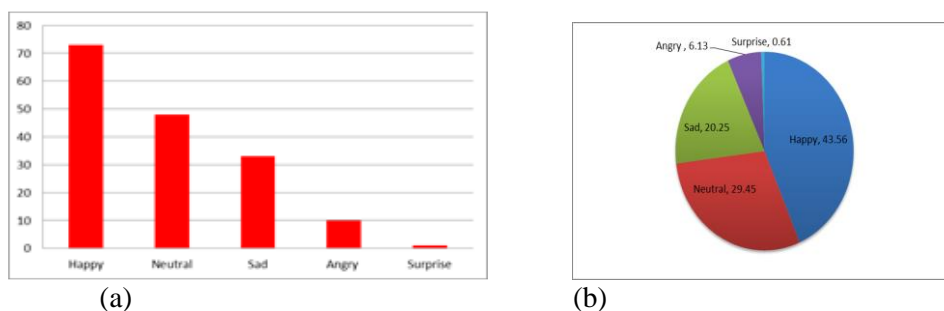


Figure 3.1. Evolution Result of Emotion Recognition System Presenting
a) Number of Times an Emotion Occurred and b) Percentage of Gathered Emotion [6]

3.2 Deep Learning-based Emotion Recognition Models

Deep learning (DL) and machine learning are becoming the next evolution in artificial intelligence. The trained model learns new things like the human brain through a neural network in deep learning. DL is employed in most province emotion recognition studies due to its efficacy in deep feature extraction.

Chao and Don [7] developed a convolutional neural network (CNN) to recognize human emotions using the ResNet algorithm. They analysed emotions from multichannel EEG signals in the time domain. Based on the position of electrode sensors the features are extracted and treated as a 3- D feature matrix. Whereas a pre-processing of EEG signals is carried out by principal component analysis before applying the classification with CNN is captured in [8]. Similarly, an emotion recognition system based on EEG signals is experimented with tuned CNN, which adjusted with the tuning parameter in convolution layer and it produced 73.4% of accuracy in successful classification of emotions [9]. In most of the previous studies,. They classify the emotions obtained from multimodal physiological cues with the help of DL and ML algorithms to achieve better results. Table 3.1 summarizes the key contributions of the existing endeavour.

Table 3.1. Summary of significant emotion recognition models in practice

Reference	Modalities	Emotions	Techniques Used	Dataset/Accuracy
X Zhang et al. [11]	EEG, EMG,GSR, RES, MEG, EOG	Arousal, Valence	SVM-FLF (Support VectorMachine-Future Level Fusion), Fully Convolutional Network (FCN),SVM-DLF(Decision Level fusion)	DEAP-63.8% DECAF-64.2%
K. Zhang et al. [12]	Text, audio,visual	Happy, sad, neutral, angry, excited, frustrated, average	Gated Recurrence Unit (GRU)	IEMOCAP –61.8 % CMU-MOS-81.2%
M. D. Hssayeni et al. [10]	Respiration rate, ECG, Skin temperature , EMG and acceleration	Stress, amusement	Gradient tree boosting	WESAD-79%
H. Chao et al. [7]	EEG	Arousal,Valence	CNN-ResNet, Sliding window	DEAP, Binary -85.5% Four-Class-75.7%
B. Nakisa et al. [13]	EEG, BVP signals	Arousal,Valence	ConvNet, Long Short-term Memory	MAHNOB-71.6%

Reference	Modalities	Emotions	Techniques Used	Dataset/Accuracy
G. Du et al.[14]	ECG, EEG	excitement, anger,sadness, calmness	BLSTM, CNN	Kinect2.0-87.3%

In most of the previous studies, the convolutional neural network is widely used for classifying emotions in Arousal- Valence space Hence the researchers employed CNN in producing high-end emotion detection mode with promising accuracy.. Also, the performance analysis is captured in Figure 3.1. Further, they can achieve an increased rate of accuracy by combining more than one deep learning algorithms.

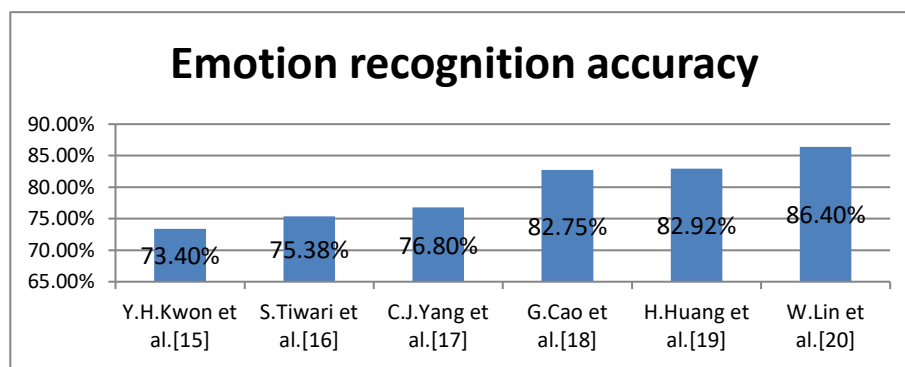


Fig 3.1. The Efficiency of Neural Network Assisted Emotion Detection Models

4. CONCLUSION

Building deep architecture-based real-time multimodal emotion identification system is an emerging topic of research. Affect recognition is becoming increasingly popular among researchers because of its growing applicability in the education and healthcare industry. Physiological signals exhibit more advantages in emotion recognition, as they are uncontrollable, unaffected by culture or education, and strongly linked to people's emotional states. A review of the study broadly addresses the emotion models, interesting modalities to be considered as input in the process of emotion evaluation, and the scope for the multimodal emotion detection system. The emerging scope of deep learning practices in this domain and its exploitation level and attained efficiency is well investigated.

5. REFERENCES

- [1] M. Ali, A.H. Mosa, F. Al Machot, K. Kyamakya, 'Emotion Recognition Involving Physiological and Speech Signals : A Comprehensive Review', In: K. Kyamakya, W. Mathis, R. Stoop, J. Chedjou, Z. Li (eds) Recent Advances in Nonlinear Dynamics and Synchronization. Studies in Systems, Decision and Control, Springer, Cham, 109, 287-302, 2018.
- [2] M. Ali, F. Al Machot, A. H. Mosa, and K. Kyamakya, 'CNN Based Subject-Independent Driver Emotion Recognition System Involving Physiological Signals for ADAS', In: Advanced Microsystems for Automotive Applications, Springer InternationalPublishing.pp.125–138, 2016.
- [3] A.A. Selcuk, 'A Guide for Systematic Reviews: PRISMA', Turkish Archives of Otorhinolaryngology.57(1),pp.8,2019, <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6461330/>

- [4] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, ‘The PRISMA Group (2009), Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement’, *PLoS Med*, 6(6): e1000097, 2009
- [5] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J.M. Grimshaw, A. Hrobjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting, D. Moher, ‘The PRISMA 2020 statement: an updated guideline for reporting systematic reviews’, *BMJ*, 372, pp.1-9, 2021.
- [6] Madhura Prakash, Aman Kumar, Anmol Saxena, and Somil Agrawal, Twinkle Singh, ‘Audience Feedback Analysis using Emotion Recognition’, *Int. J. Eng. Res.*, 9(5),pp.1090–1094, 2020.
- [7] H. Chao, L. Don, Emotion Recognition Using Three-Dimensional Feature and Convolutional Neural Network from Multichannel EEG Signals, *IEEE Sensors Journal*. 21(2) (2021) 2024-2034.
- [8] G. Cao, Y. Ma, X. Meng, Y. Gao, M. Meng, Emotion recognition based on CNN, *Chinese Control Conf. CCC*, 2019(61372023) (2019) . 8627–8630.
- [9] Y.H. Kwon, S.B. Shin, S.D. Kim, Electroencephalography based fusion two dimensional (2D)-convolution neural networks (CNN) model for emotion recognition system, *Sensors*. 18(5):1383 (2018) 1-13.
- [10] M.D. Hssayeni, B. Ghoraani, Multi-Modal Physiological Data Fusion for Affect Estimation Using Deep Learning, *IEEE Access*. 9 (2021) 21642-21652.
- [11] X. Zhang, J. Liu, J. Shen, S. Li, K. Hou, B.H.J. Gao, T. Zhang, B. Hu, Emotion Recognition From Multimodal Physiological Signals Using a Regularized Deep Fusion of Kernel Machine, *IEEE Transactions on Cybernetics*. 51(9)(2021)4386 – 4399.
- [12] K. Zhang, Y. Li, J. Wang, Z. Wang, X. Li, Feature Fusion for Multimodal Emotion Recognition Based on Deep Canonical Correlation Analysis, *IEEE Signal Processing Letters*. 28 (2021) 1898 -1902.
- [13] B. Nakisa, M.N. Rastgoo, A. Rakotonirainy, F. Maire, V. Chandran, Automatic Emotion Recognition Using Temporal Multimodal Deep Learning, *IEEE Access*. 8 (2020) 225463 -225474.
- [14] G. Du, S. Long, H. Yuan, Non-contact Emotion Recognition Combining Heart Rate and Facial Expression for Interactive Gaming Environment, *IEEE Access*. 8(2020),11896 – 11906.
- [15] Y.H. Kwon, S.B. Shin, S.D. Kim, Electroencephalography based fusion two dimensional (2D)-convolution neural networks (CNN) model for emotion recognition system, *Sensors*. 18(5):1383 (2018) 1-13.
- [16] S. Tiwari, S. Agarwal, K. Adiyarta, M. Syafrullah, Classification of physiological signals for emotion recognition using IoT, *Int. Conf. Electr. Eng. Comput. Sci. Informatics*. (2019) 106–111, 2019.
- [17] C.J. Yang, N. Fahier, C.Y. He, W.C. Li, W.C. Fang, An AI-edge platform with multimodal wearable physiological signals monitoring sensors for affective computing applications, *IEEE International Symposium on Circuits and Systems (ISCAS)*. (2020) 3–7.
- [18] G. Cao, Y. Ma, X. Meng, Y. Gao, M. Meng, Emotion recognition based on CNN, *Chinese Control Conf. CCC*, 2019(61372023) (2019) . 8627–8630.
- [19] H. Huang, Z. Hu, W. Wang, and M. Wu, “Multimodal Emotion Recognition Based on Ensemble Convolutional Neural Network,” *IEEE Access*, vol.8, no. 2, pp. 3265–3271, 2020.
- [20] W. Lin, C. Li, S. Sun, Deep convolutional neural network for emotion recognition using EEG and peripheral physiological signal, In: Zhao Y., Kong X., Taubman D. (eds) *Image and Graphics. ICIG 2017. Lecture Notes in Computer Science*, Springer, Cham. 10667 (2017) 385-394.