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Human Emotion Detection Based on Machine Learning

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Abstract:

Emotion is a mental and physiological state associated with a wide variety of feelings, thoughts and behaviors. Emotions are fundamental in the daily life of human beings as they play an important role in human cognition, namely in rational decision-making, perception, human interaction, and human intelligence.

This paper investigates the effect for the emotion-discriminating precision of Different wave levels of EEG signals and a particular number of channels.

It using various sets of EEG channels, the proposal classified affective states in the equivalence and excitability dimensions. To begin, DEAP normalized the pretreated hypothetical data. Following that, discrete wavelet transduction was used to divide the EEG into four bands, The scales used were the features of the K-nearest neighbor Algorithm entropy and energy algorithm.

The highest classification accuracy was using the K-NN algorithm for channels (4-10-14-18, 32) in the four dimensions (valence, arousal, dominance, and liking). They are channel 18 (99.7656%, 99.7656%, 99.7656%, 99.7656%) respectively. While the highest classification accuracy for the frequency bands is the gamma frequency greater from beta and alpha and theta frequency for the four dimensions is (99.7656%).

Keywords: "Valence", "Arousal “, multi-channel EEG, discrete wavelet transform (DWT), frequency bands

1 Introduction:

Electroencephalogram(EEG) is the recording of the electrical activity of the human brain in terms of current (Raghav et al., 2018). EEG is a clinical tool captures to monitor patient’s status in order to determine his/he neurological issues (Azeez et al., 2020b). Classic approaches of analysing EEG are considered not suitable because they required huge time and burden for neurologists. However, Visual inspection of patient’s recordings could cause errors and misdetection (Azeez et al., 2020a)

The Emotion is a (psychophysiological) reaction to the "aware" and/or "unconscious" experience of a "thing" or "situation." It's linked to ("mood", "personality" ,"temperament",, and "disposition" and " motivation") (Mohsen & Miften, 2021).

Human emotions are a mixture of human thinking, feeling, and behavior. Passion has an important role in people's daily lives. In research for psychology, cognitive Studies, neuroscience, computers science, analyzing and understanding emotion is a multi-applied research subject.

Emotions can be divided into three basic methods: Someone relies on non-physiological studies such as facial expressions (Zhu et al., 2014) as well as Verbal sound (Ang et al., 2002), and these emotions are characterized by ease of implementation and do not require special devices, and the defect can be hidden, as they are not reliable. Also, it cannot be used if the persons are disabled or have Difficult diseases.

As for the third method, it depends on the multimodal merger, and is by groups speech and facial expressions, and signs, such as (sadness, happiness, anger and neutrality).

In the last few decades, investigators in various applications have suggested several techniques of recognizing emotions, which can be reduced to three main ways. The disadvantage is that by masking destination gestures and vocal overtones, persons can conceal the true emotional responses. These physiological markers are normal manifestations that are not under the influence of the person.

As a result, they are more apt and successful at recognizing emotions. EEG, In contrast to many other physiological signals, would be a non-invasive technique that provides adequate temporal and spatial resolution. As a result, EEG can Contribute a key role in directly sensing emotions in the Brain structure at greater temporal and Procedures in space (Y. Liu et al., 2010).

The third approach is multimodal fusion-based emotion detection. for instance, Busso et al. use facial expressions and speech to four emotions to categorize (sadness and anger and neutrality and happiness). With highest classification precision of 91.01 percent, Liu et al. EEG and EMG signals are combined. (W. Liu et al., 2016). For emotion regression and classification, Koelstra and Patras combine electroencephalogram (EEG) signals and facial expression in (the valence and arousal). And valence refers to an individual's level of satisfaction, Arousal refers to the degree to which an emotion is triggered, and a shift in arousal from low to high suggests a shift in a state of emotion (Calm case to excitement case). with a change in valence value from small to large suggesting a shift in emotion from negative case to positive case.

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2 Related Works:

Regardless, various method for emotion classification Based on (EEG) are used, the research's ultimate objectives are the same. One of the aims is to use various analytic techniques to discover appropriate features for emotion classification and then use an optimization recognition model to category and increase the accuracy of (emotion recognition). last aim is to identify the most important bands and regions of the brain for emotion classification operations.

(CAMPOS, ATKINSON) enhance emotion recognition accuracy by groups a feature Choose technique basis of mutual data with the kernels classifier. In the arousal and valence dimensions, accuracy ratio of emotion recognition using a "SVM" algorithm are as follows: There are three groups: two (73.14 percent, 73.06 percent), three (62.33 percent, 60.70 percent), and five (73.14 percent, 73.06 percent) (45.32 percent, 46.69 percent) (Atkinson & Campos, 2016). The "gamma band" is taken into account comfortable for (EEG) dependent on emotion recognition, as the mean precision of the three experiments is 93.5 percent (Mu Li & Lu, 2009).

This paper examined the impact of the 10, 14, and 18 channels EEG signals dependent on experiencing Choose, and also All channels (32) of (EEG), on emotion classification accuracy using the DEAP data set (Koelstra et al., 2012). Multiple- time windows were created from the EEG signals. DWT was used to subdivide one time window into multiple bands . this is paper used the KNN classifier to describe the emotional states by extracting energy and entropy as feature from every one of (band).

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3 Review:

The model for emotion and the time window selection are all defined in detail in this portion.

3.1 Model of emotion:

When it is Emotion Recognition analysis have been complex and unsatisfactory. Persons emotions are constantly shifting. Scholars are still discussing whether each emotion occurs individually or whether there are associations between them.

To define the general state of emotion, four types of models are used:

1. The discrete emotion, which consists of the main emotions, is one example. for instance (sadness- fear- anger- surprise- happiness and disgust). nevertheless, there is debate about which essential emotions should be selected. Different scholars hold contrasting perspectives.
2. "A multi-dimensional" emotional. It starts out as a two labels arousal and valence. An individual's level for joy is represented by valence, which ranges from negative to positive. Arousal refers to the level of emotional arousal, which may vary from (calm to excitement) Which are shown in the figure 1.
3. "A three dimensional" emotional with (valence and arousal and preference) emerges. In a three-dimensional model, "Xu and Plataniotis" .(Xu & Plataniotis, 2016) define two styles of emotion in every label.
4. Emotional models that are "four-labels" they ("valence", "arousal", "dominance", and preference) has been seen as well. Liu et al (W. Liu et al., 2016), for example, define two forms of emotion in every for 4- labels of emotion.

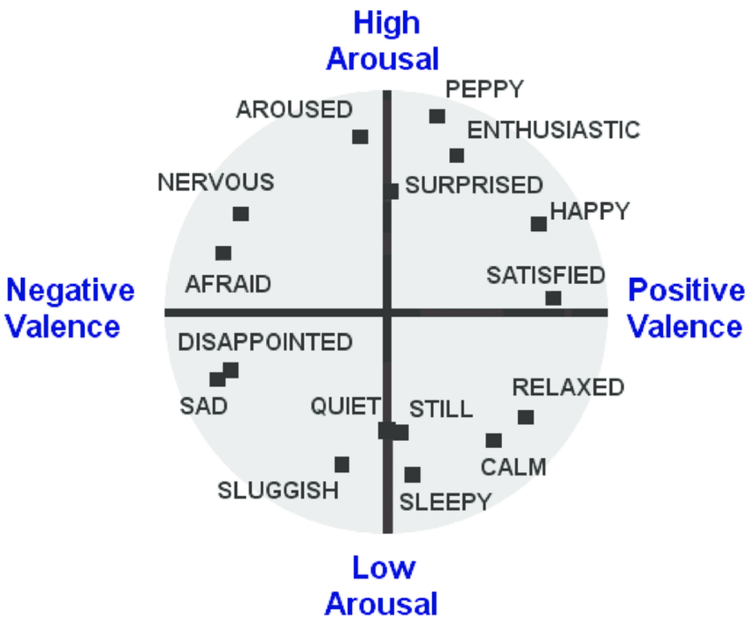

Figure ١: The 2-D emotion model.

3.2 Temporal window:

The duration of the acquisition of EEG is ordinarily taller than the time to accurately differentiate emotional case. To accurately define emotional case, EEG signals are Typically windowed into pieces. Nonetheless,, the length for windows is a different title for researchers. Kumar et al. (Kumar et al., 2016) He fired a 30-second window for the EEG signals. Use EEG windows 1 to 8 seconds to recognize emotion. Thammasan et al The results show that small windows (1-4 s) have better and superior performance than greater windows (5-8 seconds) (Thammasan et al., 2016). Levenson et al. determine Hold on to time was 0.5-4 seconds for emotions (Levenson et al., 1992).

Mohammadi et al (Mohammadi et al., 2017). The length for the test window is 2 seconds and 4 seconds, and the result is that the length of the window is 4 seconds, the best for emotional Recognition. Zhang et al. Choose the length of the 4-second window to classify the four emotions (Zhang et al., 2016). There are other opinions.

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4 Materials and methods:

4.1 EEG Recordings and Dataset Acquisition:

used DEAP dataset. To stimulate different emotions, used in this dataset, 32 people who watched 40 videos, and each video was 60 seconds long. The contents of the database are summarized in Table 1. Each subject presented one of four dimensions in the personal classifications of (valence and "arousal" and "dominance" and "liking"), and they ranged Begins from (1 – 9), the lowest being 1, and the largest being 9.

The emotional state increases from left to right with increasing personal classifications. As an example, the degree of valence (degree of pleasure) changes from the smallest to the greatest Begins from (negative case to positive case), the alteration in the degree for arousal ("degree for activation") Begins from smallest to greatest ("of calm case to excited case).

Table 1: DEAP Dataset details

Physiological Experiment	
Number of participants	32
Number of videos	40
Selection method	Subset of online annotated videos with clearest responses
Rating scales	Arousal ,Valence, Dominance, Liking
Rating values	Familiarity: discrete scale of 1- 5 Others: continuous scale of 1-9
Recorded signals	EEG with 32 channels at 512 Hz

One of the aims of this paper is to analyze emotion in two dimensions, namely, "valence and arousal". The level of arousal, valence is high if the person result appears above 4.5, while level is low in the two-dimensions if The person's score is less than 4.5. [22].

4.2 Choosing a channel:

this is paper talked about channels (4, 10, 14, 18, and 32) on EEG's emotion classification. The Choose of channels (4, 10-14-18) was based on some people's experiences. they also used 32-channels in the DEAP data. According to Mohammadi et al, the left frontal brain regions are indicative of positive emotions, and the right frontal brain regions are indicative of negative emotions (Murugappan et al., 2007). In Table 2 shows the channel details.

Table 2: the channel details

Four channels	FP1 F3 FP2 F4
Ten channels	FP1,FP2, F3, F4, F7, F8, FC5, FC6 , FC1, FC2
Fourteen channels	FP1,FP2, F3, F4, F7, F8, FC5, FC6 , FC1, FC2, AF3, AF4, C3, C4
Eighteen channels	FP1,FP2, F3, F4, F7, F8, FC5, FC6 , FC1, FC2, AF3, AF4, C3, C4, T7, T8, Fz and Cz
Thirty-two channels	FP1,FP2, F3, F4, F7, F8, FC5, FC6 , FC1, FC2, AF3, AF4, C3, C4, T7, T8, Fz and Cz , CP5, CP6, CP1, CP2, P3, P4, P7, P8, PO3,PO4,O1, O2, Oz, Pz

4.3 Preprocessing:

In preprocessing, Was used a method called "average mean reference (Mohammadi et al., 2017) to procedure the data. Then, was normalized to eliminate the differences in the channel. Was used normalization (min-max normalization) of all channels all available channels for anyone [0, 1] To reduce computational complexity (Ang et al., 2002) . The figure 2 shows the proposed method in a diagram.

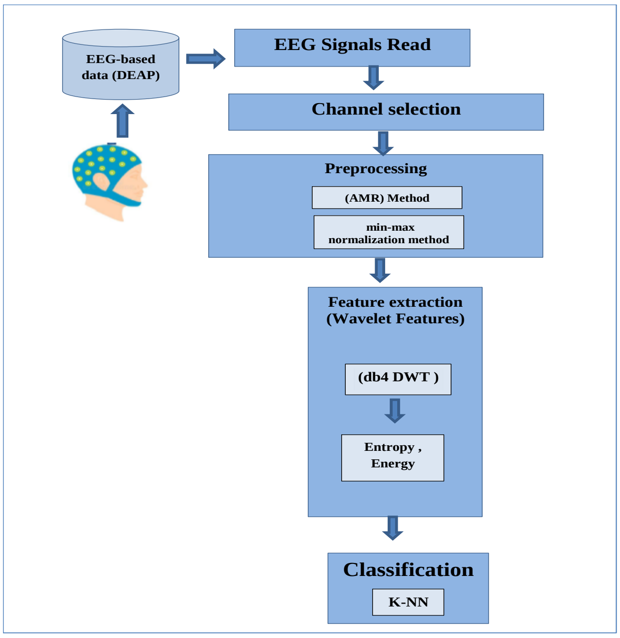

Figure 2: Diagram of the proposed method classification

4.4 Feature extraction:

In the research, was used to extract the features of the EEG, DWT. And to obtain a series for "wavelet coefficients" and through means for " shifting and stretching " of EEG Which used what is known "wavelet mother function". These various functions have a various effect on "emotion classification.

For each (EEG) channel in our study, a four-time window was used, with every window overlapping the previous one by two seconds, for a sum of (29 windows), Which is one of the important steps. Then, using "db4 DWT," every "window's" dataset was decomposed to four times, yielding all of the " High wave components as "four bands, which are shown in the Table 3. Finally, each band's (entropy, energy) was computed as features. As a result, each band has "two features" for each channel. In "10 channels," there are 20 (2*10) features, while "14, 18," and "32 channels," respectively, have 28, 36, and 64 features.

Table 3: Four waves

Frequency band	Frequency range (Hz)	Frequency bandwidth (Hz)	Decomposition level
Theta	4–8	4	D4
Alpha	8–16	8	D3
Beta	16–32	16	D2
Gamma	32–64	32	D1

4.4.1 Entropy:

The signal Rhythm is exemplifying by the entropy. The degree of Rhythm increases as entropy increases. It is capable of analyzing "time series signals.
According to the following equation Listed below:

$$ENT_j = -\sum_{k=1}^{N} (D_j(k)^2) \log(D_j(k)^2) = 1 \ldots\ldots N$$

4.4.2 Energy:

It is extracted in the following equation:

$$ENG_j = \sum_{k=1}^{N} \left(D_j(k)^2\right), k = 1 \ldots\ldots N$$

Where

j: the number of "wavelet coefficients"

D: the level of "wavelet decomposition."

4.5 Classification:

The "k-closest-to-neighbor" (KNN) algorithm is a moderated machine learning algorithm that is simple and easy to understand and uses both classification and regression., used in mature classification algorithm. Its main mechanism of operation is to find the K instances that are the most similar to any unidentified points and classify the unknown instances from the rest of the K instances. Algorithm (4.5) describes the steps of K-NN algorithm.

(4.5): Classification k-nearest neighbors algorithm **(K-NN)**
Input: Features Matrix. Output: the predicted class. Begin Step1: Load data. Step2: divide data randomly into (testing, training) Step3: Initialize the value for k. Step4: For getting the predicted class, repeat from Step5 to Step8 For all other training samples. Step5: Calculate the distance between test samples and each training sample. Using the Euclidean distance. Step6: Sort and arrange the distances in ascending order depending on the distance values. Step7: Get the highest k samples from the sorted matrix. Step8: Get in this matrix on top frequent class. Step9: Return the predicted class. Step10: compute accuracy for training. Step11: compute accuracy for test. End

The KNN algorithm was used to classify the emotions and the validation was done by comparing the subject number 29 with the subject 28 of the rest. The results were good, and the value of K = 3, It can change.

5- Results and discussion:

5.1 variance full band Channel groups:

Then compared (the) in the "valence and arousal" accuracies for channels (4, 10, 14 and 18, and 32). All a channel combination has similar Recognition precision in (the valence and arousal Which Are Represented in the table 4. The Recognition accuracy of the emotional situation improves, for example, how many channels were used increases in both dimensions. The highest Recognition accuracies were 99.7656 percent (valence) and 99.7656 percent (arousal) when 18 channel (EEG) signals were used.

Table 4: Classification results by channels

Emotion dimensions	No.channels				
	4	10	14	18	32
valence	95.3906	99.5313	99.6094	99.7656	99.6875
Arousal	95.5469	99.4531	99.5313	99.7656	99.6875

5.2 Change the EEG bands with Channel groups:

Was evaluated the Recognition accuracies of various bands, which is (gamma- beta- alpha- and theta) and as well channel groups, which is (4, 10, 14, 18, and 32).

The Recognition Accuracies Especially for the gamma and beta are much higher than those of the alpha and theta. and Table 5, in any case for the number of channels used or Whether, if the arousal or valence is taken into consideration.

Table 5: Classification results by bands

Emotion dimensions	Frequency bands	No.channels				
		FP1, FP2, F3, F4	FP1-FP2, F3-F4, F7-F8, FC5-FC6, FC1-FC2	FP1-FP2, F3-F4, F7-F8, FC5-FC6, FC1-FC2, AF3-AF4, C3-C4	FP1-FP2, F3-F4, F7-F8, FC5-FC6, FC1-FC2, AF3-AF4, C3-C4, T7-T8, Fz, Cz	Fp1, AF3, F3, F7, FC5, FC1, C3, T7,
		4	10	14	18	32
valence	Gamma	94.1406	99.5313	99.6094	99.7656	99.69
	Beta	29.2969	70.2344	77.5781	81.1719	86.56
	Alpha	16.0938	47.1094	57.1094	64.8438	72.73
	Theta	4.7656	18.6719	24.6875	28.4375	36.33
Arousal	Gamma	94.5313	99.4531	99.5313	99.7656	99.69
	Beta	28.2031	69.2188	76.0156	80.3125	86.8
	Alpha	16.9531	47.9688	58.3594	64.9219	72.42
	Theta	5	17.7344	24.4531	28.0469	36.02

The gamma band has a higher Recognition accuracy than the beta band, and the theta band has the lowest Recognition accuracy.

The Classifier accuracy improves with the Numeral Channels for various channel combinations, with the highest classification accuracies in "the gamma wave that use 18 channel being 99.7656 percent (valence) and 99.7656 percent (arousal).

5.3 Comparison of results:

In this subsection, was compare our findings to those of other studies using the DEAP dataset. The findings of this comparison are listed in The table 6, which show that our study's classification accuracy on combinations of (channels) (10, 14 and 18, 32) is Excel to that for other studies.

Table 6: Accuracy comparison for previous studies

Reference	Classifier	No. channels	Accuracy (Valence)	Accuracy (arousal)
(Mohammadi et al., 2017)(2016)	KNN	10	86.75	84.05
(Mi Li et al., 2018)(2018)	KNN	10	89.54	89.81
		14	92.28	92.24
		18	93.72	93.69
		32	95.70	95.69
Our research (2021)	KNN	4	95.3906	95.5469
		10	99.5313	95.5469
		14	99.5313	95.5469
		18	99.5313	95.5469
		32	99.5313	95.5469

6 Conclusions:

Correct rates of EEG emotional Recognition is affected by the Techniques of EEG dataset preprocessing, and also the features for EEG, as well the feature Choose system used (If it exists), As well the position and number for channels, Recognition of EEG data, and as well the option for classifier, it’s hard to compare the effects of various variables on the accuracy Recognition for EEG in different papers except the treatment for EEG data is identical, And from other things. Every paper compares the impact of one or more of the aforementioned factors on EEG Recognition accuracy. The impact of channels (10-14-18-32) on Recognition accuracy is investigated. Was used The DEAP dataset was preprocessed using a normalization tool. Using the db4 DWT (4-time) decomposition, data from four-second windows are divided into 4 bands, it's (gamma wave and beta and alpha and theta wave). And also The energy and entropy for every range are then measured as KNN classifier input features. The results, show that (the gamma band) has the best Recognition accuracy, whatever the case "valence" or "arousal". The valence Recognition accuracies of channels (10, 14, 18, 32) in (the gamma wave) he was 99.5313 percent, 99.6094 percent, 99.7656 percent, and 99.6875 percent, correspondingly, and the arousal Recognition accuracies he was 99.4531 percent, 99.5313 percent, and 99.7656 percent, 99.6875 percent. In comparison to the low band, (the gamma band) It was more important to the emotional situation in labels (valence, arousal). Furthermore, it demonstrates that increasing the number for (channels) will increase the rigor of emotional case Recognition. The results are serve as a guide for choosing channels for (emotion recognition).

References:

1. Ang, J., Dhillon, R., Krupski, A., Shriberg, E., & Stolcke, A. (2002). Prosody-based automatic detection of annoyance and frustration in human-computer dialog. *Seventh International Conference on Spoken Language Processing*.
2. Atkinson, J., & Campos, D. (2016). Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers. *Expert Systems with Applications*, *47*, 35–41.
3. Azeez, R. A., Miften, F. S., & Hayawi, M. J. (2020a). *Epileptic Automated Detection from EEG Signal Using Statistical Features and Machine Learning Technique*. *June*. https://doi.org/10.37200/IJPR/V24I8/PR281540
4. Azeez, R. A., Miften, F. S., & Hayawi, M. J. (2020b). *Epileptic EEG Signals Classification Based on Determinant of Matrix as a Feature*. *4*, 461–465.
5. Koelstra, S., Mühl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., & Patras, I. (2012). DEAP: A database for emotion analysis; Using physiological signals. *IEEE Transactions on Affective Computing*, *3*(1), 18–31. https://doi.org/10.1109/T-AFFC.2011.15
6. Kumar, N., Khaund, K., & Hazarika, S. M. (2016). Bispectral analysis of EEG for emotion recognition. *Procedia Computer Science*, *84*, 31–35.
7. Levenson, R. W., Ekman, P., Heider, K., & Friesen, W. V. (1992). Emotion and autonomic nervous system activity in the Minangkabau of West Sumatra. *Journal of Personality and Social Psychology*, *62*(6), 972.
8. Li, Mi, Xu, H., Liu, X., & Lu, S. (2018). Emotion recognition from multichannel EEG signals using K-nearest neighbor classification. *Technology and Health Care*, *26*(S1), S509–S519. https://doi.org/10.3233/THC-174836
9. Li, Mu, & Lu, B.-L. (2009). Emotion classification based on gamma-band EEG. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1223–1226.

10. Liu, W., Zheng, W.-L., & Lu, B.-L. (2016). Emotion recognition using multimodal deep learning. *International Conference on Neural Information Processing*, 521–529.

11. Liu, Y., Sourina, O., & Nguyen, M. K. (2010). Real-time EEG-based human emotion recognition and visualization. *2010 International Conference on Cyberworlds*, 262–269.

12. Mohammadi, Z., Frounchi, J., & Amiri, M. (2017). Wavelet-based emotion recognition system using EEG signal. *Neural Computing and Applications*, *28*(8), 1985–1990.

13. Mohsen, M. M., & Miften, F. S. (2021). Human Emotion Perception Based on K-Nearest Neighbors Classifier. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(13), 3670–3681.

14. Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Zunaidi, I., & Hazry, D. (2007). EEG feature extraction for classifying emotions using FCM and FKM. *International Journal of Computers and Communications*, *1*(2), 21–25.

15. Raghav, G. K., Nongmeikapam, K., Dixit, A., Bose, S., & Singh, D. (2018). *Evaluating Classifiers for Emotion Signal on DEAP Dataset*. *December*, 36–42.

16. Thammasan, N., Fukui, K., & Numao, M. (2016). Application of deep belief networks in eeg-based dynamic music-emotion recognition. *2016 International Joint Conference on Neural Networks (IJCNN)*, 881–888.

17. Xu, H., & Plataniotis, K. N. (2016). Affective states classification using EEG and semi-supervised deep learning approaches. *2016 IEEE 18th International Workshop on Multimedia Signal Processing (MMSP)*, 1–6.

18. Zhang, J., Chen, M., Zhao, S., Hu, S., Shi, Z., & Cao, Y. (2016). ReliefF-based EEG sensor selection methods for emotion recognition. *Sensors*, *16*(10), 1558.

19. Zhu, J.-Y., Zheng, W.-L., Peng, Y., Duan, R.-N., & Lu, B.-L. (2014). EEG-based emotion recognition using discriminative graph regularized extreme learning machine. *2014 International Joint Conference on Neural Networks (IJCNN)*, 525–532.

20. Abdel-Reheim, E. S**.** (2016) . "Cardioprotective Efficacy of Taurine on Lipid- Metabolism of Isoproterenol induced Myocardial Infraction ." *International Journal of Pharmacy and Pharmaceutical Sciences*., 8:135-141

Abi, B. G .; Mohamed, S. A .; Sivakumar, V. and Jaya, S. R. (2014) . "Cardioprotective Activity of Methanolic Extract of Croton Sparciflorus on Isoproterenol Induced Wister Albino Rats." *J Med Plants Stud*., 2:1-8.
–76.

Auda, M. A.; Majid, A. and Al-Fartosi, K. G. (2018). Protective role of polyphenolic compounds extracted from *cyperus rotundus* rhizomes and taurine on troponin-I and some oxidant/antioxidants parameters of female rats treated with isoproterenol – induced myocardial infraction. Journal of Thi-Qar University., 13(2): 61-76.

Bishop, M. L.; Fody, E. P. and Schoeff, L**.** (2005). "Clinical Chemistry:Principles, Procedures, Correlations." *5th Edn. eds.Lippincott Williams and Wilkins.Philadelphia.*, 200–202,285,290, 370,372,503–508.

Dang, G. K.; Parekar, R. R.; Kamat, S. K.; Scindia, A. M. and Rege, N. N. (2011). "AntiinFlammatory Activity of Phyllanthus Emblica, Plumbago Zeylanica and Cyperus Rotundus in Acute Models of Inflammation." *Phytother. Res.*, 25:904–908.

Gayon, T. A. (1972). "Plant Phenolic." *Oliver and Boyed, Edinboura*.,p: 254.

Jagadeesh, G. S.; Meeran, M. F. N. and Selvaraj, P. (2016). "Activation of β1-Adrenoceptor Triggers Oxidative Stress Mediated Myocardial Membrane Destabilization in Isoproterenol Induced Myocardial Infarcted Rats: 7-Hydroxycoumarin and Its Counter Action." *European Journal of Pharmacology*., 777: 70–77.

Kesarwani, N. and Azmi, L . (2014). "Evaluation of Cardioprotective Effect of Tinospora Cordifolia against Isoprenaline Induced Myocardial Infraction in Rats." *International Journal of Current Microbiology and Applied Sciences*., 5: 543–55.

Kulkarni, J. M. and Swamy, A. V. (2015). "Cardioprotective Effect of Gallic Acid against

Doxorubicin-Induced Myocardial Toxicity in Albino Rats." *Indian J Health Sci*., 8: 28–35.

Majid, A.: Auda, M. A. and Al-Fartosi, K. G. (2018). Cardioprotective Activity of Polyphenolic Extract of Tubers of Cyperus Rotundus and Taurine against Isoproterenol - induced Myocardial Infraction in Rats: Troponin-I and Histological Findings. Journal of Global Pharma Technology. 10(03):479-487

Okigbo, R. N.; Anuagasi, C. L.; Amadi, J. E. and, Ukapabi, U. J. (2009). "Potential Inhibitory Effect of Some African Tuberous Plant Extracts on Escherichia Coli, Staphylococcus Aureus and Candida Albicans." *International Journal of Interactive Biology*., 6: 91–98.

Opie, L. H. (2004). "Heart Physiology from Cell to Circulation." *4 Th Edn. Ed. Lippincott Williams& Wilkins. USA*., 561.

Parikh, H.; Tripathi, C. B.; Shah, P.; Pharm, V.; Ghori. M. and Goyal, R. K. (2015). "Investigation of the Cardioprotective Effects of Crataegus Oxycantha and Its Molecular Mechanism." *Curr Res Cardiol*., 2:161-167.

Raza, S. M.; Tomar, V. and Siddiqui, H. H. (2012). "Cardioprotective Effect of Alcoholic Extract of Cyperus Rotundus Rhizome on Isoproterenol - Induced Myocardial Necrosis in Rats." *International Journal of Pharmaceutical Sciences and Research (IJPSR).*, 3: 2535–38.

Sabeena, Farvin. K. H.; Anandan, R.; Kumar, S. H.; Shiny, K. S. Sankar, T. V. and Thankappan, T. K. (2004). "Effect of Squalene on Tissue Defense System in Isoproterenol-Induced Myocardial Infarction in Rats." *Pharmacol Res*., 50: 231–36.

Sadiya, Khwaja.; Tarique, Mahmood. and Hefazat, H. Siddiqui. (2016). "Effect of Ethanolic Extract of Cyperus Rotundus L. against Isoprenaline Induced Cardiotoxicity."*Indian Journal of Experimental Biology*., 54: 670–75.

Shi, M.; He, W.; Liu, Y.; Li, X.; Yang, S.; Xu, Q. (2013). "Protective Effect of Total Phenylethanoid Glycosides from Monochasma Savatieri." *Phyto Medicine*., 20: 1251–55.

Shivakumar, S. I.; Suresh, H. M.; Hallikeri, C. S.; Hatapakki, B. C.; Handiganur, J. S.; Sankh, K. and Shivakumar, B. (2009). "Anticonvulsant Effect of Cyperus Rotundus Linn. Rhizomes in

Upaganlawar, A.; Gandhi, C. and Balaraman, R. (2009). "Antioxidant Activities of Cyperus Rotundus L. Rhizome and Areca Catechu L. Seed." *Plant Foods Hum. Nutr*., 64: 75–80.