# HUMAN EMOTION CLASSIFICATION USING KNN CLASSIFIER AND RECURRENT NEURAL NETWORKS WITH SEED DATASET

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***Abstract:*** Emotions which can be commonly called to be as human feelings are variable and numerous. They vary according to the situation or according to perception. Analyzing and classifying those emotions are very crucial in current situations. For example, for knowing the review of the product, the developer can use this emotion detection to see whether the client is satisfied with the product and can understand the likeliness of the product. Accordingly, he can vary it, and in health care for finding the depression in a person. So this makes the classification of human feelings more vulnerable. Here initially the data is being collected from the brain via EEG Signals and it is fed into a mock dataset and then we can extract these EEG Signal features by using Knn Classifier to Classify the data but To improve several parameters like time of execution and accuracy this seed data can be classified using the RNN(recurrent neural networks). For a small dataset, K nearest neighbor may work efficiently but for large datasets and more classifications, a Recurrent neural network is more efficient. Here when a small seed dataset is being considered, It produces good accuracy and classification of the data. Computing using this process produces the Best accuracy of 96.22% by the Knn classifier and Test accuracy of 85.71% by Recurrent Neural Networks.

***Keywords: EEG Signal, Emotion Classification, Seed dataset, KNN Classifier, RNN.***

## I. INTRODUCTION

The human brain is more valuable. The human brain controls almost every facet of the body fluctuating from emotional functions to physical abilities. one of the parts of the brain cerebrum is split into four lobes. They are Frontal, Parietal, Occipital, and temporal. There's a system within the brain referred to as the visceral brain which is situated between the brain system and therefore the two cerebral hemispheres which control emotion and memory. The brain consists of three parts: 1) Cerebrum 2) Cerebellum 3) Brainstem

The cerebrum is the greater part of the brain. It accomplishes tasks like touch, vision, emotions, and control of movement.

The cerebellum harmonizes muscle movements and maintains balance. whereas, the brainstem accomplishes many functions like heartbeat, breathing, etc[1-4].

The brain-computer interface allows connection between a human brain and computer devices. Our intentions from the brain are decoded with the assistance of a brain-computer interface. In this project, we have used the SEED dataset which was developed by SJTU[5-7].

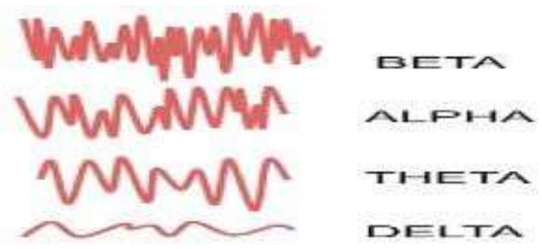
Researchers have proposed numerous methods for emotion recognition. Among them, the foremost popular technique is electroencephalography(EEG). The EEG records the electrical activity of the brain from the scalp. EEG is non-invasive, it means to gather brain signals we don't have to cut the skull. The energy obtained by the brain employing a series of electrodes placed on the scalp is recorded by EEG. The electrodes on the scalp detect brain activity, which is within the sort of electricity obtained from the brain[8-14].

Emotion recognition from electroencephalography(EEG) signals is virtually contemporary within the domain of intuitive enumeration. On the contrary, signals from the central systema nervosum like EEG are encapsulated from the inception of emotional circumstances. Besides, EEG signals which have clear firmness are easy to trace with economical cost[15-19].

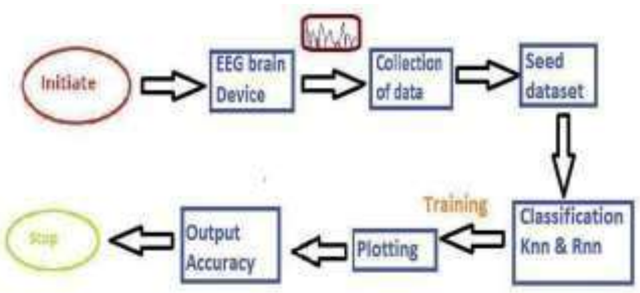
These Human emotions are classified using EEG signals. By applying EEG signals from the SEED dataset according to the valence/arousal model to recognize emotion. To extract information from electroencephalography (EEG) signals we use EEG analysis methods. Using discrete wavelet transform (DWT) these EEG signals decay into alpha, beta, gamma, and theta frequency bands. EEG signals are broadly seen in sleep pattern analysis. These EEG analysis methods intrude into four categories[20-22][26]: They are:

1) Time-domain [22]
2) Frequency domain [23]
3) Time-frequency domain [24]
4) Non-linear methods.[25]

In this project, we classify these EEG signals using a classification technique of the KNN algorithm. The first EEG recording was recorded on July 6 1924 by Berger in the course of neurosurgical operation on a 17 years old boy. EEG is a medical imaging technique. It devours scalp electrical activity engendered by brain structures. Within a single second the EEG sensors can record up to a couple of grand snapshots of electrical activity generated by the brain.



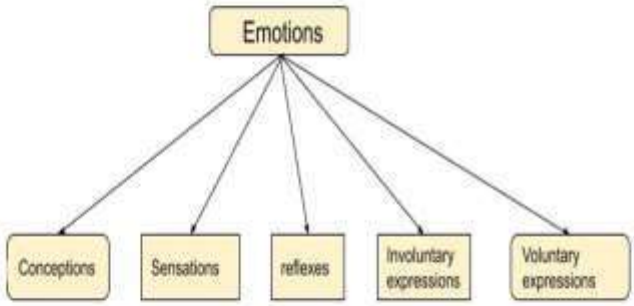

A. *Schema Chart:*




B. *Classifying of emotions:*

The feeling could be a portion of a person's character which comprises their sentiments. Emotions have a predominant role in daily life. Not only in human interplay but also in judgment processes. These emotions are classified into many types. Among them, the main are classified into two types. They are:

1) Primary emotions
2) Secondary emotions




Primary emotions are such as love, surprise, joy. Whereas, secondary emotions are affection, relief, pride, and so on. Primary emotions are the emotions that occur as a result of an


unexpected situation. Distinct sorts of procedures have been invented to recognize the rudimentary emotion of a person.

*C. KNN vs RNN:*

*KNN:*

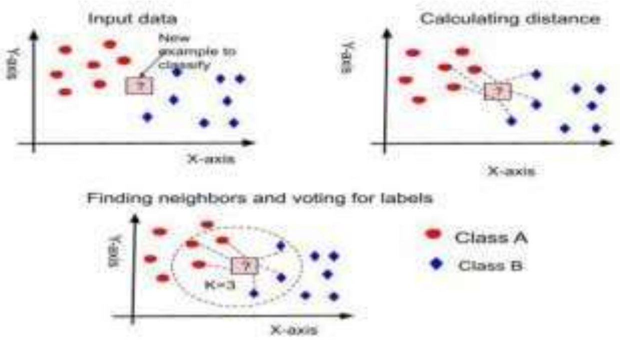
In machine learning, there are different types of algorithms used for classification and regression. Among them, the simplestand easiest algorithm is the K-nearest neighbor (KNN). It is a supervised learning technique.

- It can be used for regression and also for classification but ultimately it is used for classification.
- It means that immediately it doesn't learn anything from training the dataset instead, it stores the dataset and itperforms an action of the dataset at the time of classification.
- At the time of the training phase the knn stores the dataset and when it gets new data, it classifies that data into thecategory which is similar to that new data.
- Its working is done in four steps:

First, we have to define the value of K. Usually there is no specific way to decide the value of k[knn]. The most preferredvalue is 5.

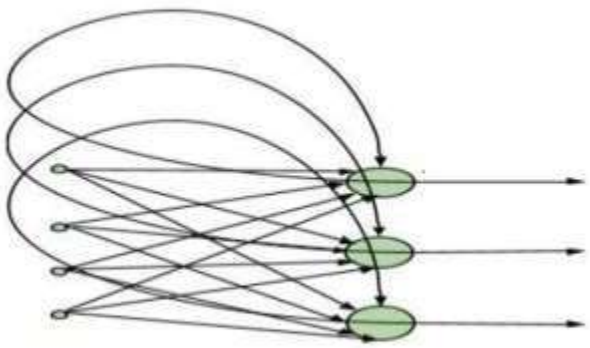
1. After defining the value of K we have to calculate the Euclidean distance between two points.
2. After the calculation of Euclidean distance, we will get k nearest neighbors. Among these neighbors, we have tocalculate the data points in each category.

3. And the last step is we have to assign the new data point to the category which is having maximum data points.




*RNN:*

RNN stands for Recurrent Neural Network. It's a kind of artificial neural network mainly planned to identify patterns in data sequences. In this neural network the information cycles



through a loop. It considers present input and also considers what it has learned the inputs it had received previously while taking the decision.

RNN is used for natural language processing, speech, and voice recognition. To predict/estimate the output of the layer the RNN saves the output of the particular layer and feeds it back to the input.

- Let's see how to convert the feed-forward network into recurrent neural networks.

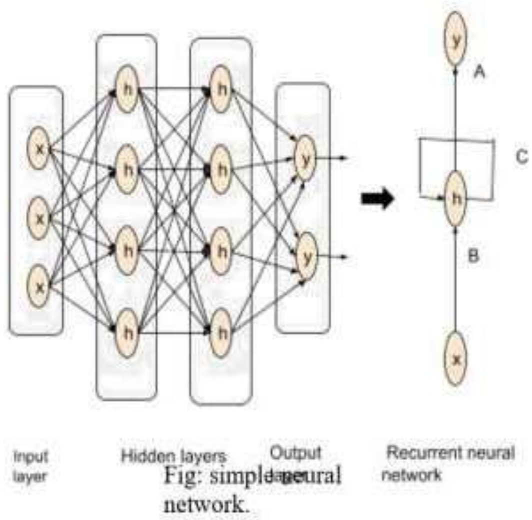
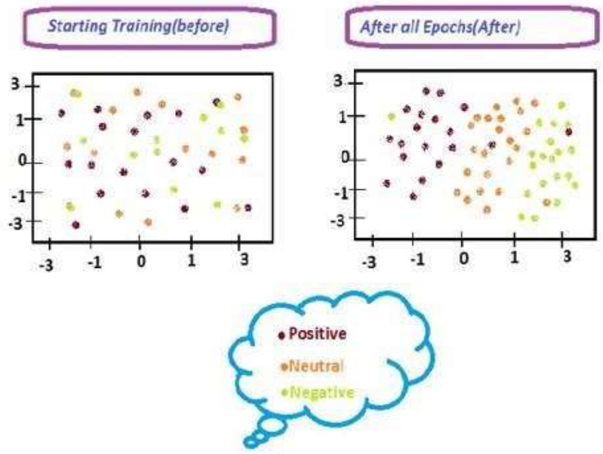



Fig:1 simple neural network.

There are different nodes in the feed-forward network. The nodes from these different layers are compressed and are formed into a single layer of recurrent neural network.

## II. CLASSIFICATION RESULT:

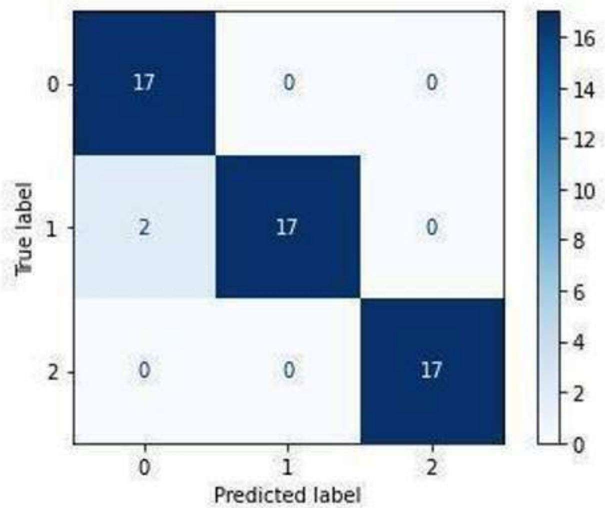
The classification process is deployed in two stages. They are Training and testing. In this emotion classification function, there are three categories: Positive, Negative, and Neutral. Upon these three categories, two classes are calculated: valence and arousal . Depending upon the size of testing and training data and also on the classifier's runtime and performance the comparison between the classifiers is done.




### A. *Obtained Results and Analysis:*

The best of Acquired results are given below:

- For KNN Trainin accuracy 0.9622641509433962 For confusion matrix:



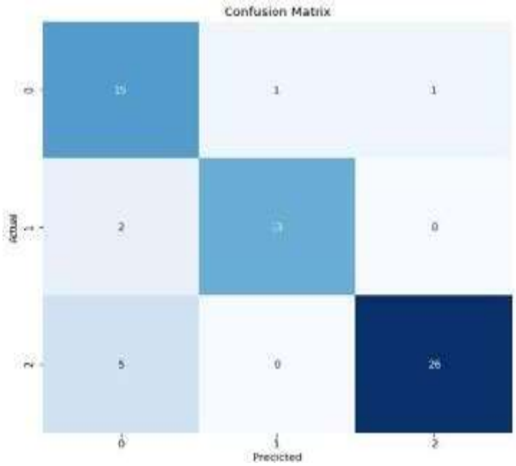

### B. *Classification:*

| | **Precision** | **recall** | **f1-score** | **support** |
|---|---|---|---|---|
| 0 | 0.89 | 1.00 | 0.94 | 17 |
| 1 | 1.00 | 0.89 | 0.94 | 19 |
| 2 | 1.00 | 1.00 | 1.00 | 17 |
| accuracy | | | 0.96 | 53 |
| macro | 0.96 | 0.96 | 0.96 | 53 |

| | | | | |
|---|---|---|---|---|
| avg | | | | |
| weighted avg | 0.97 | 0.96 | 0.96 | 53 |

- For RNN Test accuracy:85.714%

*C. For confusion matrix:*




*D. Classification:*

| | Precision | Recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.68 | 0.88 | 0.77 | 17 |
| 1 | 0.93 | 0.87 | 0.90 | 15 |
| 2 | 0.96 | 0.84 | 0.90 | 31 |
| accuracy | | | 0.86 | 63 |
| macro avg | 0.86 | 0.86 | 0.85 | 63 |
| weighted avg | 0.88 | 0.86 | 0.86 | 63 |

## III. CONCLUSION AND FUTURE SCOPE

The obtained best accuracy shows That classification of human emotions can be done by the respective machine learning algorithms and classifiers. Both knn and rnn helps to classify the feelings but here because of the small dataset knn had performed more accurate compared with the neural network process like Rnn but if considered large dataset Rnn would produce best accuracy. Here the result classifies the data as positive ,negative and neutral which gives a better accuracy. The emotions or feelings like happy, enthusiasm can be categorized as positive feelings, sad, depression, Anxiety can be categorized as negative feelings and pleasant, faithful feelings can be categorized as neutral feeling. Further these classifications can be done by using RGNN(Regularized graphical neural networks)in future.

***References:***

[1] Ang J, et al., Prosody-Based Automatic Detection Of Annoyance And Frustration In Human-Computer Dialog. in Icslp. 2002.
[2] Wang XW, Nie D, Lu BL. Emotional state classification from EEG data using machine learning approach. Neurocomputing, 2014. 129(4): 94-106.
[3] Witvliet CVO, Vrana SR. Play it again Sam: Repeated exposure to emotionally evocative music polarises liking and smiling responses, and influences other affective reports, facial EMG, and heart rate. Cognition & Emotion, 2007. 21(1): 3-25.
[4] Cai J, Liu G, Hao M. The Research on Emotion Recognition from ECG Signal in International Conference on Information Technology and Computer Science. 2009.
[5] Lee C, et al., Using neural network to recognize human emotions from heart rate variability and skin resistance in International Conference of the Engineering in Medicine & Biology Society. 2005. - PubMed
[6] Liu Y, Sourina O, Nguyen MK. Real-Time EEG-Based Human Emotion Recognition and Visualization in: International Conference on Cyberworlds. 2010.
[7] Liu W, Zheng WL, Lu BL. Emotion Recognition Using Multimodal Deep Learning. 2016. 521-529.
[8] Zhang J, et al., ReliefF-Based EEG Sensor Selection Methods for Emotion Recognition. Sensors, 2016. 16(10): 1558. - PMC - PubMed
[9] Mert A, Akan A. Emotion recognition from EEG signals by using multivariate empirical mode decomposition. Pattern Analysis & Applications. 2016: 1-9.
[10] Atkinson J, Campos D. Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers. Expert Systems with Applications. 2016; 47: 35-41.
[11] Li M, Lu BL. Emotion classification based on gamma-band EEG. Conf Proc IEEE Eng Med Biol Soc. 2009: 1323-1326. - PubMed
[12] Thammasan N, Fukui KI, Numao M. Application of deep belief networks in eeg-based dynamic music-emotion recognition. in: International Joint Conference on Neural Networks 2016.
[13] Li X, et al., Emotion recognition from multi-channel EEG data through Convolutional Recurrent Neural Network in: IEEE International Conference on Bioinformatics and Biomedicine. 2017.
[14] Cheng B, Liu G. Emotion Recognition from Surface EMG Signal Using Wavelet Transform and Neural Network. Journal of Computer Applications. 2008; 28(2): 1363-1366.
[15] Kyamakya K, et al., A novel EEG-based emotion recognition approach for e-healthcare applications. in: ACM Symposium on Applied Computing. 2016.
[16] Koelsch S. Brain correlates of music-evoked emotions. Nature Reviews Neuroscience. 2014; 15(3): 170. - PubMed
[17] Hamann S. Mapping discrete and dimensional emotions onto the brain: controversies and consensus. Trends in Cognitive Sciences. 2012; 16(9): 458-66. - PubMed
[18] Xu H, Plataniotis KN. Affective states classification using EEG and semi-supervised deep learning approaches. in: IEEE International Workshop on Multimedia Signal Processing 2017.
[19] Kumar N, Khaund K, Hazarika SM. Bispectral Analysis of EEG for Emotion Recognition. in: Procedia Computer Science. 2016; 84: 31-35.
[20] Levenson RW, et al., Emotion and autonomic nervous system activity in the Minangkabau of west Sumatra. Journal of Personality & Social Psychology, 1992. 62(6): 972-88. - PubMed
[21] Koelstra S, et al., DEAP: A Database for Emotion Analysis; Using Physiological Signals. IEEE Transactions on Affective Computing, 2012. 3(1): 18-31.
[22] Mohammadi Z, Frounchi J, Amiri M. Wavelet-based emotion recognition system using EEG signal. 2017: Springer-Verlag. 1-6.

[23] Murugappan M, et al., EEG feature extraction for classifying emotions using FCM and FKM, in: Wseas International Conference on Applied Computer and Applied Computational Science, 2008.

[24] Wichakam I, Vateekul P. An evaluation of feature extraction in EEG-based emotion prediction with support vector machines. in International Joint Conference on Computer Science and Software Engineering 2014.

[25] Verma GK, Tiwary US. Affect representation and recognition in 3d continuous valence – arousal – dominance space. Multimedia Tools and Applications, 2016: 1-25.

[26] Doma, V., Pirouz, M. A comparative analysis of machine learning methods for emotion recognition using EEG and peripheral physiological signals. J Big Data 7, 18 (2020). https://doi.org/10.1186/s40537-020-00289-7