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A Novel Deep Learning based Improved Cluster based Region Classifier Algorithm to Recognize and Categorize Emotions using EEG Signals

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***Abstract*- Nowadays deep learning plays vital role in emotion recognition. It distinguishes emotions as easy or multi-models for visual capturing. This works to provide an automatic version for identifying feelings primarily based on EEG signals. The proposed version specializes in developing an effective model, which combines the basic ranges of EEG signal handling and feature extraction. A system is developed based on Independent component analysis (ICA) algorithm to overcome the recognition task which removes noise object and to extract the independent components, for the obtaining components. The channels were selected based on the threshold average activity value. K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) are used to categorize emotional states and extracted the features, together with the unconventional improved Cluster-based region Classifier (ICBRC). Based on EEG signals Average recognition rate up to 94% for three emotional states and 95% for binary states can be achieved with this system.**

***Keywords: Independent component analysis (ICA), electroencephalogram (EEG), Deep Learning, Artificial Neural Network, ICBRC*.**

I. INTRODUCTION

Human excitements play a crucial part in Human-Computer Interaction (HCI). Emotions can impact the way people interact with technology, and can affect their perception of the technology and their overall experience. In HCI, emotions are typically categorized into basic emotions, such as happiness, grief, irritation, and amazement, and complex emotions, such as contentment, frustration, and confusion. To design effective HCI systems, it is important to understand how emotions can affect the user's behavior and perception. For example, a system that can recognize and respond to a user's emotional state can provide a more personalized and satisfying experience. Several techniques, like facial expression recognition, speech analysis, and physiological measures, such as electroencephalography [1] and electrocardiography (ECG), are used to detect and classify emotions in HCI. In addition, several prototypes must be anticipated to understand how emotions can be represented and classified, such as the isolated emotion model and second dimensional emotion. The field of Sentimental Computing, which is the learning of how computers can recognize, understand, and reply to human emotions, is also closely related to HCI and emotions. In conclusion, understanding human emotions and how they affect HCI is crucial for designing effective and user-centered technology. Techniques such as facial expression recognition, and physiological actions, as well as models such as the discrete model and the dimensional emotion model, can be used to detect and classify emotions in HCI.

Catching emotional interfaces between the human beings and computers is an important and growing field of research. The ability to understand and respond to human emotions is crucial for creating more natural and effective human-computer interactions. One key area of research in this field is in the advancement of natural language processing and natural language understanding algorithms[2].

Another area of research is in the development of affective computing, which aims to enable computers to recognize, interpret, and respond to human emotions. This is done through the use of sensors and cameras that can detect facial expressions, body language, and other cues, as well as through the use of machine learning algorithms that can analyze this data and determine the user's emotional state. There are also many potential applications for this technology, including in fields such as healthcare, education, and customer service. For example, in healthcare, emotional recognition technology [3] could be used to help doctors and nurses detect and respond to patients' emotional needs. In education, it could be used to help teachers understand and respond to students' emotional states, and in customer service, it could be used to help agents better understand and respond to customers' needs.

However, there are also some ethical concerns related to this technology. One concern is that it could be used to manipulate or exploit people's emotions, such as by using emotional recognition algorithms [18] to target advertising or political campaigns. Additionally, there are concerns about privacy and data security related to the collection and use of emotional data. In conclusion, capturing emotional interactions between humans and computers is an emergent arena of research that has the potential to improve human-computer interactions [5] and create new applications in various fields. However, it is important to consider ethical concerns and guarantee that the machinery is used in answerable and respectful manner.

A. Russell's 2d Emotion Model:

Russell's 2D emotion model is a psychological theory of emotion proposed by psychologist Paul Russell in 1980. The model is based on the idea that emotions can be represented on two dimensions: valence [8] (the degree of emotion) and arousal (the degree to which an emotion is active or passive). According to the model, emotions can be located on a 2D plane, by means of valence on the x-axis and arousal on the y-axis. This creates a 2D emotional space in which all emotions can be represented. For example, happiness is located in the upper-right corner of the plane (high valence, high arousal), while sadness is located in the lower-left corner (low valence, low arousal).

Russell's model has stayed used to study an extensive sort of emotional experiences, including basic emotions, complex emotions, and emotional states. It has also been applied in various fields such as psychology, neuroscience, computer science, and artificial intelligence.

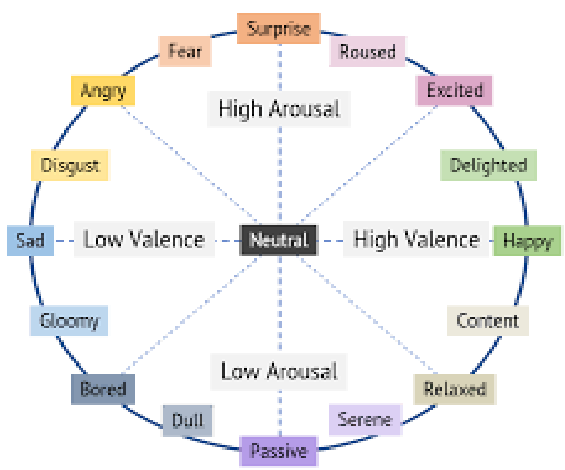

Fig.1 Russell's 2d Emotion Model

One of the advantages of the model is that it allows for a more fine-grained understanding of emotions, as it can distinguish between emotions that may seem similar but have different valence-arousal profiles [19], such as contentment and satisfaction. Additionally, the model has been used in the development of affective computing and the scheme of human-computer interfaces, where it can be used to classify and understand the emotional state of the users based on their input, such as speech or facial expressions. However, it should be noted that while the model has been well received, it has also received some criticisms, mainly on the assumption that emotions can be reduced to two dimensions, and that the model may not be able to capture all the nuances of human emotions. HAPV (high-arousal positive valence) [7] and LANV (low-arousal negative valence) are two quadrants of Paul Russell's 2D emotion model. HAPV emotions are those that are characterized by high arousal and positive valence. These emotions are generally considered to be very intense and pleasant, such as excitement, joy, or love. On the other hand, LANV emotions are those that are characterized by low arousal and negative valence [9][10]. These emotions are generally considered to be less intense and unpleasant, such as sadness, boredom, or apathy.

The Russell's 2D emotion model can be useful to understand how emotions can be exemplified on a 2D space, but also to design human-computer interactions, since the model can be used to classify and understand the emotional state of the users based on their input, such as speech or facial expressions [11-13]. It should be noted that the model is just a theoretical framework, and that emotions are not always easy to classify or represent in a two-dimensional space, as there can be variations and nuances on each individual's emotions.

The rest of the paper classified as background survey, proposed methodology, results section and finally concluded with conclusion section.

II. BACKGROUND SURVEY

Y. Zhang [1]et.al, titled a paper "EEG-based classification of emotions using empirical mode decomposition and autoregressive model", discussed on emotion classification which involves decomposition model to reduce the latency while classifying and improved fast. L. Santamaria-Granados [2] et.al, focused on layered CNN model for detecting of human emotions which is titled, "Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset".

X. Li, D et.al [3] in their research, explored various ways for Emotion recognition from multi-channel EEG data through CNN, and also reduced noise ratio while capturing image and improved accuracy.

X. Jie, R. Cao, and L. Li [4], "Emotion recognition based on the sample entropy of EEG," entropy based classification with different CNN layers were filtered. M. Ali et.al [6], "EEG based emotion recognition approach for e-healthcare applications," explained where emotion recognition used in various real time applications and also described the emotions classification depends on some qualitative parameters.

Bazgir, O. et.al[14], adopted advanced concepts from machine learning paradigms to segregate emotions with parameters and shown improved efficiency by means of quality ,efficiency and reliability. Alhagry et.al [15] implemented a novel mechanism called LSTM based RNN model to Emotion Recognition based on EEG using LSTM Recurrent Neural Network, where it consumed the long and short memory storage.

Li, J.; Zhang et.al [17], in their research told which is a hierarchical way of layering called HCNN. It follows a standard layering to classify emotion based clips. Petrescu et.al[20], titled paper on Ml based classification technique,. J. H. Yoon et.al [21] implemented a wavelet based noise detection model called "Wavelet-based statistical noise detection and emotion classification method for improving multimodal emotion recognition,", for improving the recognition and classification rate. W.-L. Zheng et.al, in their research work, , invented a meter for emotion calculations by using parameterized classification and analyzing with phases.

S. Farashi et.al[22], a tree based emotion classification for fast and dynamic recognition. It involves a sophisticated way of image quatization level by level image capturing technique. Finally a spanning tree structured categorization of emotion based images was deployed by involving EEG signals. Zhang et.al[23], developed a deep learning model for emotion classification and categorization titled "Respiration based emotion recognition with deep learning", which captures respiration of human beings to analyze the actual emotion and applies a DNN model to capture and strengthen the quality and improved speed. Li M et.al [23] wrote an article "Emotion recognition from multichannel eeg signals using k-nearest neighbor classification", used an ML based KNN classifier model to filter and capture emotions which are multichannel and multi model classification based.

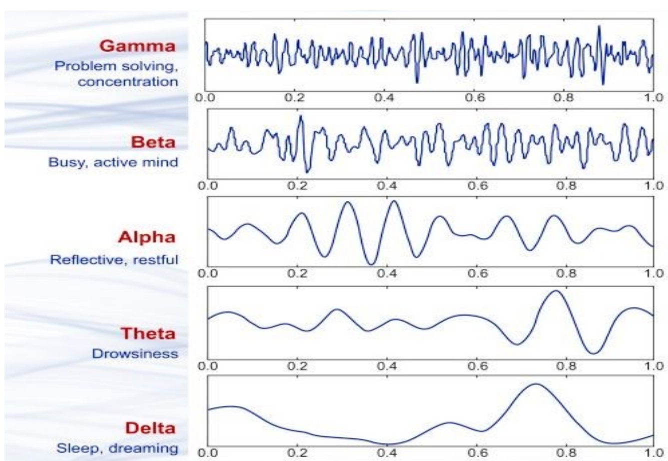

Fig.2 EGG Waves Spectrum

Above diagram represents EEG waves spectrum and these are named based on their frequency range .Most commonly studied wave forms ranges from 0.5 Hz to 30Hz. Supplementary the effect of eye intermittent is utmost leading below 4 Hz, and heart-functioning origins artifacts about 1.2 Hz, while muscle artifacts disturb the EEG band beyond 30 Hz. Non-physiological artifacts initiated by power outlines spotted at 50-60 Hz.

we use a band pass filter to separate each channel's audio into five distinct frequency ranges.One may choose from 01–03 Hz, theta (04–07 Hz), alpha (08–013 Hz), beta (014–30.0 Hz), and gamma (31.0–50.0 Hz) as the frequency ranges.

III. PROPOSED METHODOLOGY

Electroencephalography (EEG) is a non-invasive method that registers the electrical activity of the brain through electrodes positioned on the scalp. The electrical activity measured by EEG is known as brain waves, which are the result of the synchronized activity of millions of neurons in the brain. EEG is widely used in neuroscience, psychiatry, and neurology to study the brain and its functions. It is also used in the diagnosis and treatment of certain brain disorders, such as epilepsy and sleep disorders. EEG is a relatively simple and safe technique that can be used in both research and clinical settings. It is typically done by attaching electrodes to the scalp, which are connected to a machine that records the electrical motion of brain. The person being tested sits or lies down and is asked to relax or perform certain tasks, such as opening and closing their eyes or performing mental arithmetic. EEG can measure dissimilar kinds of brain waves, like alpha, beta, theta and delta, which are associated with diverse states of consciousness and cognitive functions. Alpha waves are associated with relaxation, beta waves with alertness, theta waves with drowsiness, and delta waves with deep sleep. EEG is also used in combination with other neuroimaging techniques such as fMRI, to provide a more complete picture of the brain's activity.

One of the limitations of EEG is that it can only record the activity of the intellectual cortex, which is the outmost film of the brain, and it cannot image the deeper structures of the brain. Additionally, the electrodes can only detect the activity of large groups of neurons, and not of individual neurons.

In Human-Computer Interaction (HCI), the use of Electroencephalography (EEG) data to classify emotions plays an important role. To achieve this, several techniques are used including Classifiers, Feature Extraction, Convolutional Neural Networks and Deep Neural Networks Classifiers are algorithms that are used to train a model to forecast the class of an input data. In HCI, classifiers are used to predict the emotional state of any person built using EEG data. Common classifiers used in HCI include Support Vector Machines (SVMs) and Random Forest.

A. Feature Extraction:

Feature extraction is the progression of decreasing the dimensionality of the EEG data by identifying the most relevant features for the classification task. The features are chosen based on their ability to differentiate between different emotional states.

B. CNN and ANN:

CNN and ANN are neural network architectures that are used to classify EEG data in HCI. They are particularly useful for image classification tasks, such as classifying emotions based on EEG data. CNNs are designed to process 2D images, while ANNs are designed to process 1D time-series data. To translate the EEG time-series data into 2D images, the data is typically segmented into smaller windows, and then transformed into a 2D format using a technique called time-frequency representation. This allows the CNNs to route the data and categorize the emotional state of the person based on the EEG data. In summary, Classifiers, Feature Extraction, CNN, and ANNs are essential in converting EEG time-series data into 2D images for active emotion cataloguing in HCI. These techniques are used to train a model to forecast the emotional state of the human based on their EEG data, and to extract the most relevant features for the classification task.

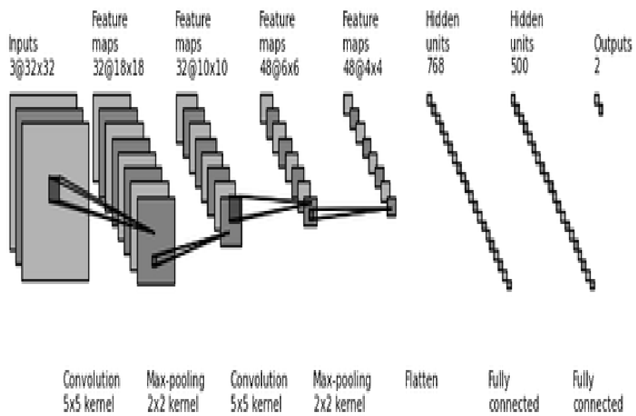

Fig.3 CNN layering structure

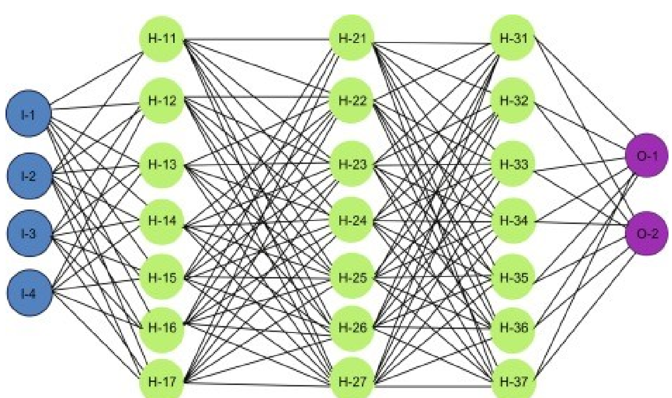

Fig.4 ANN structure

C. KNN:

K-Nearest Neighbor is easy Machine Learning strategy of Supervised Learning method.. KNN algorithm adopts the contrast between the new data and available cases and put the fresh case into the type that is most likely to the formed groups. K-NN stores all the presented data and classifies a fresh data point constructed on the likeness.

D. Improved Cluster based Region Classifier (ICBRC):

<u>ICBRC algorithm:</u>

Initialize: Define number of gray level and determine square matrix,

A = ∑∑P (xk,yl) and image matrix, P = ∑∑P(xi,yj)

Then, define Template Tmn = P⨁A

Determine coarse image, B(xi,yj) from template, Tmn

Reshape template based k means segmented image,

P1 = ki=1∑Cj=1Pij | | xi−cj | | 2×∑Mi=i+1∑Nj=j+1B(xi,yj)

Repeat step 2 to 4 until, Tmn≤∑Gk=1∑Sl=1[Tmn(k)−Tmn(l)]

Determine cluster centroid, C and degree of fuzziness, m

Initialize membership function Uij(0) of FCM

Calculate cluster center,Vi(l)⟺Uij(l) , (i=1,2,3,...,C) and (l=1,2,3,...)

Determine image features, F(xj,vi(l))⟷vil

Update Ui With d(xj,vi(l)) untill | | Uij(l)−Uij(l+1) | | ≤ϵ

Return

IV. RESULTS AND DISCUSSIONS

In this section the datasets and respective classification outcomes and the conversation concerning these will demonstrate. Below table represents the valence and arousal comparisons on dreamer data set.

A. Dreamer: contains 23 persons data:

Table:1 precision, recall and f1 score for various models(Dreamer dataset)

	Valence			**Arousal**		
	Precision	Recall	F1 score	Precision	Recall	F1 score
KNN	93.49	93.66	93.45	94.13	93.57	93.75
ANN	92.68	94.48	92.42	92.97	94.35	94.66
CNN	94.68	93.46	91.68	95.1	93.88	93.21
ICBRC (Proposed)	95.26	95.28	94.56	95.36	96.35	95.22

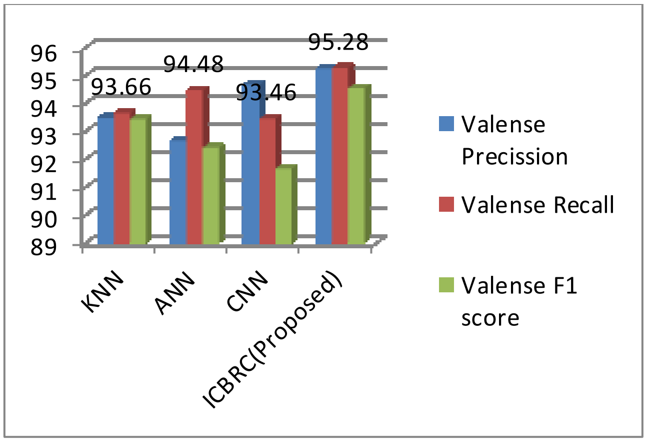

Fig.5 Precision, Recall and F1score for Valence

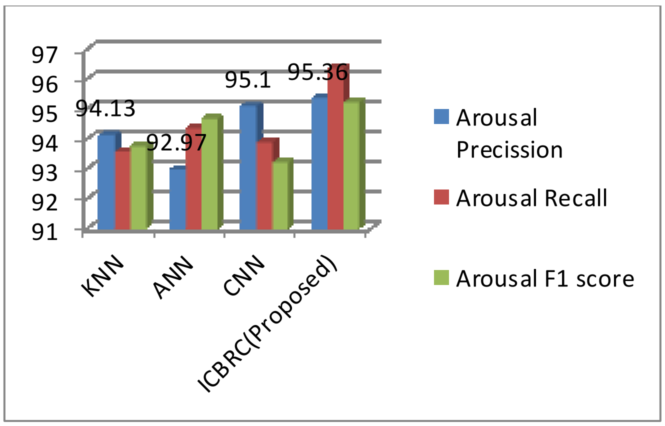

Fig.6 Precision, Recall and F1score for Arousal

B. FER-2013 : contains 28000 labelled images :

Table:2 precision, recall and f1 score for various models(FER-2013 dataset)

	Valence			Arousal		
	Precision	Recall	F1 score	Precision	Recall	F1 score
KNN	93.16	93.52	92.68	93.85	94.52	93.66
ANN	93.11	94.31	90.93	91.56	92.22	93.16
CNN	95.01	93.65	92.4	92.68	93.21	93.59
ICBRC (Proposed)	95.63	95.23	94.36	94.61	95.99	95.33

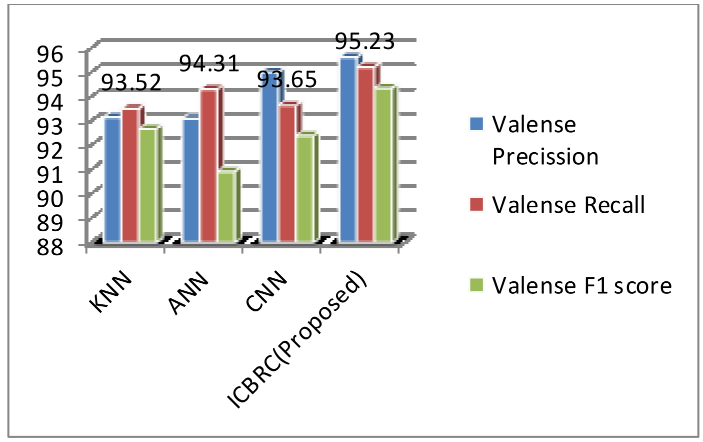

Fig.7 Precision, Recall and F1score for Arousal

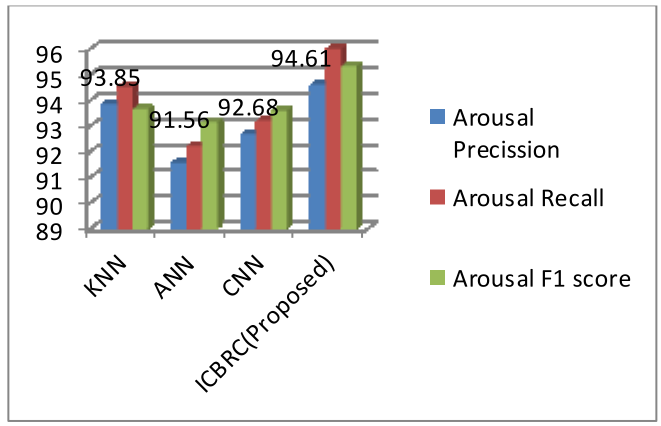

Fig.8 Precision, Recall and F1score for Arousal

Table 3:Layers,hnodes and their performance for CNN and ANN

CNN Layers			ANN layers		
Layers	hnodes	Results	Layers	hnodes	Results
5	10	91.46	5	10	91.58
10	20	93.96	10	20	92.66
20	30	92.71	20	30	92.11
40	40	91.68	40	40	91.65
100	50	92.87	100	50	91.76

The accuracy of CNN, KNN, ANN and Improved Cluster based Region Classifier (ICBRC) models with different emotions with music and video as a stimulus can vary depending on the specific dataset and experimental setup used. However, here are some general trends based on studies that have been published: ICBRC models have been found to perform well in classifying emotions in music and video.

Pre-trained Improved Cluster based Region Classifier (ICBRC) models are also a good option for emotion classification in music and video. A study found that a pre-trained CNN model achieved an accuracy of 92.37% in classifying emotions in music videos. It's worth noting that the specific accuracy for ICBRC(Proposed) 94.31% of these models may vary depending on the dataset and experimental setup used. Moreover, the architectures and methods used in these studies may also change and improve over time, so the accuracy of these models may change as well.

Table 4: Specivity, Positive Prediction Rate (PPR) & Accuracy of different algorithms

	Specivity	**Positive Prediction Rate (PPR)**	**Accuracy**
KNN	93.68	94.01	94.16
ANN	93.28	93.96	93.65
CNN	92.73	92.35	92.37
ICBRC(Proposed)	93.88	93.39	94.31

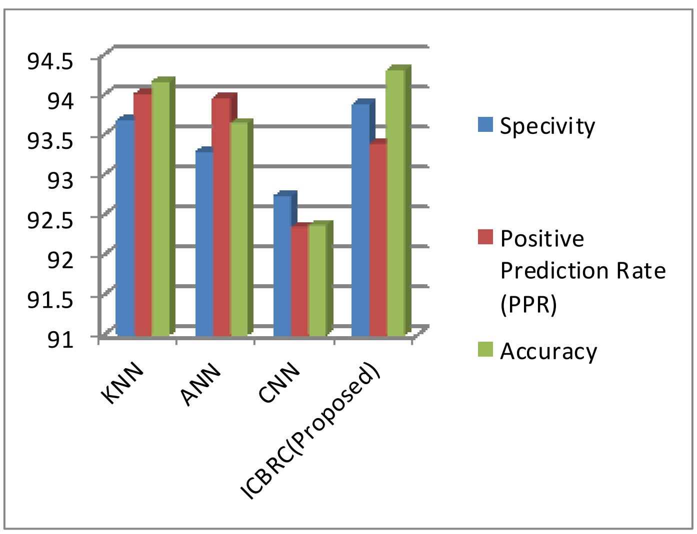

Fig.9 Specivity, Positive Prediction Rate (PPR) & Accuracy graph

V. CONCLUSION

In this article by using two different datasets the possibility of EEG signals is assessed for the classification of emotions of human beings. To confiscate the artifacts, initially the data should be pre-processed and 8 features should be extracted from the processed data. To make two varieties of dataset two different combinations were made among 8 different features. For the classification each dataset was structured in aquatic manner. By using KNN, CNN and the proposed ICRBC the classification is carried out. Even nevertheless proposed results achieve good results but still it needs improvement to get uniform improved result. Such improvement can be achieved by adding more subjects which increases the size of the dataset. EGG data processing uses thresholding technique.EEG signals can also be insulated into separate occurrence band of Alpha and Beta to check if that gives some provocative result. For the classification three different sorts are extracted in the proposed system. With this improved feature, the average accuracy of a network can reach the appropriate results as 93.46% on valance, 95.43% on arousal for DEAP.

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