Emotion Recognition using EEG based Topographic Images

A Thesis submitted in partial fulfilment of the Requirements for the award of degree of

Master of Engineering
In
Electronic Instrumentation and Control

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DECLARATION

I hereby certify that the work is being presented in this thesis work entitled "**Emotion Recognition using EEG based Topographic Images**" in partial fulfilment of award of degree of **Master of Engineering** in **Electronics Instrumentation & Control** submitted in Electrical & Instrumentation Engineering Department, Thapar University, Patiala is an authentic record of my own work carried under the supervision of **Dr. M.D. SINGH**, Assistant Professor, Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, Punjab.

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ABSTRACT

Emotional recognition play a vital role in developing affective computing applications. Brain electrical activity bears the emotional cues needed for emotion detection, but very modestresearch has been done to extract those cues. Most of the work are either classification of emotion on arousal-valance scale or recognizing basic emotions but no work has been done so far for predicting the actual response of user which is self-assessment feedback after each stimuli presentation. Only user knows what he felt after stimuli presentation, so self-assessment feedback is the actual state of mind of user. In this thesis we proposed a method to predict the response of user after stimuli presentation. For this purpose we used event related topographic images extracted from EEG. We extracted pattern related features from this topographs and this features are used by artificial neural network for emotion recognition.

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Chapter 1 Introduction

1.1 Overview

Affective computing is a rising topic of human-computer interaction that tries to make computing as productive as possible. As user is an affective human being, many needs are related to emotions and interaction. The need for computer applications which can detect the current emotional state of the user is increasing[1].

With the rising interest for Affective computing, Users Electroencephalograms have been analyzed as well for emotion detection. Currently, correct EEG-based recognition of artificially evoked emotion is low, but many research shows the suitability of EEG for this kind of task [2][3][4]. This field of research is still relatively new, and there is still much to be done to improve on existing elements in BCI, but also to discover new possibilities. There are two types of emotion recognition algorithms subject-dependent and subject-independent. Subject-dependent algorithms have much better accuracy than subject independent ones but the subject-dependent algorithms need the system training sessions. Generally, the available algorithms consist from two parts: feature extraction and classification. In the case of subject dependent algorithm implementation, the user needs to train the classifier by recording the EEG data and labeling the data with emotions[5].

Therefore, in this thesis, we proposed use of time-frequency Spatial Pattern based features for subject-dependent EEG-based emotion recognition algorithm following the Valence-Arousal-Dominance emotion model. The emotion recognition algorithm was tested on the proposed and implemented EEG database and on the benchmark affective EEG database DEAP where up to 9 levels of valence, arousal and dominance were available. Databases follow the Valence-Arousal-Dominance emotion model[6].

After that, the proposed algorithm was applied for recognition of emotions defined by values of arousal, valance and dominance dimensions. Numerical prediction for each dimension of Valence-Arousal-Dominance emotion model is done by use of neural network.

1.2 Relevance of Emotions for Human-Computer Interaction

In 1995 Reeves and Nass proposed media equation, which says that human-computer interaction follows the same principles as human-human interaction. A study showed that people feeling to build a team with the computer will think better of a computer and will cooperate and agree more with the computer than people who feel not to build a team[7]. The same way politeness for human-computer interaction and human-human interaction as people tend to give positive feedback about a computer when asked by the computer itself than when being asked by a different computer [8].

Human-computer interaction is comparable to the inter-action between humans, a computer that is able to recognize and respond to a user's emotion should be able to improve human-computer interaction significantly. Dryer and Horowitz showed that people interacting with partners that are similar to themselves perform better when working in the same team. Therefore, a computer that adapts to a user's emotional needs should also help to increase the user's performance[9].

There are also significant differences in human behavior when people interact with an affective system compared to a normal computer, as people tend to act more emotional when they believe to be interacting with an affective system[10].

1.3 Affective Applications

Before designing an application to make computing affective, there are three important issues that have to be kept in mind[11]:

"What is the relevant set of emotions for this application?

How can these best be recognized / expressed / modeled?

What is an intelligent strategy for responding to or using them?"

It strongly depends on application’s domain how these questions are answered. Let’s see various applications for affective computers as suggested by [12].

1.3.1 Communication like a Human

Nowadays, people spend more time interacting with a computer than with other humans. In addition, more and more people communicate with each other through computers[13]. The problem when communicating with computers is that computers usually are not able to show any emotional reactions. Making this communication human-like may enhance productivity.

Making communication more human-like is text-to-speech-synthesis which is usually monotonic. People who have to use a synthesized voice could use their own emotions to be added to speech by trying to recognize emotional signals from the speaker. Story that is read with an emotional voice does not only increase interest and enjoyment of a story but also improves speed of understanding for children and emotional text-to-speech synthesis could enhance written text experience for blind people[14].

Computers usually do not ask before they interrupt somebody with a notification. If a person is in a state of high cognitive load or emotional pressure, a notification by the computer can be irritating. So, it would be a great if the computer could derive from the user's emotional state if it is a good moment to interrupt a person or not.

Computers could be enabled to make small talk. For example a friendly spoken 'good morning' could replace the traditional 'login name'. This could make a positive influence on the user's attitude towards the computer.

1.3.2 Learning Environment

In learning environments learning can be improved if computers are able to recognize the user's emotion and respond to them. According to the Yerkes-Dodson principle arousal can be helpful for cognitive performance until a certain level of arousal is reached. After reaching this level performance decreases. The best learning performance can be achieved if a person is kept on an optimal level of arousal. Furthermore, the optimum level of arousal is inversely related to the difficulty of a task.

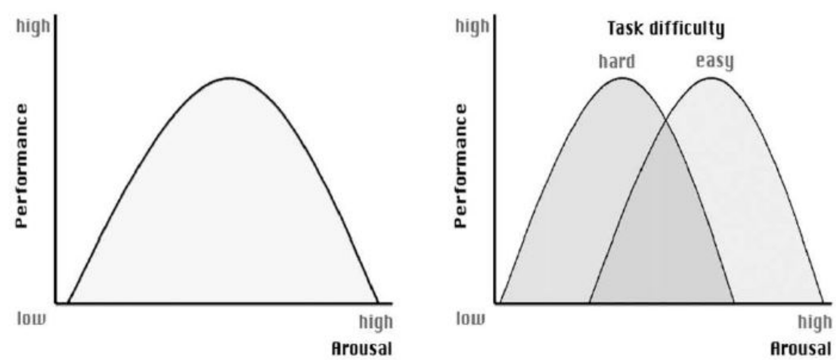

Figure 1-1The Yerkes-Dodson principle[15].

For instance, frustration (and therefore a higher arousal) can be avoided by making a quiz easier if the computer notices that the user is overstrained. Similarly, if the computer notices a decrease in arousal from the optimum, a quiz could be made more challenging.

1.3.3 Providing Help

There are many applications where a computer can provide help to a user if it is aware of the user's emotions. One important application is to react to a user's preferences. To learn a user's preferences, the computer could gather information about what a person likes and dislikes from its emotional responses. In Addition, contents could be adapted to the actual emotional situation. For example, if a person is stressed, only the most important icons are shown on the desktop.

1.3.4 Gaming and Entertainment

In Gaming and entertainment we can create wide range of applications for computers which are able to deal with emotions.

In most computer games success is based on the actions that are taken not on how they are performed. Physiological signals can be used to adapt the game to the current emotional state of a user. For example, a calmer behavior might be rewarded by introducing a new companion or a brave action while someone is highly aroused lead to some extra points.

1.4 Affective Computing

In human-human-interaction important role is played by emotions’. The ability to recognize the emotional state of people surrounding us is an important part of natural communication. The attempt to make this information available to computers and thereby making human-computer-interaction natural is the objective of affective computing.

The concept of affective computing was mainly influenced by Picard, who defines affective computing as 'computing that relates to, arises from, or deliberately influences emotions' [12].

Table 1-1Four categories of affective computing, focusing on expression and recognition[11].

Computer Can	Express Affect No Yes
Perceive No	(I) (II)
Affect Yes	(III) (IV)

Most computers fall in category (I) because they having no affect perception and expression at all. Out of the remaining three categories, category (II) is the most advanced technology: computers that have voices with natural intonation or faces with natural expressions fall into this category. Category (III) enables a computer to perceive a person's affective state and to adjust its response to this information. The last category provides truly ‘personal’ computing by maximizing the emotional communication between humans and computers. It is important to keep in mind that this does not mean that the computer would be driven by its emotions.

1.5 Emotions

"Everyone knows what an emotion is, until asked to give a definition." [16]

Emotions are very central in human behavior and communication but it is still no commonly accepted definition of emotion. There are many different approaches to find an appropriate definition which are quite often contradictory.

In 1981 Kleinginna and Kleinginna analyzed more than 92 definitions and concluded that there is little consistency among definitions and many definitions are too indefinite. They proposed the following definition to emphasize the manifold possible aspects of emotion:

"Emotion is a complex set of interactions among subjective and objective factors, mediated by neural/hormonal systems, which can give rise to affective experiences such as feelings of arousal, pleasure / displeasure; generate cognitive processes such as emotionally relevant perceptual effects, appraisals, labeling processes; activate widespread physiological adjustments to the arousing conditions; and lead to behavior that is often, but not always, expressive, goal directed, and adaptive"[17].

1.6 Dimensional Models

In 1994 Bradley and Lang proposed a three-dimensional model which includes arousal, valence and dominance[18]:

- Valence addresses the quality of an emotion (ranging from unpleasant to pleasant).
- Arousal refers to the quantitative activation level (ranging from calm to excited).
- Dominance relates to the degree of control a person feels to have over a situation (ranging from weak to strong).

Arousal and valence are the widely used dimensions. The two-dimensional Circumplex model of affect as suggested by Russel is shown in Figure 1-2. According to this model, emotions are specified by their position in the two-dimensional space spanned by the two axes valence (horizontal axis) and arousal (vertical axis).

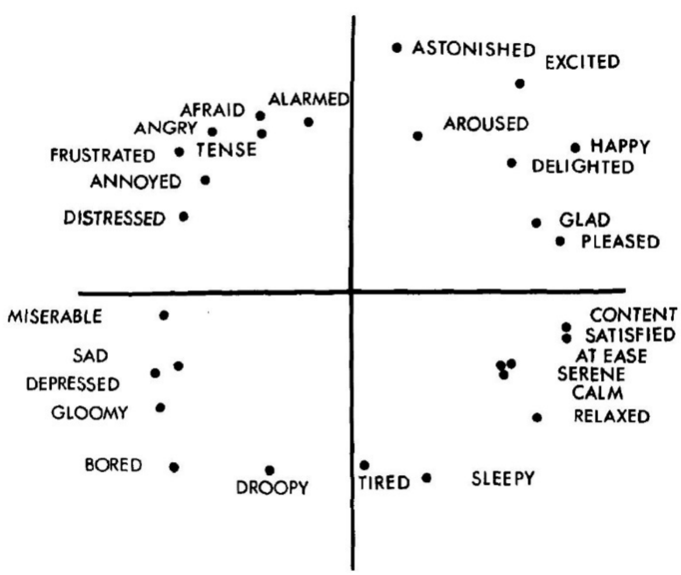

Figure 1-2 Circumplex model of affect[19].

1.7 Elicitation of Emotions

Although spontaneous emotion seem natural and most suitable kind of emotion, one has to keep in mind that one of the major drawbacks is nearly impossible to apply the sensors which are necessary to record the physiological signals without disturbing the subject and there is no possibility to control which emotion occurs at what time. This makes it hard to label the data and to get a balanced number of samples for each emotion.

There are many ways by which emotions can be elicited for experimental studies. Frequently used methods are:

- Free mental generation
- Stimuli presentation

1.7.1 Free Mental Generation

In this method stimuli are activated mentally by the subject themselves and not presented by the experimenter. It is assumed that it is possible to induce emotions by imagining emotion-related events. So in this method subjects are asked to imagine an emotional situation.

1.7.2 Stimuli presentation

In this kind method emotions are evoked by presenting different stimuli like visual, auditory, and combined to the subject. There are standard labeled databases of audio stimuli for emotion induction International Affective Digitized Sounds (IADS) and visual stimuli - International Affective Picture System (IAPS)[20][21]. DEAP (Database for emotion analysis using physiological signals) database is a benchmark database of EEG where combined stimulus (video) is used for emotion elicitation[6]. We used this DEAP database in our thesis for Emotion labeled EEG.

1.8 Emotions from EEG

To make computing affective it is necessary that the computer has information about the affective state of a user. Computer can get information about affect of human by two way. The first is to ask the human it-self to provide his or her current state to mind. Secondly the computer has ability to recognize the affective state itself by recognizing emotion related changes by the human's physiological signal (EEG).

When a neuron fires, voltage changes occur. This change in voltage is picked up by electrodes placed along the scalp which is electroencephalogram. The electrical activity measured by the electrodesrepresents the field potentials are from the combinedactivity of many neurons. The activity that is seen clearly on the EEG are those of the neurons in thecortex (near to the electrodes) and in cortex most neurons are aligned in one particular direction. Deeperstructures like the thalamus and brain stem cannot be seendirectly.

1.9 Rhythmic activity

The EEG is mostly described in terms of rhythmic activity. The rhythmic activity is generally divided into following bands by frequency.

1.9.1 Theta waves

Theta has the frequency range from 4 Hz to 7 Hz. Mostly seen in drowsiness or arousal in adults. This range of EEG has been associated with relaxed, meditative, and creative states of brain.

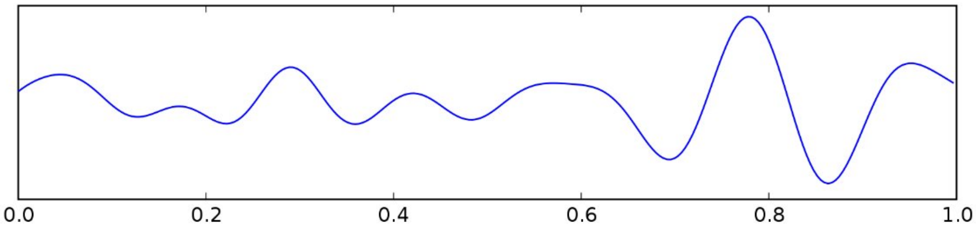

Figure 1-3 Theta wave

1.9.2 Alpha waves

Alphahas frequency range from 7Hz to 14 Hz.Hans Bergernamed the first rhythmic EEG activity he saw as the "alpha wave". Alpha waves are mostly seen in the posterior regions of the head on both sides, higher in amplitude on the active side.

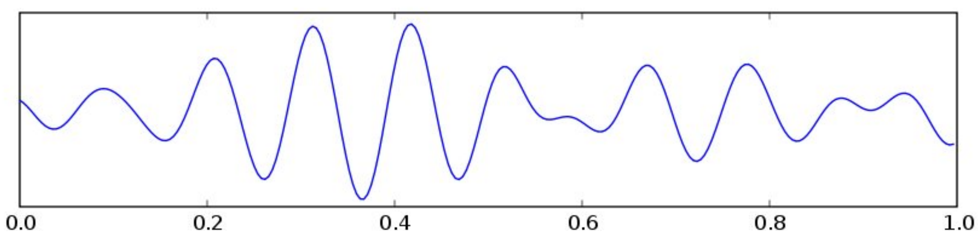

Figure 1-4 Alpha wave

1.9.3 Beta waves

Betahas frequency range of 15 -30 Hz. It is seen usually on both sides in symmetrical distribution and mostly on front side. Beta activity is associated with motor behavior and is generally attenuated during active movements. Beta of low amplitude and with multiple and changing frequencies is often associated with active or anxious thinking and concentration.

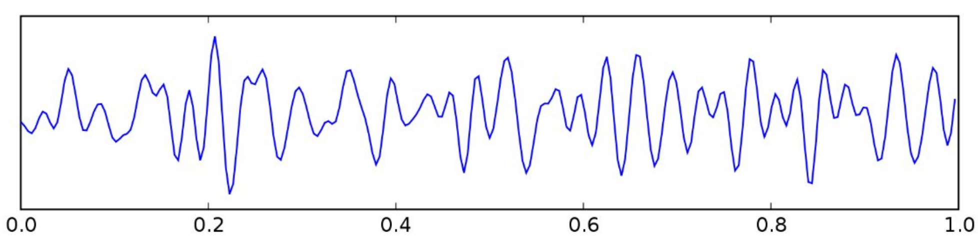

Figure 1-5 Beta wave

1.9.4 Gamma waves

Gammahas frequency range approximately 30–100 Hz. Gamma rhythms are represent working of different populations of neurons together into a network for the purpose of carrying out a cognitive or motor function.

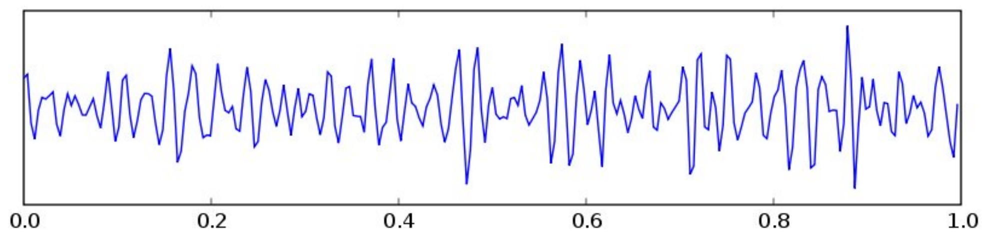

Figure 1-6 Gamma wave

1.10 Electrode Placement

Position of the skull electrodes follows the international 10-20 system[22]. According to this system, electrode positions are described depending on geometric proportions of the skull, which is divided into sections of 10 and 20 percent. Important anatomical reference points are the nation (onset of the nose on the skull) and the inion (a projection of bone at the back of the head found over the occipital area). The exact electrode positions are shown in Figure 2.5.The name of the electrode positions are according to the region of the cortex (Figure 1.3) above which the electrode is placed. The F refers to the frontal lobe, T to temporal lobe, P the parietal lobe and O to occipital lobe. Finally, C refers to central lobe which is located within the cerebral cortex, beneath the frontal, parietal and temporal lobe.

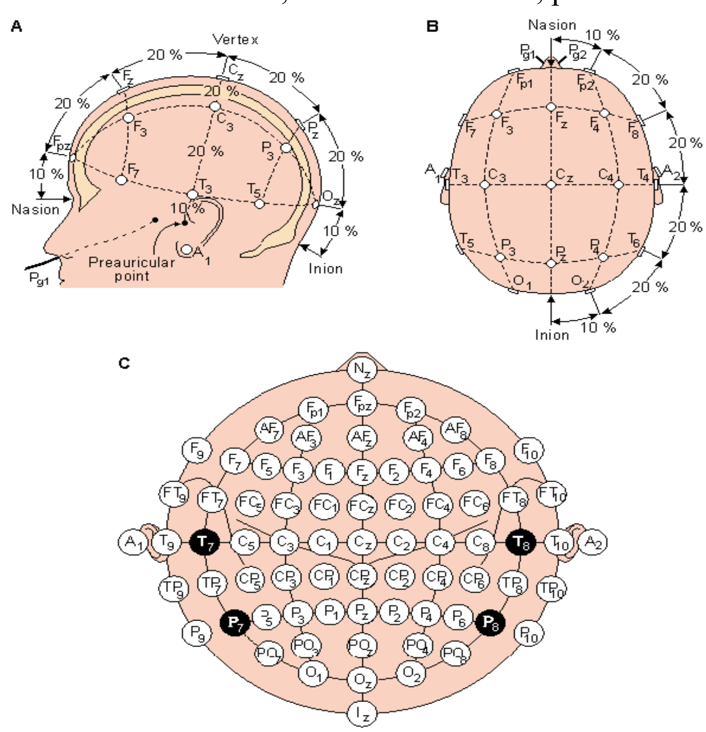

Figure 1-7Electrode positions in the 10-20-system[23]

Chapter 2 Literature Review

This chapter deals with various research works that were carried in past and contributed to the field of emotion recognition. Different approaches were deployed to carry out this work. Some of the related research works are described below.

2.1Peer work

The parameters extracted from EEG signals are useful forrecognition and classification of emotions. The chaoticity ofdifferent emotional states of brain activity using EEG signalscan be measured by the help of Kolmogorov entropy andthe principal Lyapunov exponent parameters [4]. The fractaldimension has been used as input features for classification ofhuman emotions [5]. The statistical and energy based featuresextracted by using discrete wavelet transform of EEG signalshave been used for classification of human emotions

Recently, event related potential and event related oscillation based features have been used as input feature set for classification of emotions. With Dual-Tree Complex Wavelet Packet Transform time–frequency features and feature selectionvia singular value decomposition, QR factorization with column pivoting and F-Ratio based feature selection, the average classification rates achieved are 65:3% for valance, 66:9% for arousal, 71:2% for liking and 69:1% for dominance. Support vector machine is used for classification[24].

In[25], sample entropy based emotion recognition approach was presented. The SampEn results of notable EEG channels screened by K-S test were fed to the support vector machine weight classifier for training, after which it was applied to two emotion recognition tasks. First task is to distinguish positive and negative emotion with high arousal and the other task is genitive emotion with different arousal status. The accuracies of the present algorithm for the two tasks were 80.43% and 79.11%.

A fusion based approach called Image and Signal Analysis of Multimedia Content (ISAMC) for emotion recognition using both external (face) and internal (EEG signals) is suggested for classification of five emotions (Happy, Neutral, Sad,Disgust and Surprised). Both image analysis and EEG signal analysis is done using a video stimulus and based on wavelet approach for feature extraction.The average classification accuracy of this algorithm is 86.6%[26].

By using multiwavelet transform based features of EEG signal for classification of four basic emotions (Happy, Neutral, Sad and Fear) with Morletn wavelet kernel function of multiclass least squares support vector machines (MC-LS-SVM) accuracy achieved was 91.04% [27].

Many researches has been done on emotion recognition using EEG. The comparison of this researches are given in table 2-1 but it is very difficult to compare results of them because there are a manyaspects that make different results from different researches. The factors that should be kept in mind before comparison are participant, model of emotion, stimulus, feature, and classifier.

2.1.1 Emotion model

Many models can be used like a basic emotion and a dimensional model. The most frequently used basic emotions are anger, disgust, fear, joy, sadness, and surprise. The common dimensional model is valence-arousal model[19]. The valence dimension is negative to positive, whereas the arousal dimensionis calm to excited. This dimensional model is used in most of researches because it makes express of an emotion easy.In this thesis, we used dimensional models.

2.1.2 Stimulus

Stimulus. There are many methods by which emotion can be elicited, which are free mental generation or using external stimulus such as picture, sound or video. The widely used databases for emotion elicitation via pictures is International Affective Picture System (IAPS) [21]and via sound is International Digitized Sound System (IADS)[20] and these kind of databases are generally generated by emotional judgments of several people.

2.1.3 Classifier

Several machine learning techniques are used for emotion classification such asLinear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naïve Bayes (NB),K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP) and Support Vector Machine (SVM). As shown in Table 2.1. Support vector machine technique is used widely in emotion classification researches because of many advantages. The basic training principle of as Support Vector Machine is finding the optimal

2.1.4 Participant

More number of participants makes more reliable result. In fact, we can divide the method for emotion recognition in subject-dependent and subject-independent. The subject-independent is harder than the subject-dependent model due to interparticipant’s variability. The subject-dependent model rectify the problems related to interparticipant but for an each participant a new classification model must be built.

2.1.5 Feature

The frequently used feature is Power Spectral Density (PSD). Others such as Spectral Power Asymmetry (ASM),Self-Organizing Map, Common Spatial Pattern (CSP),Fractal Dimension (FD), Higher Order Crossings (HOC), Asymmetric Spatial Pattern (ASP) and

Entropy are used as features and some of them give a good result. In this thesis, the feature we used are extracted from frequency based 2d topographic maps.

Table 2-1 EEG-based emotion recognition researches

Reference	Year	Participant	Stimulus	Emotions	Feature*	Classifier**	Result
[28]	2006	4(SD)	Picture	Three arousal classes	PSD	NB	58%
[29]	2008	26(SID)	Music	Joy ,anger, sadness and pleasure	ASM	SVM	92.73%
[30]	2009	10(SD)	Picture	Two valance classes	CSP	SVM	93.5%
[31]	2009	10	Self-Recall	Three arousal classes	PSD	SVM	63%
[32]	2009	1(SD)	Picture	Three classes	Statistical features	QDA	66.66%
[33]	2009	3(SD)	Self-Recall	Ten classes	PSD	KNN	39.97-66.74%
[34]	2010	26(SID)	Music	Joy ,anger, sadness and pleasure	ASM	SVM	82.29%
[35]	2010	6(SD)	Video	Two valance and two arousal classes	PSD	SVM	58.8%
[36]	2010	26(SD)	Picture and Music	Calm, happy, sad and fear	SOM	KNN	84.5%
[37]	2010	15	Picture	Two classes	HOS	SVM	82%
[38]	2010	12(SD)	Sound	Two valance and two arousal classes	FD	Threshold	-
[39]	2011	20	Video	Happy, disgust, surprise, fear and neutral	Entropy	KNN	83.04%
[40]	2011	6(SD)	Video	Two valance classes	PSD	SVM	87.53%
[41]	2011	20(SID)	Game	Boredom, engagement, and anxiety	PSD	LDA	56%
[42]	2011	5	Video	Joy, relax, sad and fear	PSD	SVM	66.51%
[43]	2011	11	Picture	Three valance classes	ASM	KNN	82%

[44]	2012	27(SID)	Video	Three valance classes and three arousal classes	PSD And ASM	SVM	57%
[6]	2012	32	Video	Two valance and two arousal classes	PSD And ASM	NB	62%
[45]	2012	20 SD	Picture	Happy, angry, sad, relaxed and neutral	FD	SVM	70%
[46]	2012	5(SD)	Picture	Three classes	HOC	KNN	90.77%
[47]	2012	4	Video	Two valance and two arousal classes	ASP	-	66.05%
[48]	2012	32	Video	Stress and calm	PSD	KNN	70.1%
[49]	2012	36	Video	Three classes	PSD	ANN	-
[50]	2013	11(SID)	Picture	Two valance classes	PSD	SVM	85.41%

SD- Subject dependent, SID- Subject independent

*Feature: Power Spectral Density (PSD), Fractal Dimension (FD), Spectral Power Asymmetry (ASM) , Asymmetric Spatial Pattern (ASP), Higher Order Crossings (HOC), Common Spatial Pattern (CSP), Self-Organizing Map (SOM) and Higher Order Spectra (HOS).

**Classifier: Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbors (KNN), Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), Multilayer Perceptron (MLP), and Artificial Neural Network (ANN).

It is clear from comparison table that the most of subject-independent model have an accuracies are lower than subject- dependent model accuracies.So in this thesis we implemented a subject-dependentmodel. No research has been done so far for numerical prediction of Arousal-valance-dominance value which is feedback of user from Self-assessment test (Actual emotion felt by subject).

Chapter 3 EEG Database

3.1 Introduction

DEAP (Database for emotion analysis using physiological signals) database is a benchmark Affective EEG Database based on Valence-Arousal- Dominance emotion model was published in [6]. It has a large number of subjects who participated for the data collection. The stimuli to elicit emotions in the experiment were one-minute long music videos. This kind of stimuli are considered as combined stimuli of visual and audio. 40 selected music videos were used. In this DEAP database, 32 EEG channels of the Biosemi ActiveTwo device were used in the data recording.

3.2 Stimuli selection

Initially, in this database semi-automatedmethod was used for stimulus selection to minimizethe bias arising from manual stimuli selection.60 of the 120selected videos stimuli were selectedusing the Last.fm[51]music website for other 60 video stimulus the valence-arousal space was subdivided into 4 quadrants, namely low arousal/low valence (LALV),high arousal/low valence (HALV), low arousal/high valence (LAHV) and high arousal/high valence (HAHV) and 15 video for each quadrant was selected manually.

By using results web based subjective emotion assessment interface from the initial collection of 120 stimulus videos, the final 40 test video clips were selected. Participants watched 120 music videos online and rated them on a discrete 9-point scale for valence, arousal and dominance.

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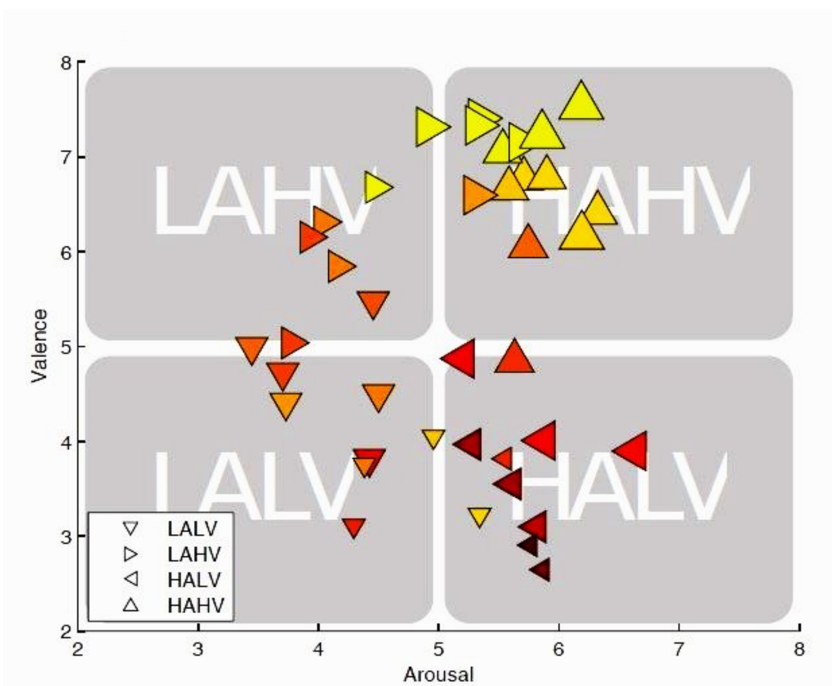

Figure 3-1 the mean locations of the stimuli on the arousal-valence-dominance plane for the 4 conditions (LALV, HALV, LAHV, HAHV). Dominance is encoded by symbol size[6].

3.3 Experiment setup

3.3.1 Materials and Setup

The experiments were performed in laboratory environments with controlled illumination. EEG signal was recorded using a Biosemi Active Two system[52]on a dedicated recording PC. Stimuli were presented using a dedicated stimulus PC and synchronization markers sent directly to the recording PC. EEG was recorded at a sampling rate of 512 Hz using 32 active Ag-Cl electrodes (placed according to the international 10-20 system).

3.3.2 Experiment protocol

32 Healthy participants (50% female), aged between 19 and 37 (mean age 26.9), participated in the experiment. The 40 videos were presented in 40 trials, each consisting of the following steps:

- A 5 second baseline recording (fixation cross).
- The 1 minute display of the music video.
- Self-assessment for arousal, valence and dominance.

3.3.3 Participant self-assessment

At the end of each trial, participants performed a self-assessment of their levels of arousal, valence, liking and dominance. Self-assessment manikins (SAM) [53] were used. To visualize the scales (see Figure 3-2).The valence scale ranges from unhappy or sad to happy or joyful. The arousal scale ranges from calm or bored to stimulated or excited. The dominance scale ranges from submissive to dominant.

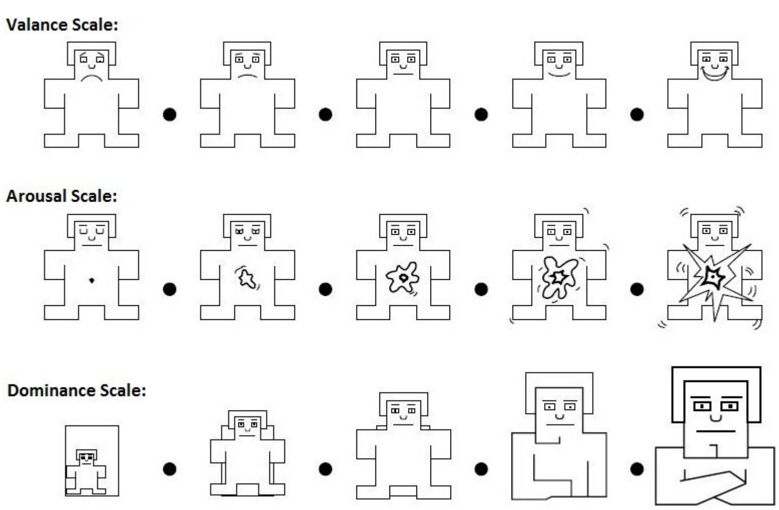

Figure 3-2Self-assessment manikins (SAM)[6].

3.4 Database content summary:

Table 3-1 Database Content Summary

Online Subjective annotation	
Number of videos	120
Video duration	1 minute affective highlight
Selection method	60 via last.fm affective tags, 60 manually selected
No. of ratings per video	14 - 16
Rating scales	Arousal Valence Dominance
Rating values	Discrete scale of 1 - 9
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 (how much do you like the video?) Familiarity (how well do you know the video?)
Rating values	Familiarity: discrete scale of 1 - 5 Others: continuous scale of 1 - 9
Recorded signals	32-channel 512Hz EEG Peripheral physiological signals Face video (for 22 participants)

Chapter 4 Methodology

As seen in literature review, most of the work are either classification of emotion on arousal-valance scale or recognizing basic emotions but no work has been done so far for predicting the actual response of user which is self-assessment feedback after each stimuli presentation. Only user knows what he felt after stimuli presentation, so self-assessment feedback is the actual state of mind of user. In this thesis we proposed a method to predict the response of user after stimuli presentation. Methodology is as given below.

4.1 EEG Signal Processing

EEG-signal influenced by artifacts due to the high amplification of signal. There are mainly two kind of artifacts are there. Technical artifacts and artifacts with a biological origin.

Technical artifacts are result of movement of electrode and electrode cables. Another source for artifacts isthe noise of an amplifier, as well as interfering fields from power supply voltage. Biological artifacts are result of physiological activity of the body. For example eye blinks produce high amplitudes which occur especially at the frontal electrodes. Eye movements can also cause artifacts due to the electrical polarity of the eye. Moreover, muscle around the scalp influence the EEG signal. So before extracting features from EEG, proper signal processing is must.

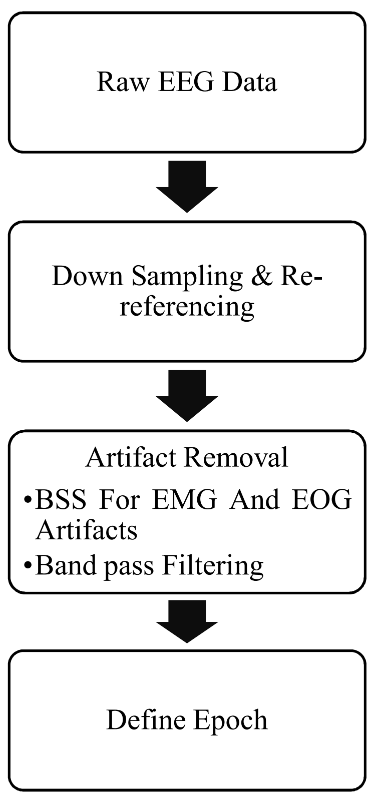

Figure 4-1 EEG signal processing flow-chart

4.1.1 Down Sampling & Re-referencing

Original data was recorded at sampling rate of 512Hz but no need of this much temporal resolution in our case, so data is first down-sampled.In bio-semi system signals are recorded with respect to the Common Mode Sense (CMS) active electrode and this mode does not provide the full CMRR. To get full CMRR a reference must be selected[54]. With multi-channel recordings it is common to compute the "average reference", i.e. to subtract the average over all electrodes from each electrodes for each time point. This distributes the "responsibility" over all electrodes[55].

4.1.2 Artifact Removal

EEG data is mostly contaminated by artifacts. The amplitude of artifacts can be quite large relative to the size of amplitude of the cortical signals of interest. Major artifact are due to eye movement and muscles near to the scalp. This elecrooculographic (EOG) and electromyographic(EMG) Artifacts are removed by AAR (Automatic Artifact Removal) tool in EEGLAB which is based on Blind Source Separation Technique [56][57][58]. We only interested in frequency range of 4-hz soEEG signal isstrictly band passed with 4-44 Hz using FIR filter of EEGLAB [59].

4.1.3 Define Epoch

EEG is recorded continuously, but for analyzing only stimulus related change EEG is to be chopped into small segments called epoch. Each epoch is EEG recording of baseline duration and video trial duration. Epochs are defined by using EEGLAB function pop_epoch ( )[60].

4.2 Time Frequency Representation

The original EEG signal is in time domain and the signal features are buried away in the noise. To extract the features, the EEG signal should be transformed into frequency domain. The features extracted in frequency domain are suitable recognize the mental tasks[61]. The widely used method for frequency domain transformation is Fast Fourier Transform (FFT) by applying the discrete FFT to the signal.

The EEG signal is non-stationary and its spectrum changes with time sothe FFT is inadequate for representing EEG signal in frequency domain. But this kind of signal can be approximated as a piecewise stationary. So, appropriate windows could be applied to the Fourier functions which provide short time Fourier transform (STFT) which is a type of Time-Frequency Representation (TFR).

In STFT, the signal is divided into overlapping data frames and fast Fourier transform (FFT) applied to each frame. The output of successive STFT provide a time-frequency representation of the signal. To analyze the complete signal, the window is translated in time and then FFT is reapplied to each one [62].

The STFT is applied to one second EEG signal segmented into a 256 point segments with 50% overlapping between each successive segments. Each segment is multiplied by a 256 point Hamming window, then the FFT algorithm is applied to each segment. The result is summated and 40 bands of 1 Hz of the frequency spectrum are used and normalized from 4 to 44Hz. In this way each 1 sec physiological signal is transformed into 40 values through a spectral transformation.

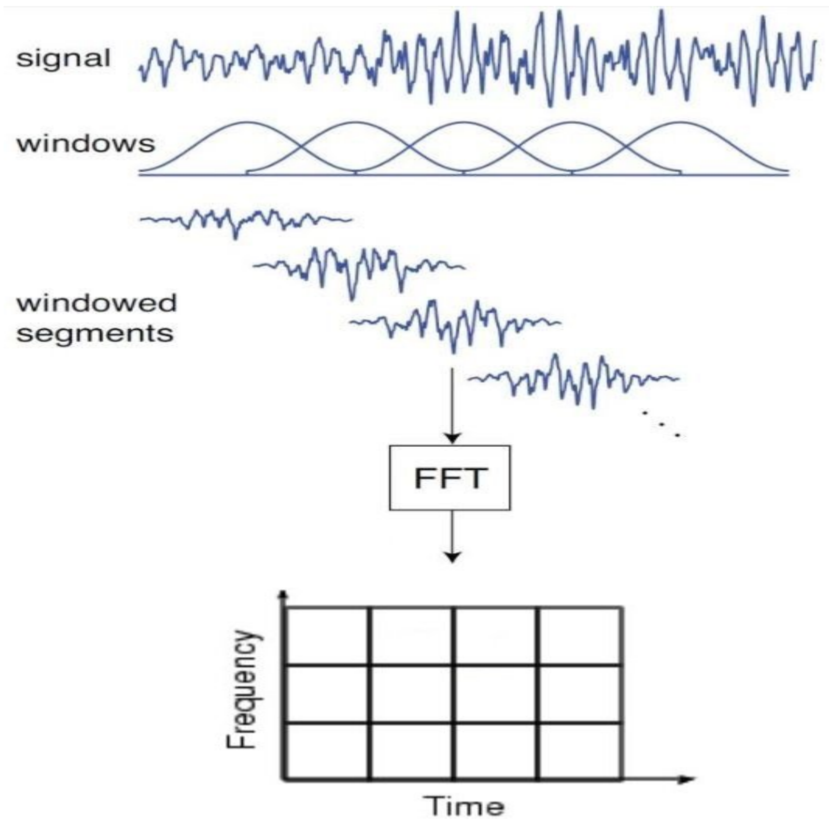

Figure 4-2 STFT Process

4.3 Topographs of EEG Time Frequency Representation

STFT is applied on entire trial starting from baseline to the end of trial on all 32 channels of EEG data. For the event-related power changes, a normalization with respect to a baseline interval must be performed. After baseline normalizationSTFT data is relative change in frequency power with respect to the baseline interval for each frequency. Ft_topoplot function ofFieldTrip software package is used to generate topographical 2-D map of the power changes due to stimuli presentation for four frequency bands of EEG (Alpha , Beta, Gamma, Theta)[63].

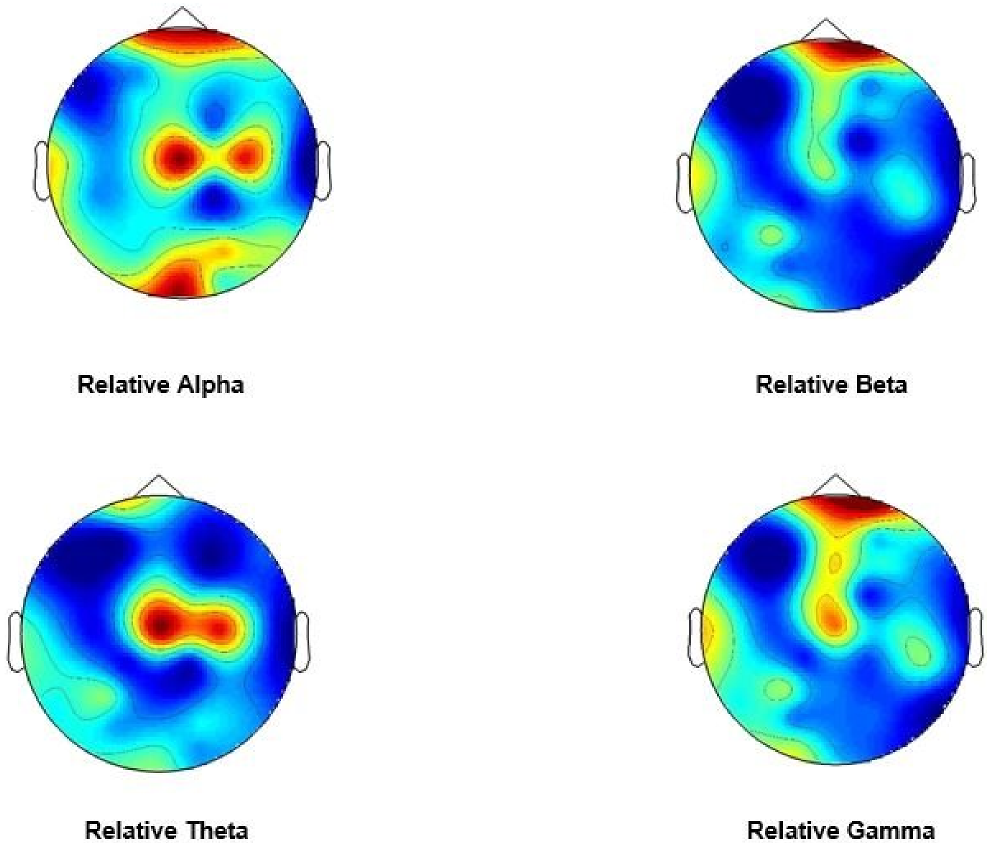

Figure 4-3 2D Topographic Map of Alpha, Beta, Gamma And Theta

4.4 Image Processing

A single topographic map contain information of change in frequency power of all 32 channel due to stimulus. So the Topographical 2-D maps represents the stimulus related change in frequency power for alpha, beta, theta and gamma band. Image Features from the Topographs of all four bands for all 40 trials are extracted.

For feature extraction we used efficient texture feature extraction method: the Segmentation-based Fractal Texture Analysis, or SFTA. The extraction algorithm consists in decomposing the input image into a set of binary images from which the fractal dimensions of the resulting regions are computed in order to describe texture patterns. The decomposition of the input image is achieved by the Two-Threshold Binary Decomposition (TTBD) algorithm[64].

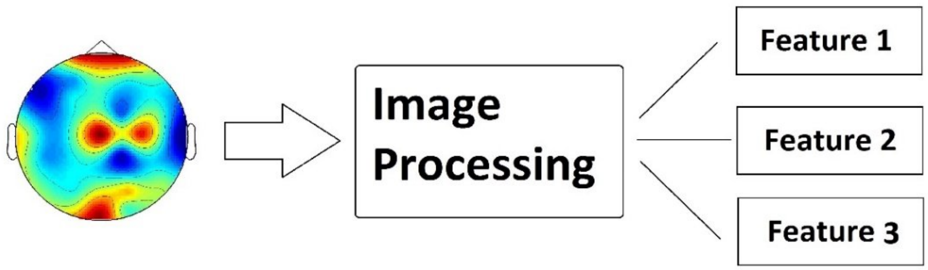

Figure 4-4 image processing of topograph.

4.5 Artificial Neural Network

Artificial neural networks (ANNs) are computational models inspired by an animal's central nervous systems (in particular the brain) which is capable of machine learning as well as pattern recognition. Artificial neural networks are generally presented as systems of interconnected “neurons” which can compute values from inputs. Like other machine learning methods - systems that learn from data - neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming.

4.5.1 Supervised learning

In supervised learning, we are given a set of example pairs of input and output and the aim is to find a function that matches the examples. In other words, we wish to infer the mapping implied by the data, the cost function is related to the mismatch between our mapping and the data and it implicitly contains prior knowledge about the problem domain. Cost is the mean-squared error, which tries to minimize the average squared error between the network's output, and the target value over all the example pairs.

4.6 Data for Artificial neural network

Each trial has a four topographic maps (Alpha, beta, gamma and theta) and by image processing features are extracted from each topographic map. Out of 40 trials features data 28 is used for Training of Artificial neural network. 6 is used for validation and 6 is used for testing.Levenberg-Marquardt backpropagation method is used for artificial neural network training.

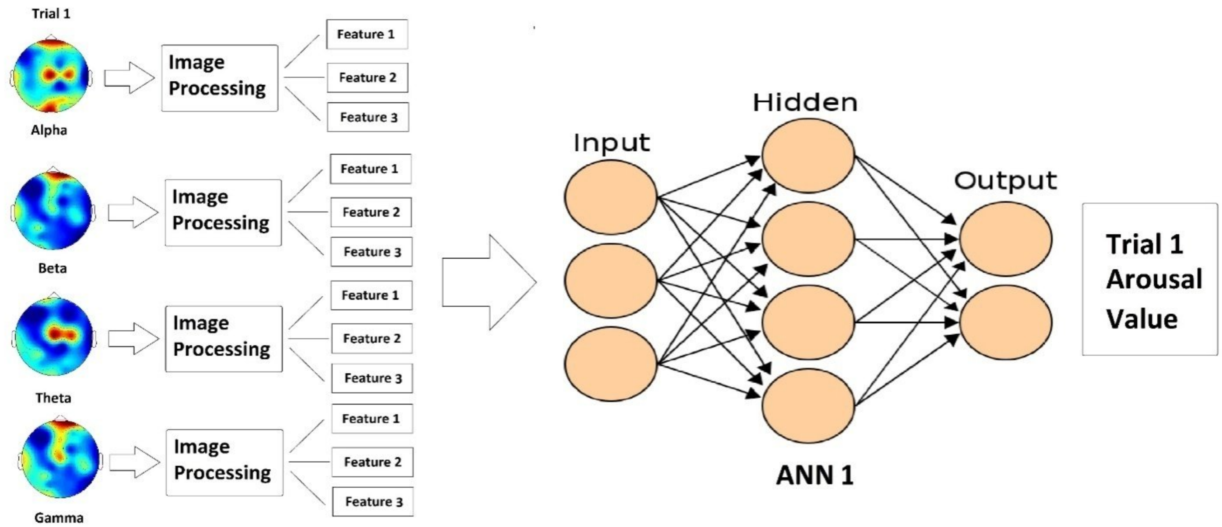

Figure 4-5 Training input-output set example for Arousal detection ANN

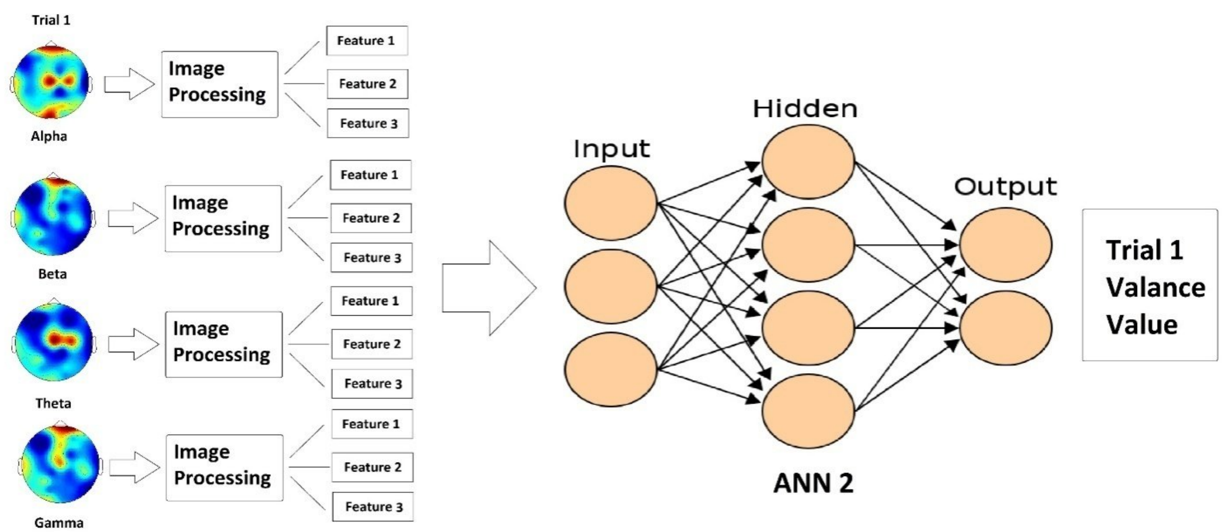

Figure 4-6Training input-output set example for Valance detection ANN

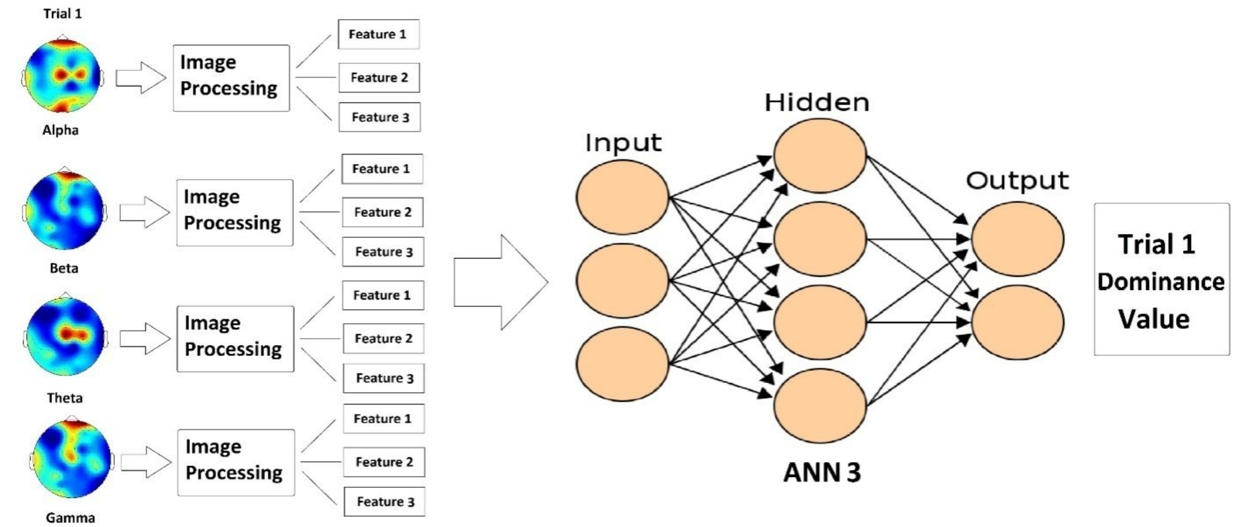

Figure 4-7Training input-output set example for Dominance detection ANN

Chapter 5 Results

This chapter deals with results of the suggested emotion recognition method. We used regression plot, error histogram, Arousal-valance-dominance plot and root mean square error to describe the performance of suggested methodology in this thesis.

5.1 Regression plot

These plots give you an idea of how close the output from your model is to the actual target values. The slope of the fitted line is equal to the correlation between targets and the output from model. The R value is a measure of the linear correlation between target and output of model. Its value ranges from +1 and −1. Where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation. It is used as a measure of the degree of linear dependence between target and output. Each neural network has regression plot for training data, validation data, testing da and all data.

5.2 Error histogram

A histogram is a graphical representation of the distribution of data. Output from neural network model and target are not always same, there are error in output of model. The error histogram graphically represents the distribution of error between output and target for training, validation, testing data.

5.3 Arousal-valance-dominance plot

Emotions are specified by their position inArousal-valance-dominance plot. Where horizontal axis is for arousal ranging from 1-9 and vertical axis for valance ranging from 1-9. Dominance is encoded by size of scatter. Four quadrants of this plots are low arousal low valance (LALV), high arousal low valance(HALV), low arousal high valance(LAHV), high arousal high valance(HAHV).

5.4 Root Mean Square Error

Root mean square (RMS) is a statistical measure of the magnitude of a varying quantity. It is especially useful when variates are positive and negative. RMS of the pairwise differences of the two data sets can serve as a measure how far on average the error is from 0. The mean of the pairwise differences does not measure the variability of the difference, and the variability as indicated by the standard deviation is around the mean instead of 0. Therefore, the RMS of the differences is a meaningful measure of the error.

5.5 Topographs of Single subject for all trials

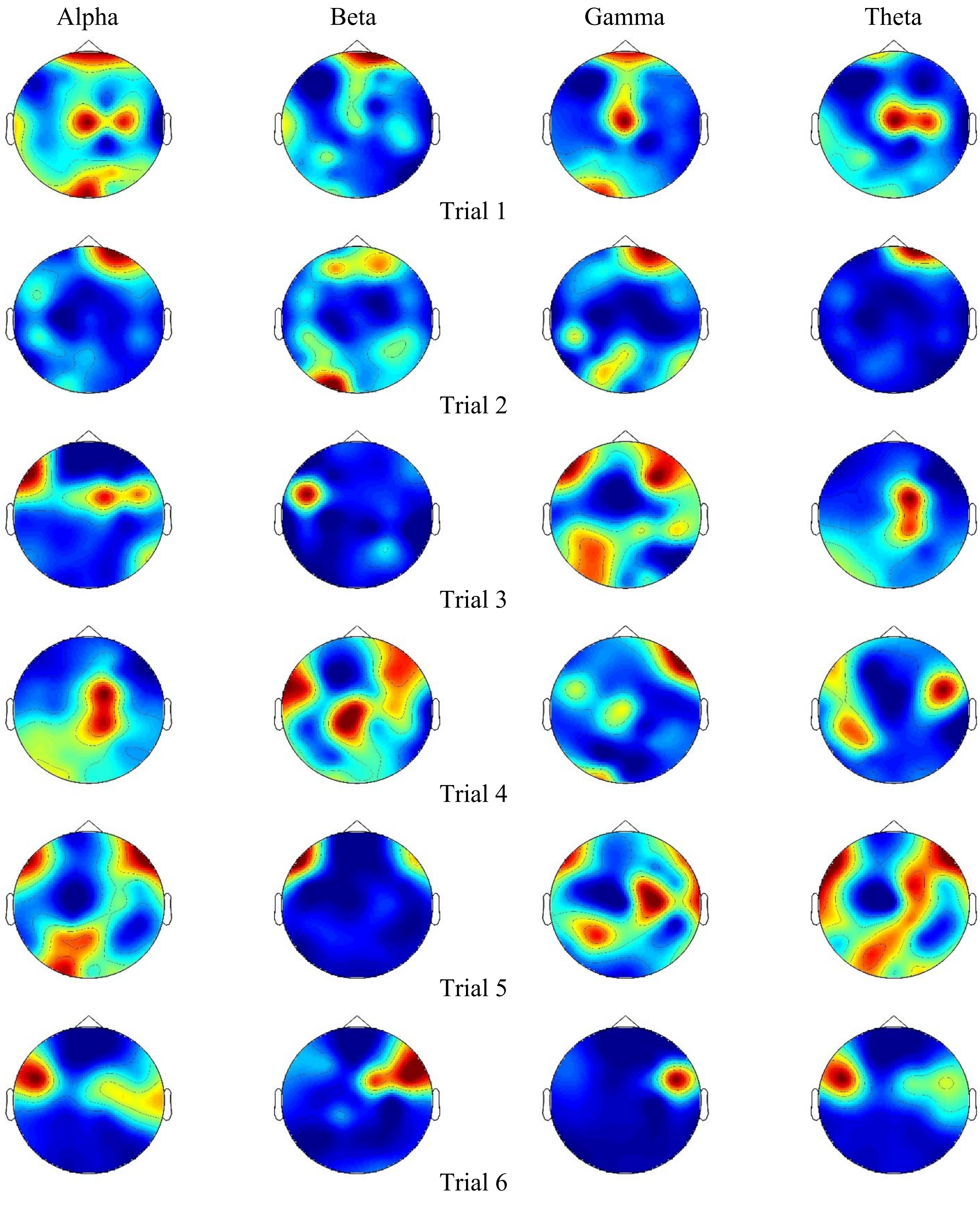

Figure 5-1 Topographs of trial 1-6.

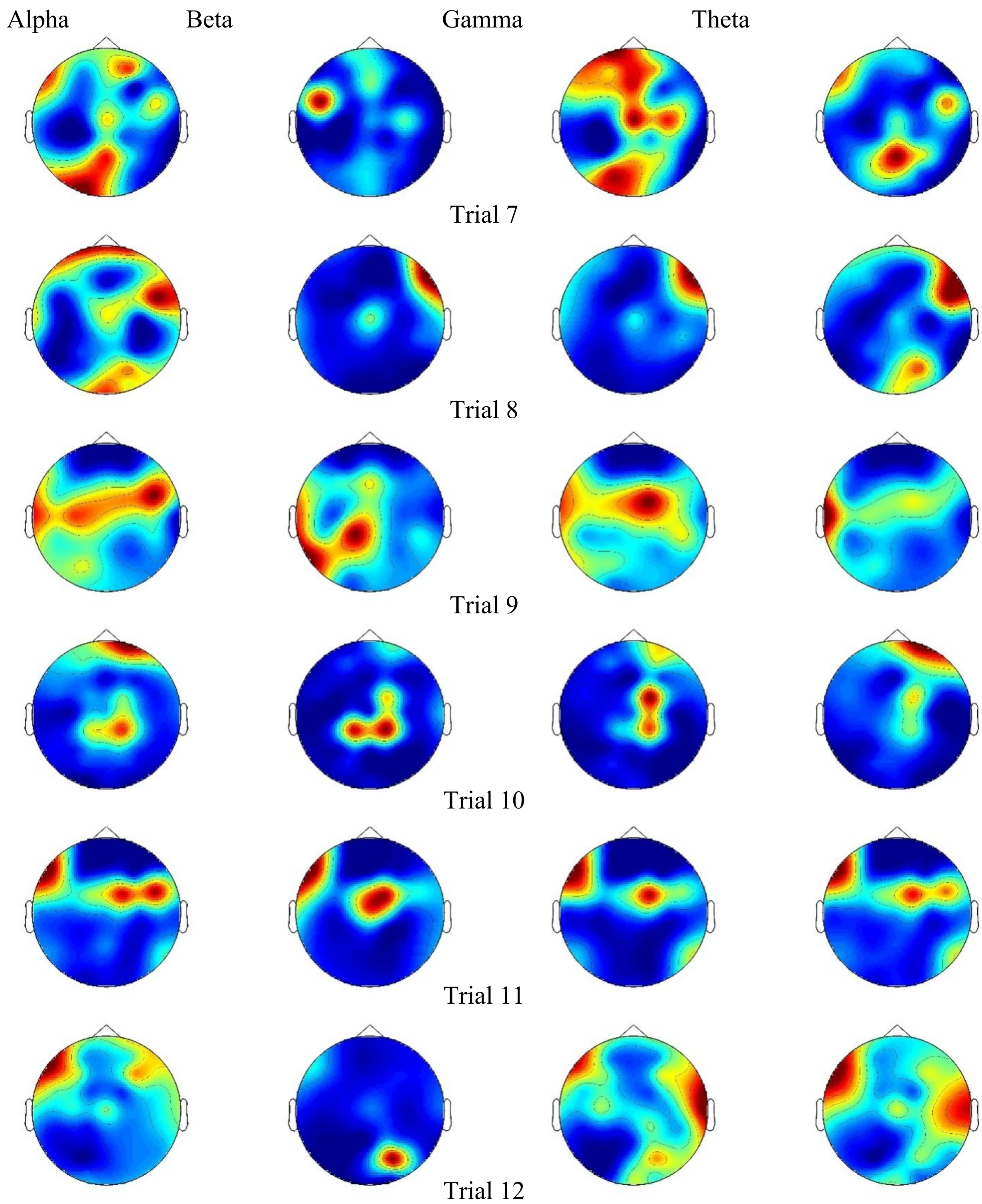

Figure 5-2Topographs of trial 6-12.

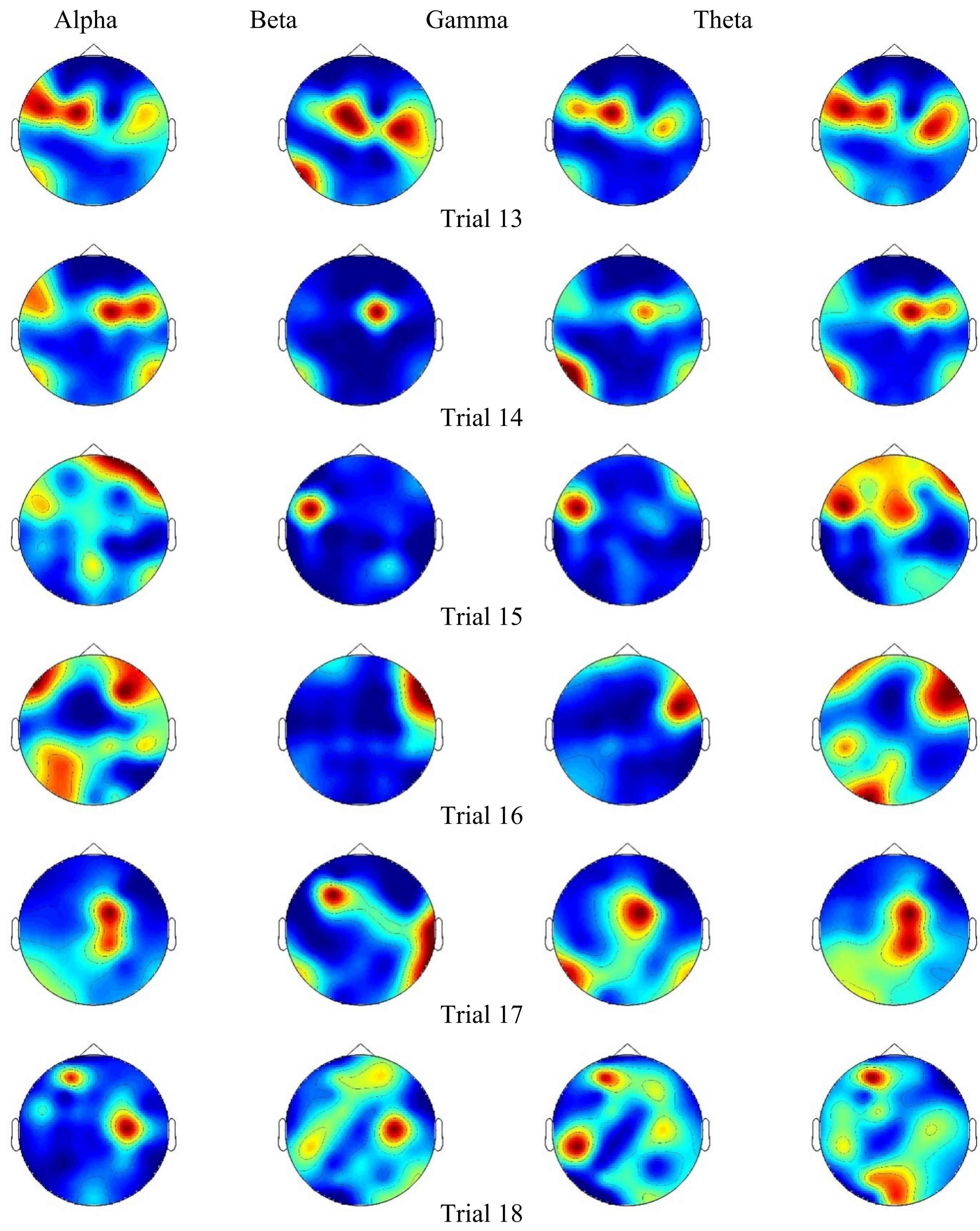

Figure 5-3 Topographs of trial 13-18.

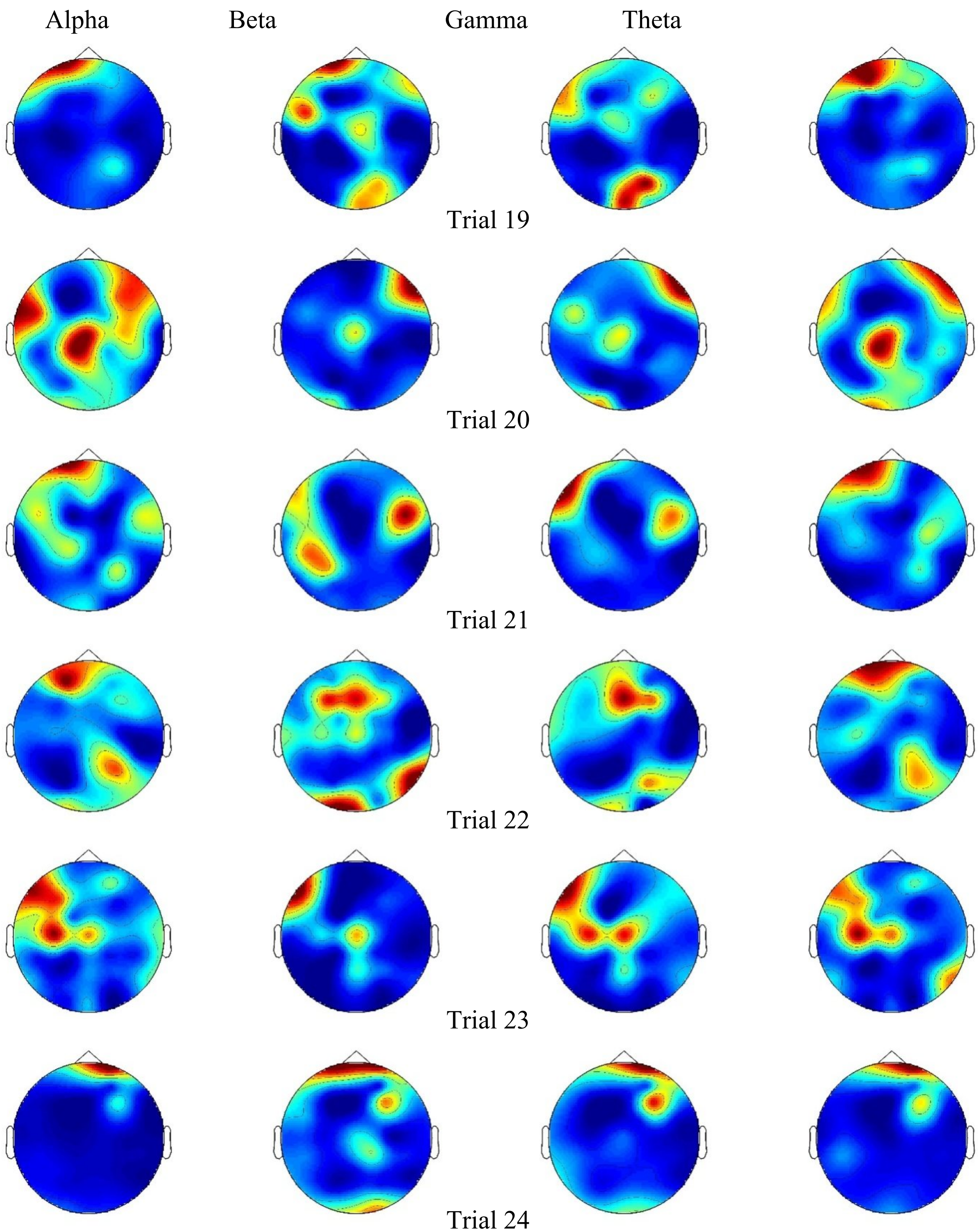

Figure 5-4 Topographs of trial 19-24.

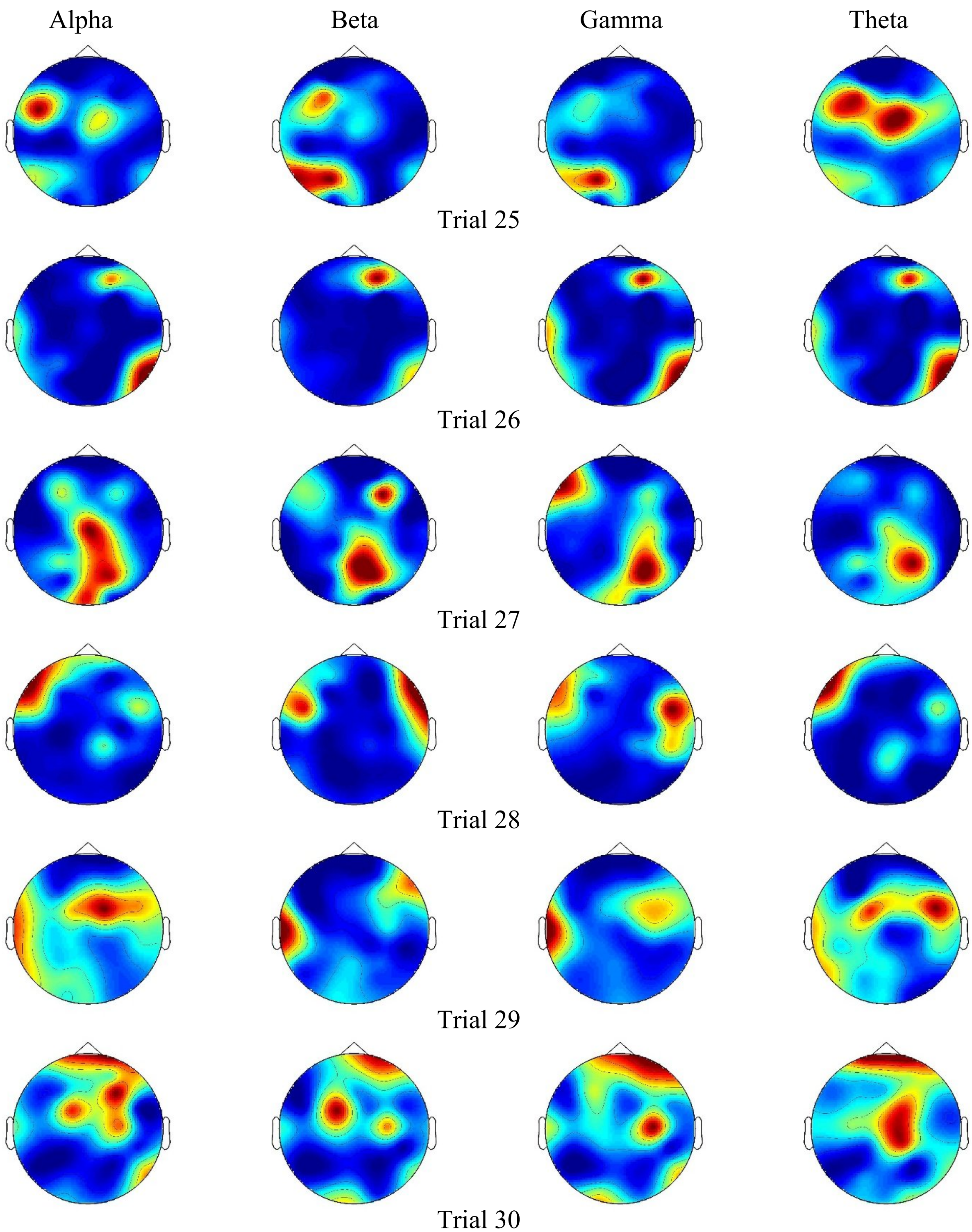

Figure 5-5 Topographs of trial 25-30.

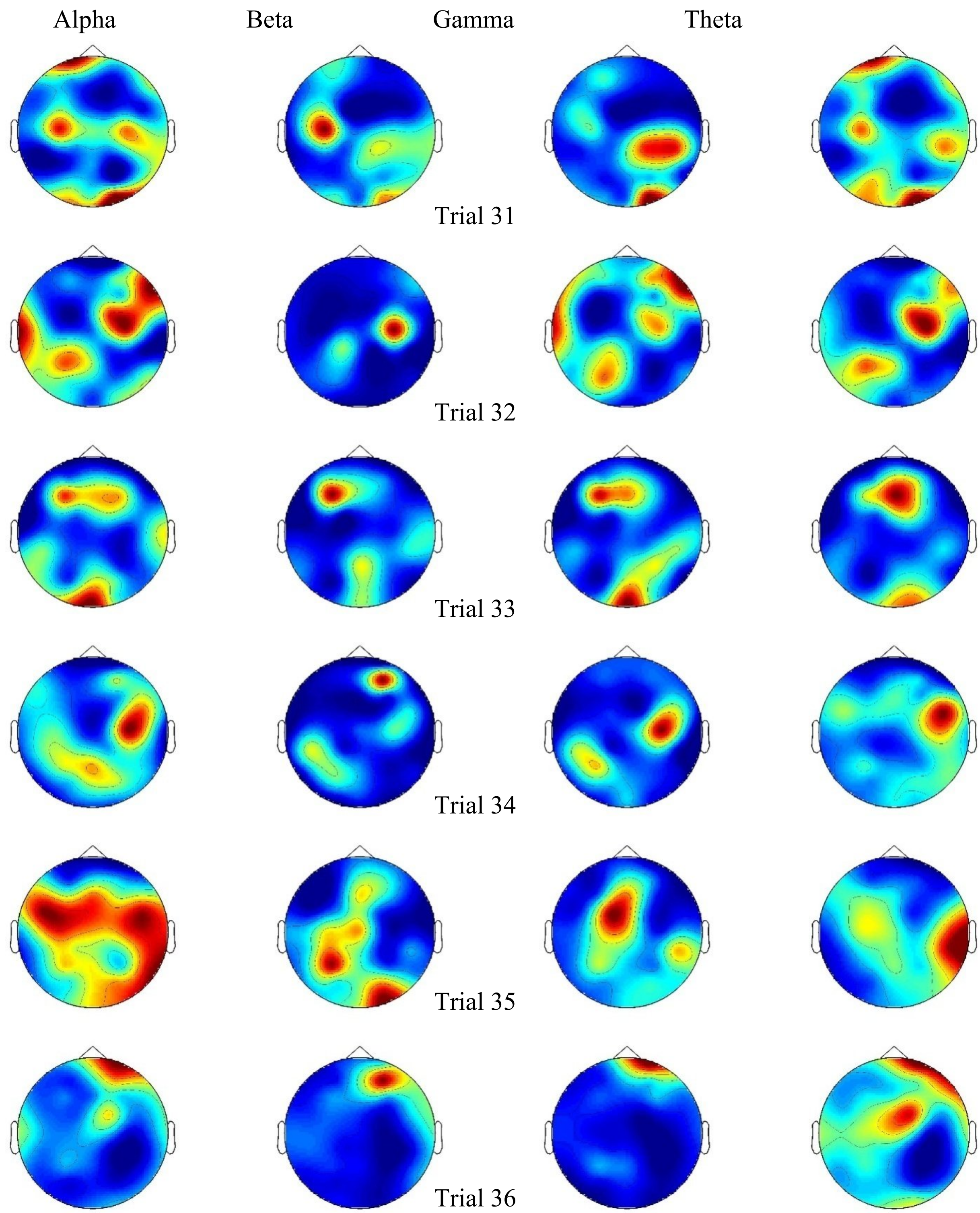

Figure 5-6 Topographs of trial 31-36.

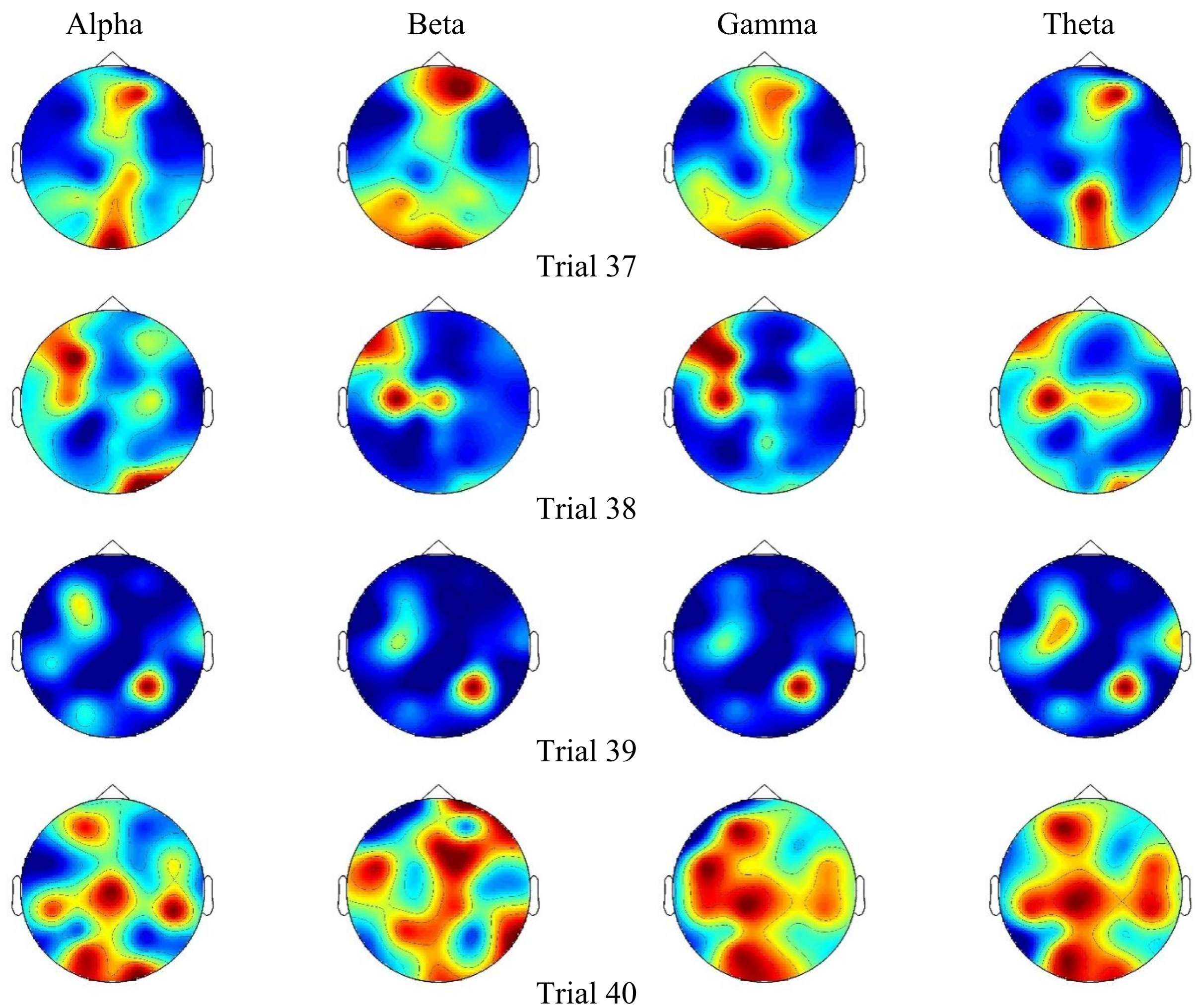

Figure 5-7Topographs of trial 37-40.

5.6 Results of Subjects

5.6.1 Subject one

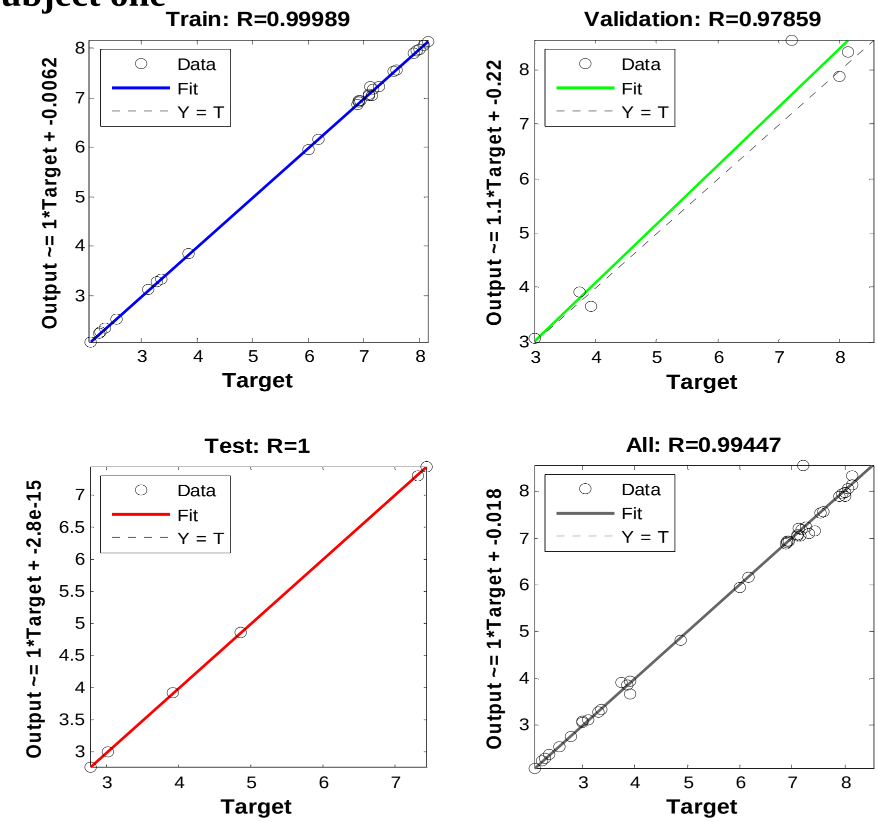

Figure 5-8 Regression plot of artificial neural network for arousal of Subject one.

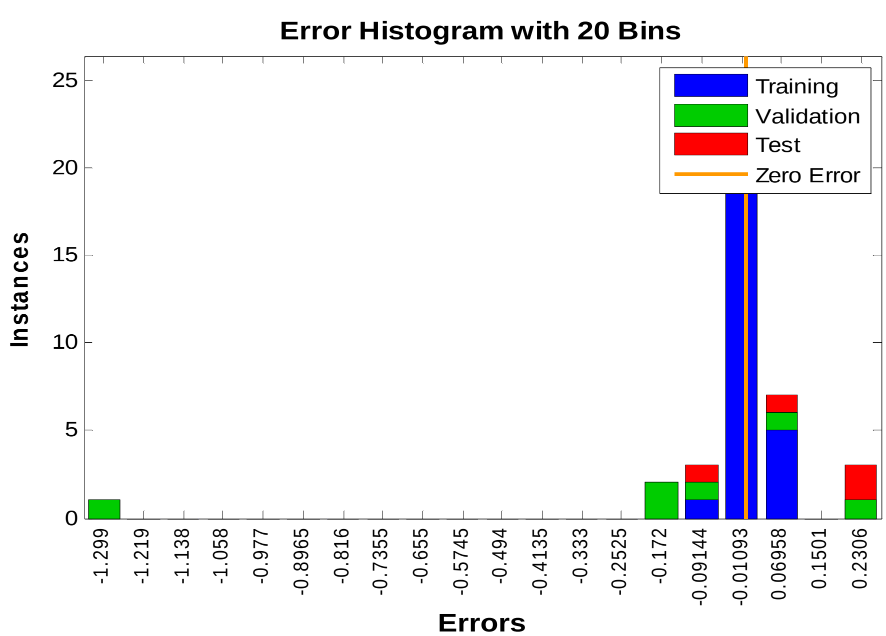

Figure 5-9Error histogram of artificial neural network for arousal of subject one.

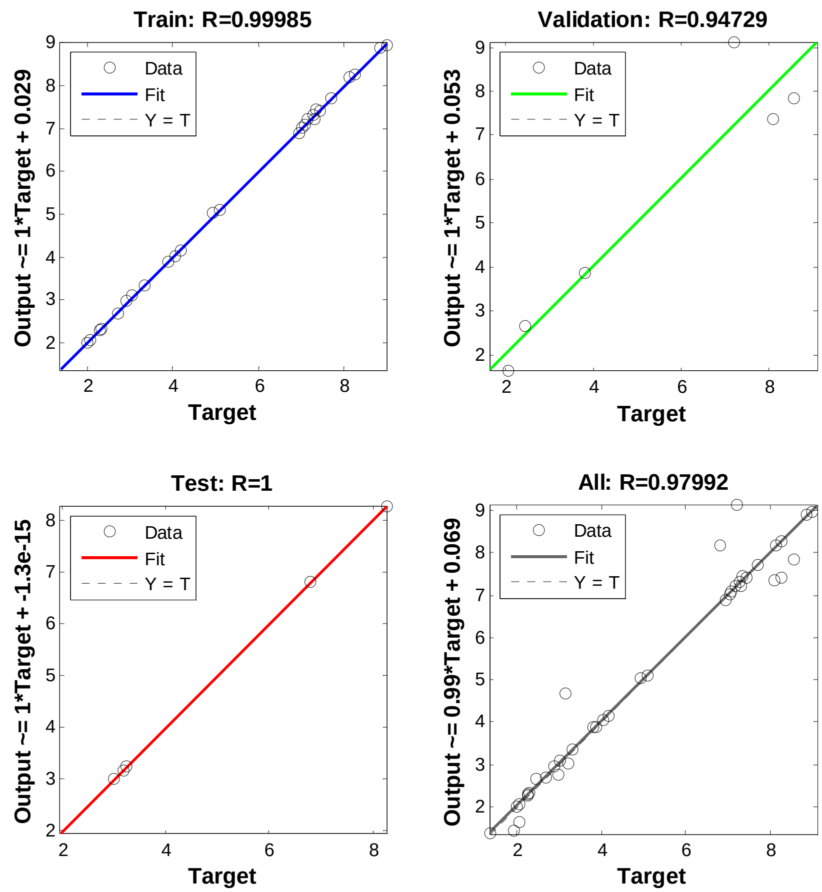

Figure 5-10Regression plot of artificial neural network for valance of subject one.

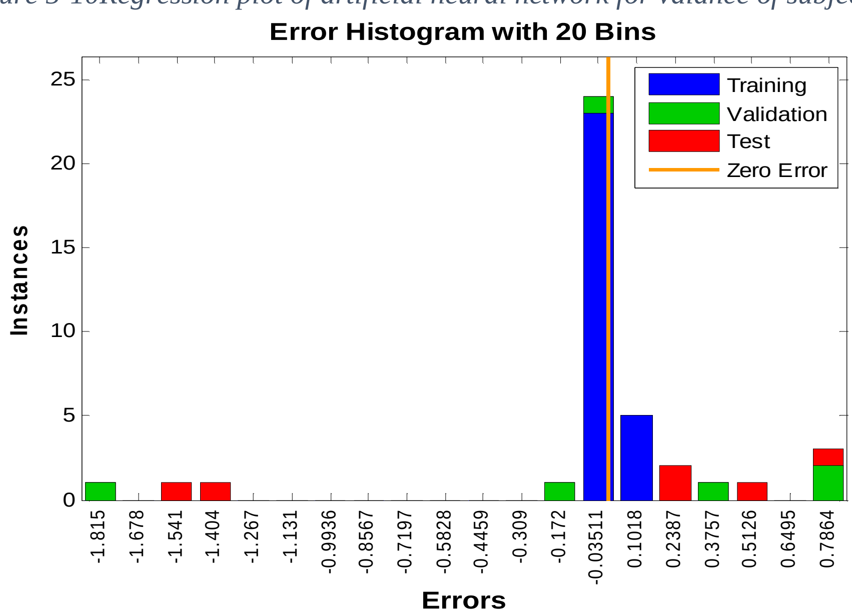

Figure 5-11Error histogram of artificial neural network for valance of subject one.

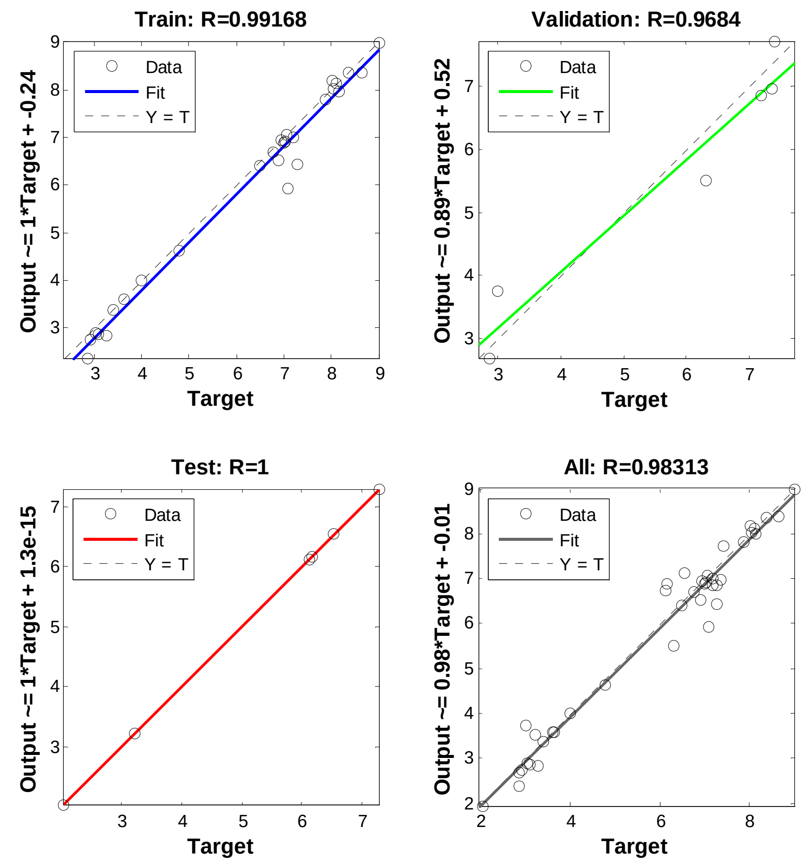

Figure 5-12Regression plot of artificial neural network for dominance of subject one.

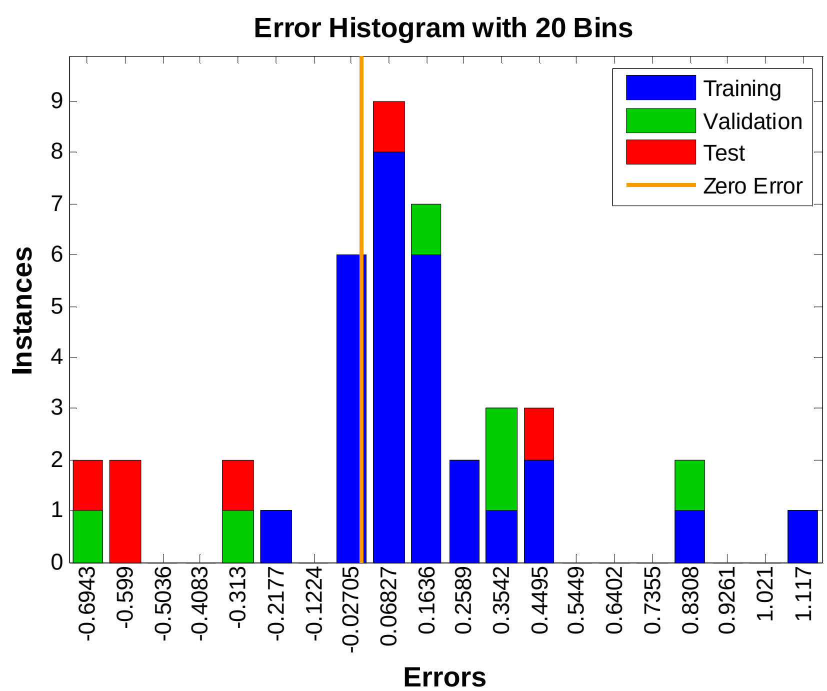

Figure 5-13Error histogram of artificial neural network for dominance of subject one.

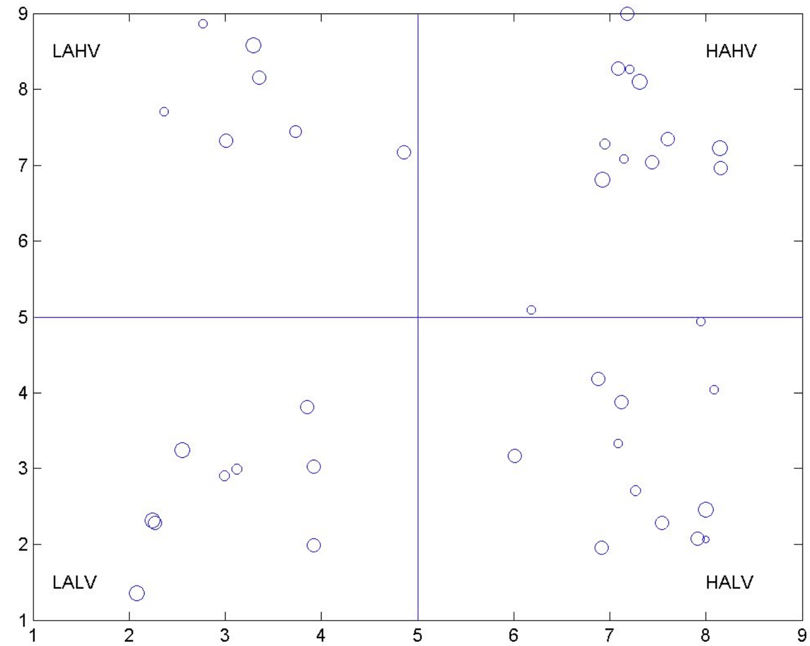

Figure 5-14 Self-assessment Arousal-valance-dominance plot for subject one.

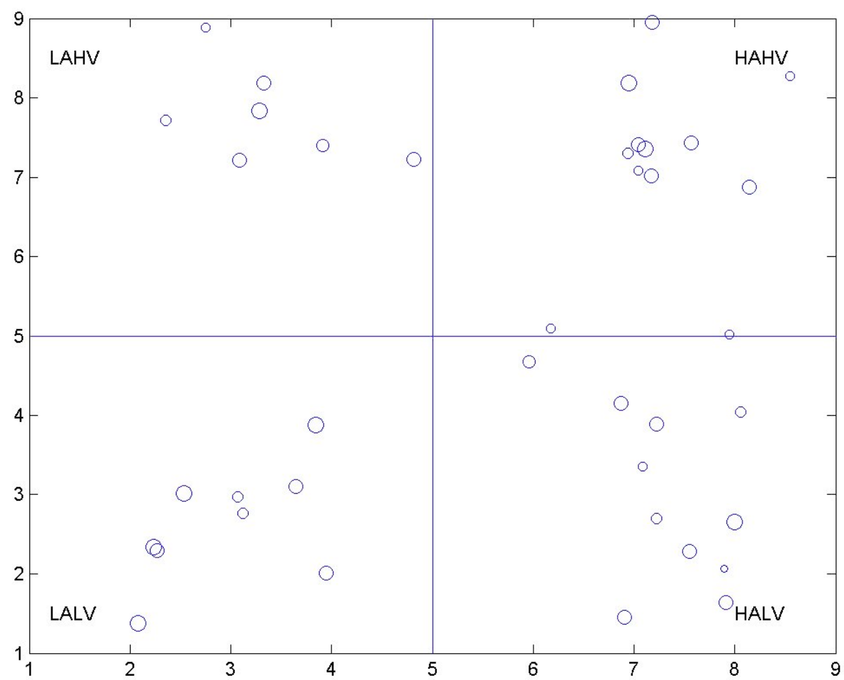

Figure 5-15Neural network model Arousal-valance-dominance plot for subject one.

5.6.2Subject two

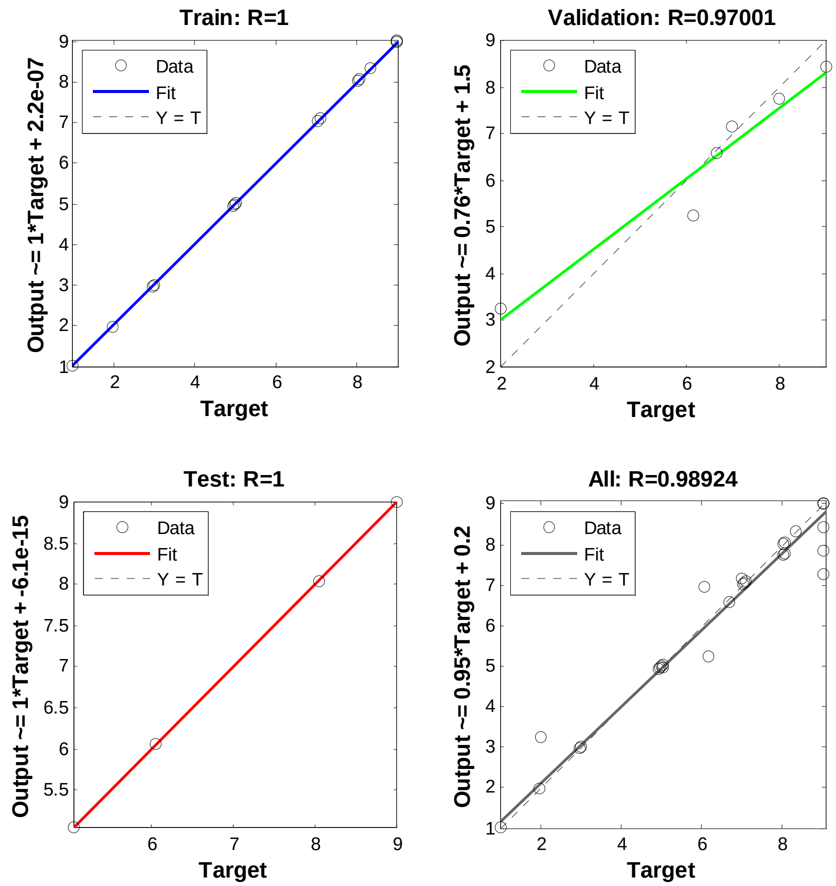

Figure 5-16Regression plot of artificial neural network for arousal of Subject two.

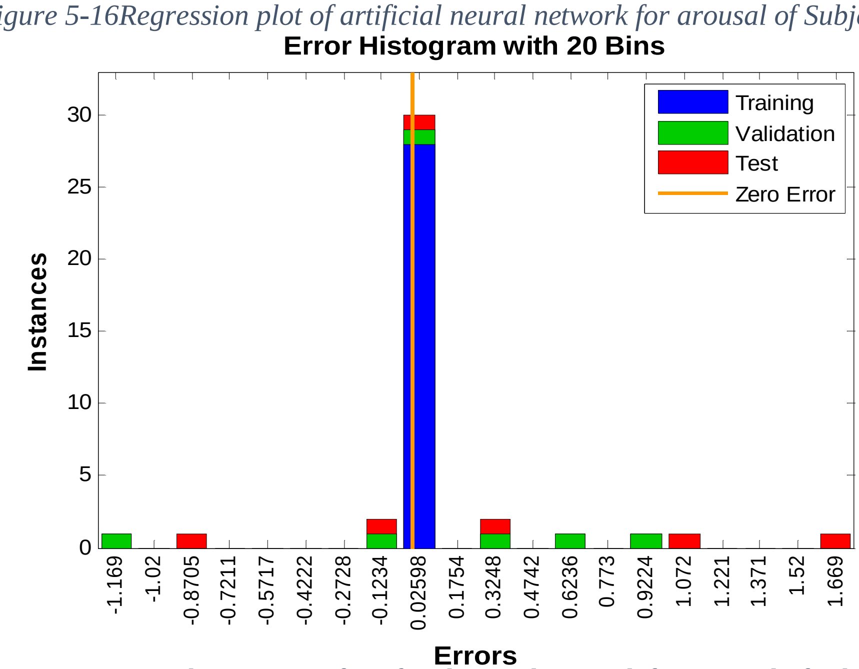

Figure 5-17Error histogram, of artificial neural network for arousal of subject two.

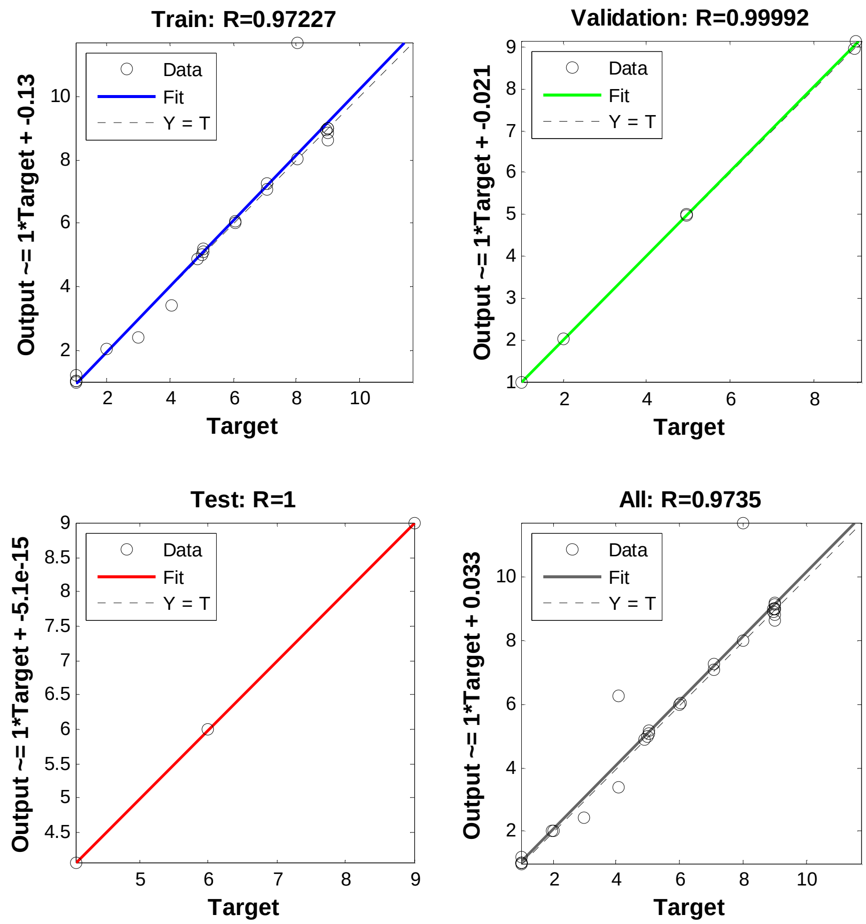

Figure 5-18Regression plot of artificial neural network for valance of subject two.

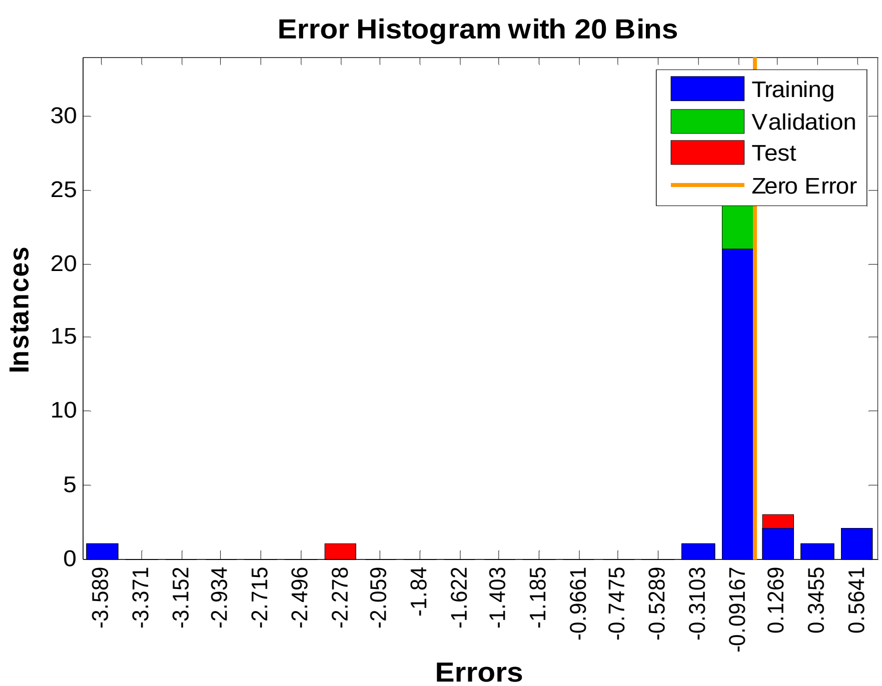

Figure 5-19 Error histogram of artificial neural network for valance of subject two.

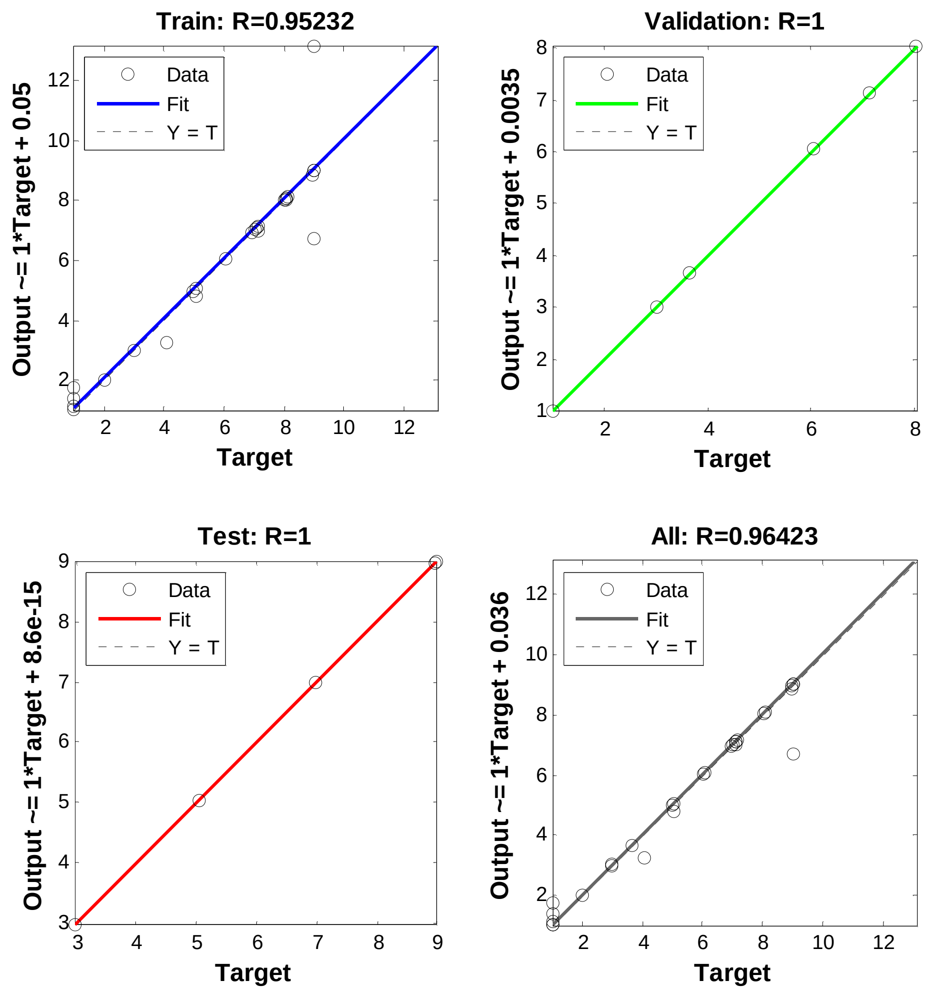

Figure 5-20Regression plot of artificial neural network for dominance of subject two.

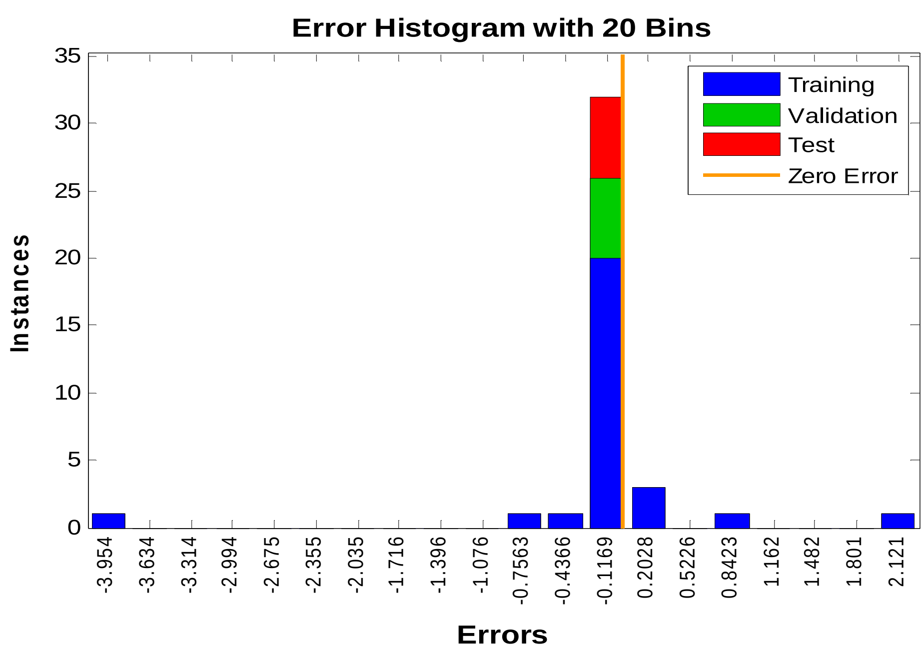

Figure 5-21Error histogram of artificial neural network for dominance of subject two.

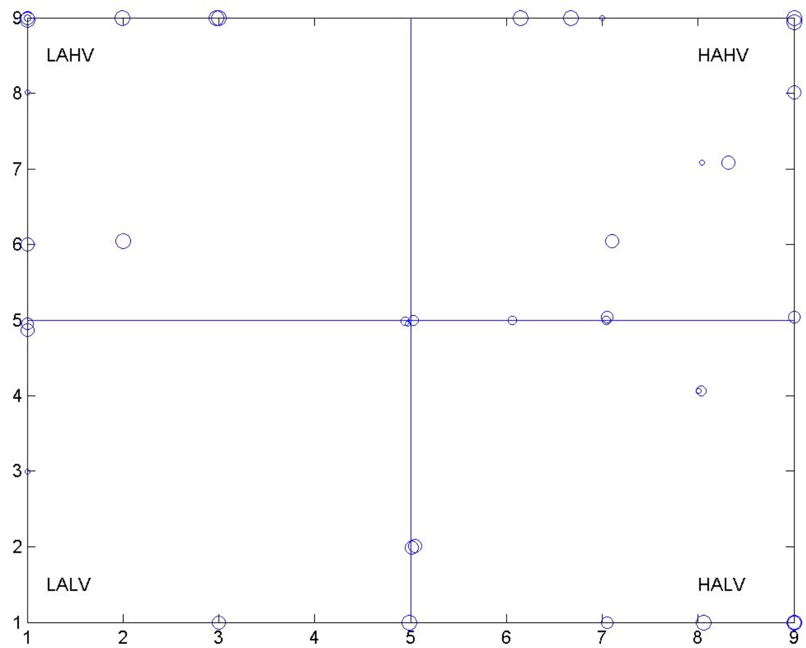

Figure 5-22Self-assessment Arousal-valance-dominance plot for subject two.

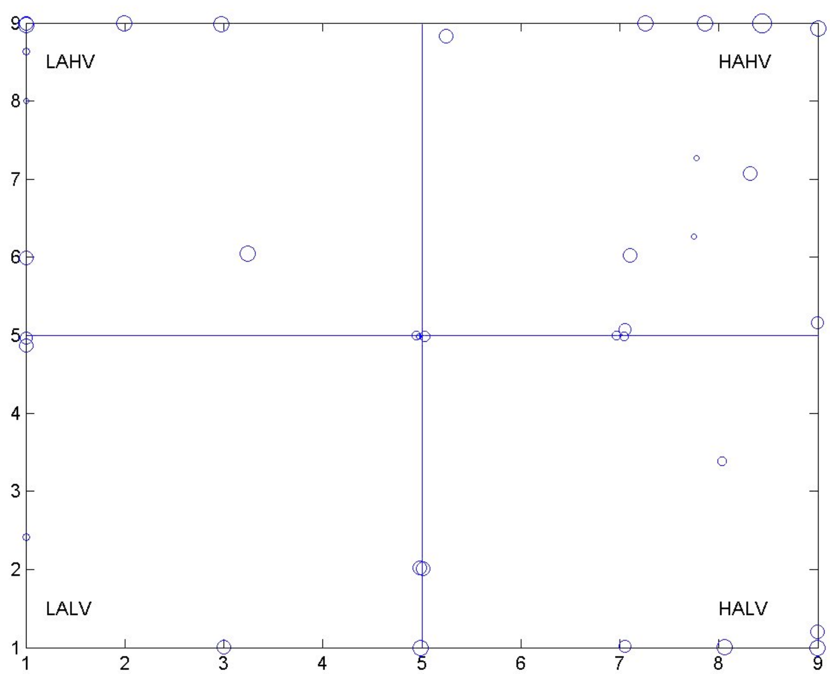

Figure 5-23Neural network model Arousal-valance-dominance plot for subject two.

5.6.3 Subject Three

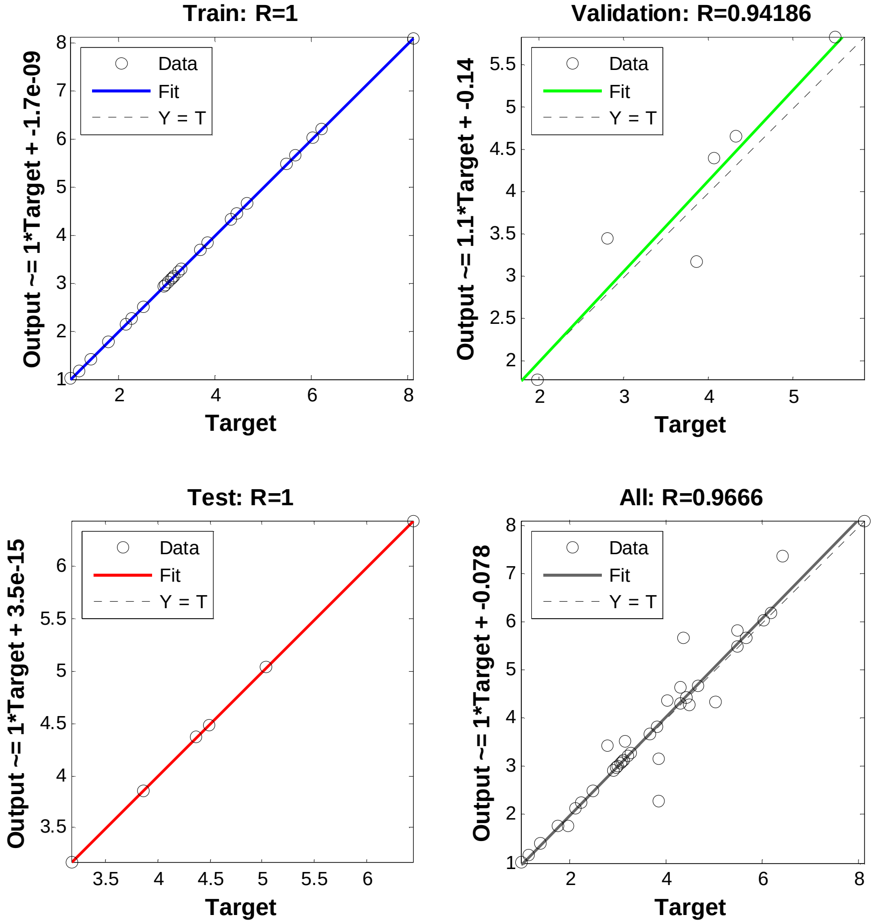

Figure 5-24Regression plot of artificial neural network for arousal of Subject three

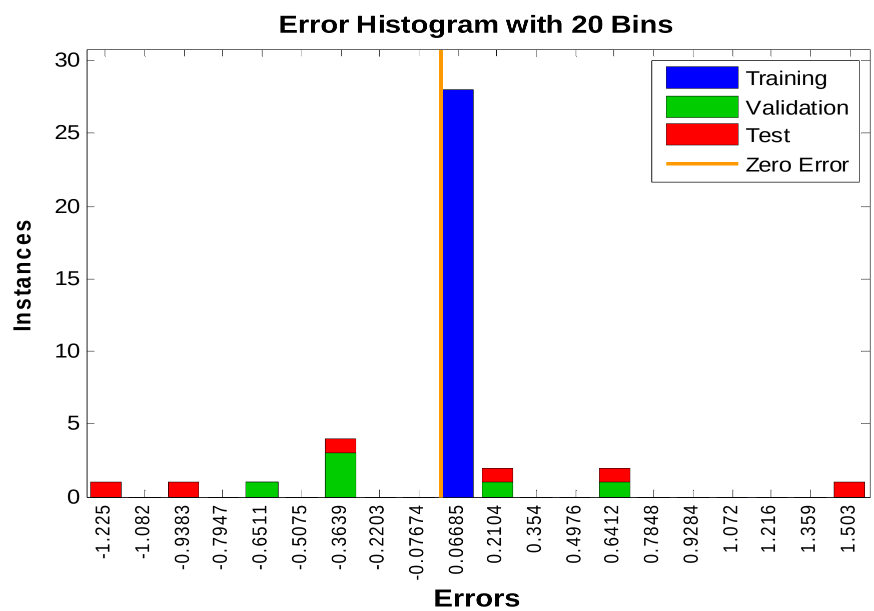

Figure 5-25Error histogram of artificial neural network for arousal of subject three

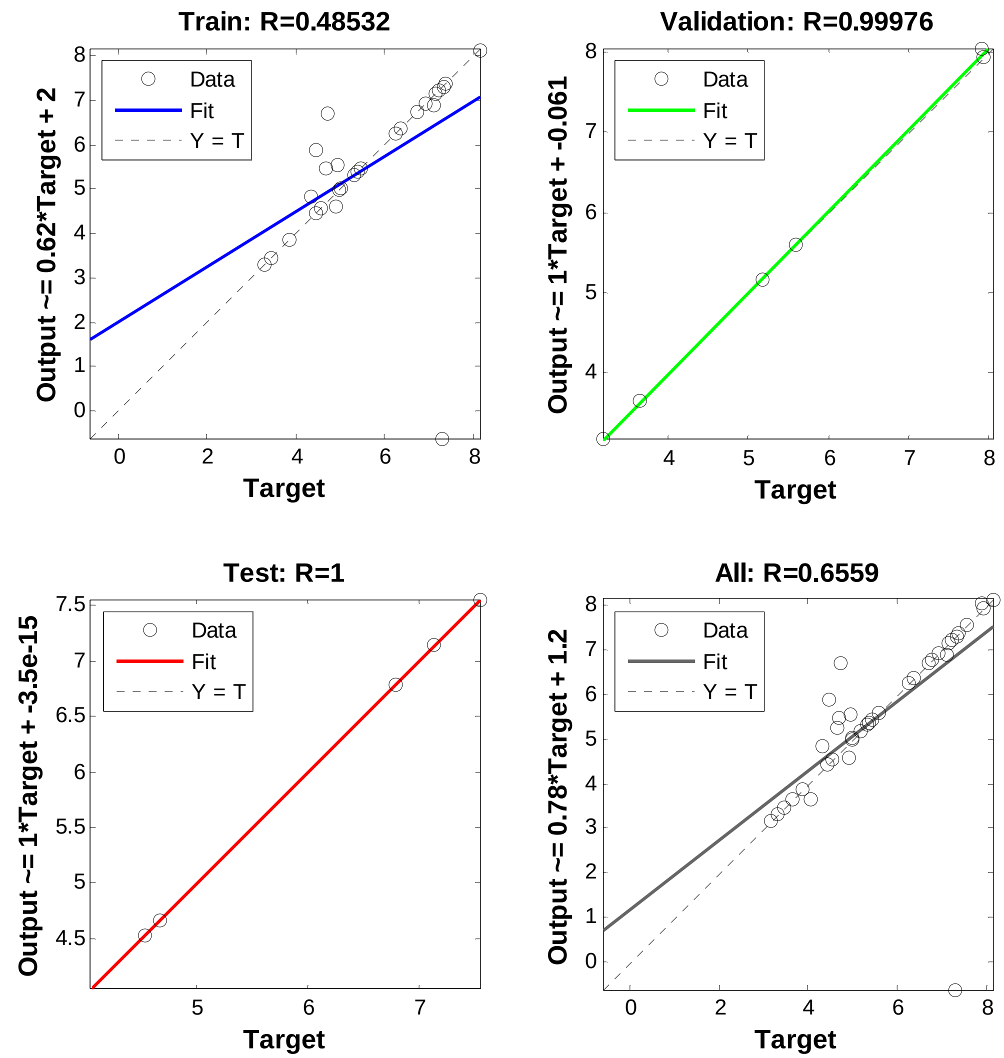

Figure 5-26Regression plot of artificial neural network for valance of subject three.

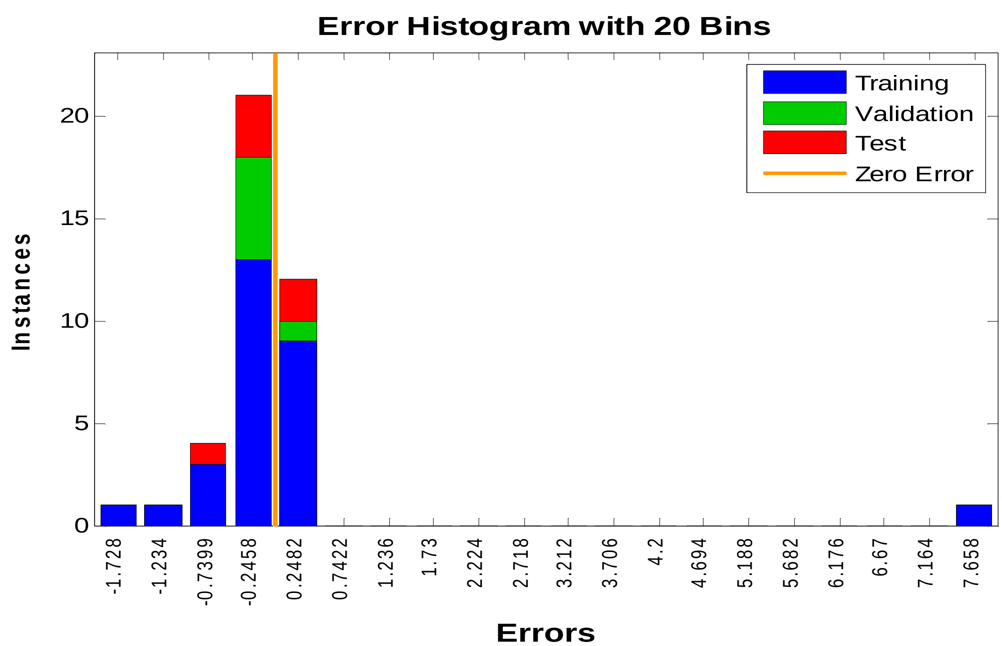

Figure 5-27Error histogram of artificial neural network for valance of subject three.

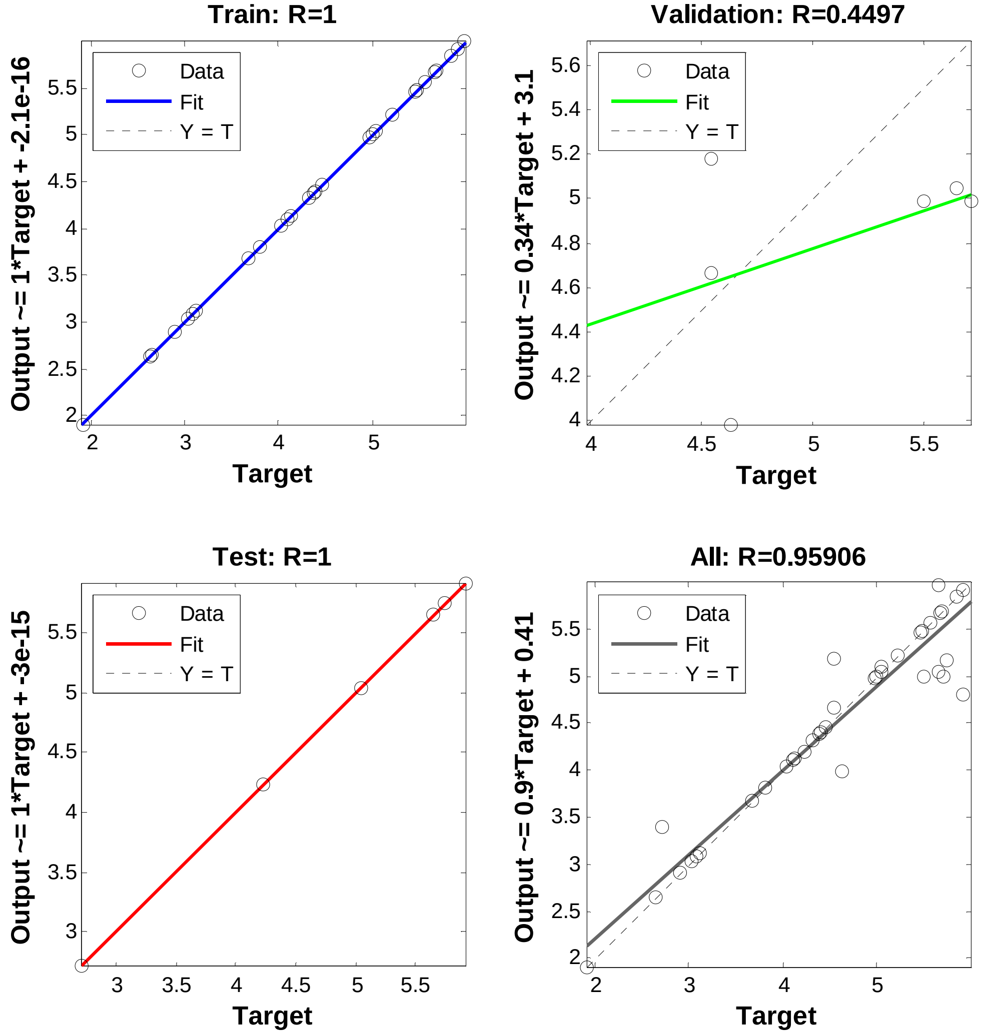

Figure 5-28 Regression plot of artificial neural network for dominance of subject three.

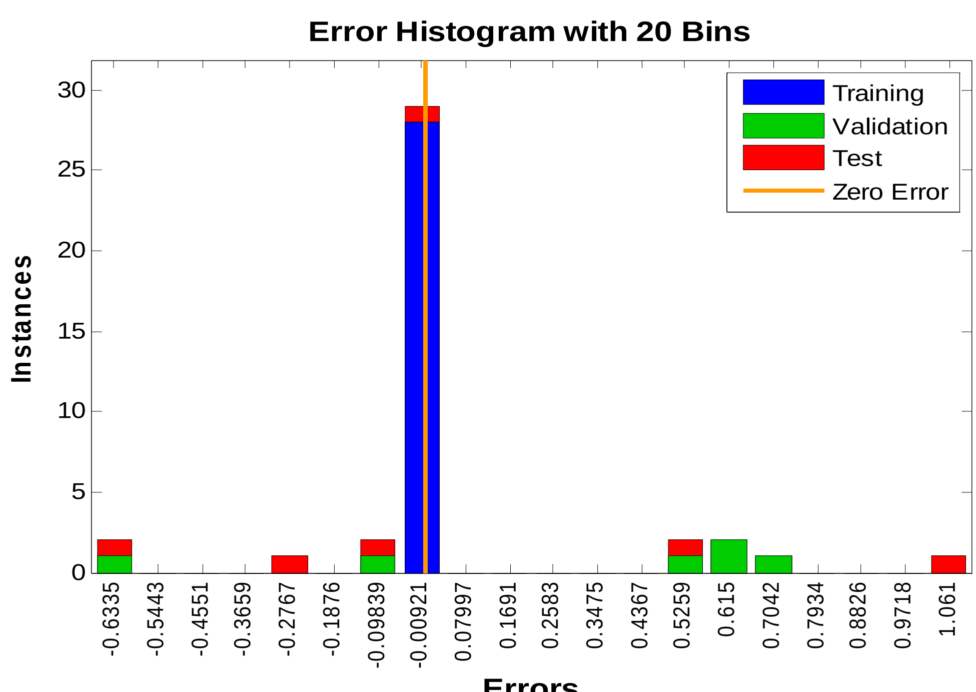

Figure 5-29Error histogram of artificial neural network for dominance of subject three.

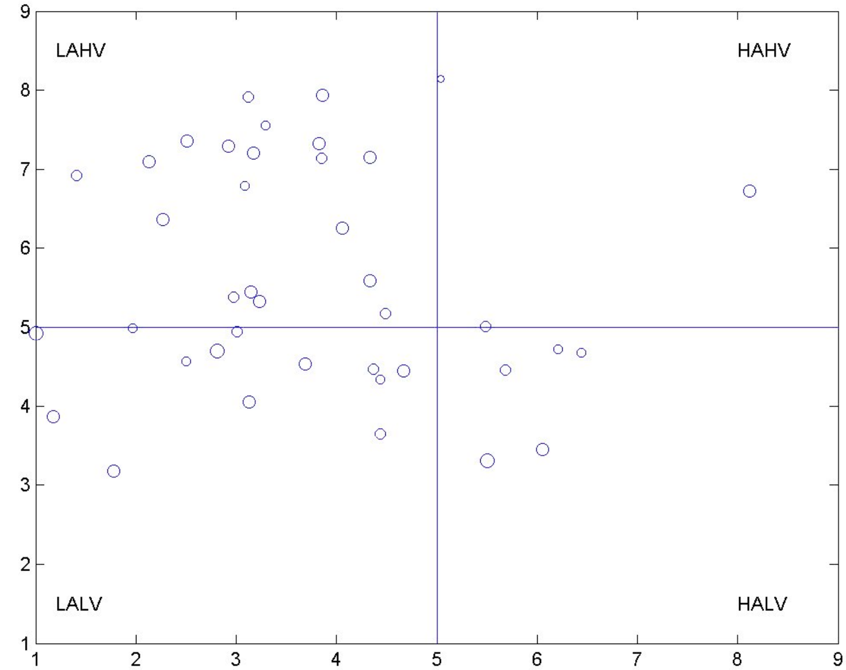

Figure 5-30Self-assessment Arousal-valance-dominance plot for subject three.

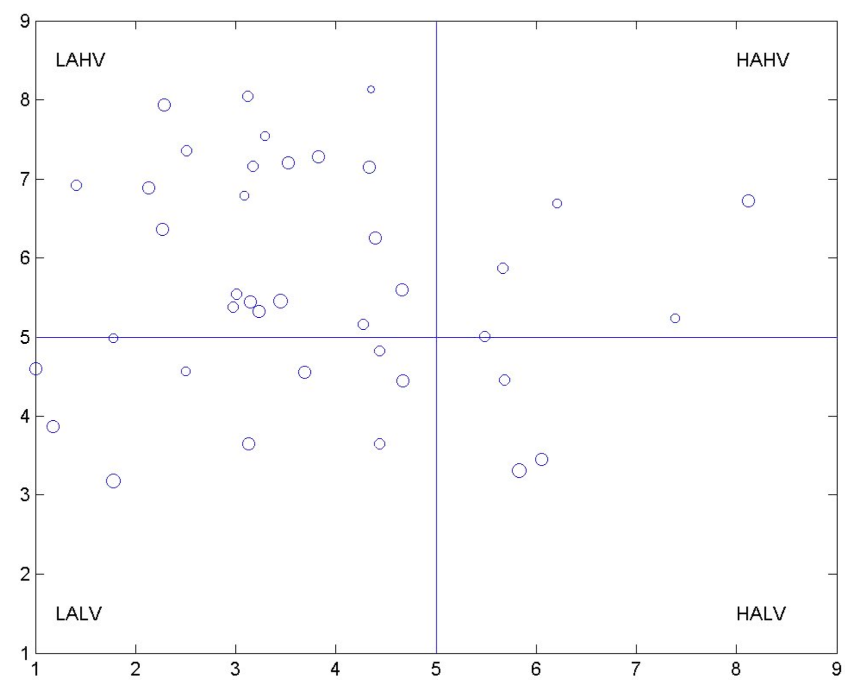

Figure 5-31Neural network model Arousal-valance-dominance plot for subject three.

5.6.4Subject Four

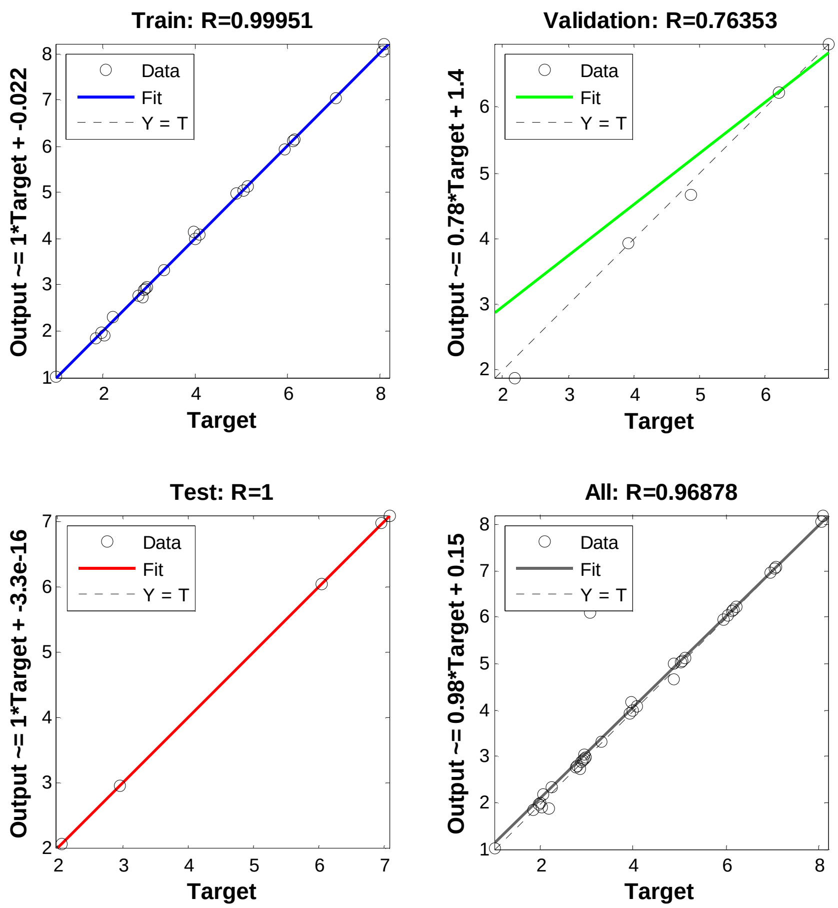

Figure 5-32 Regression plot of artificial neural network for arousal of Subject four

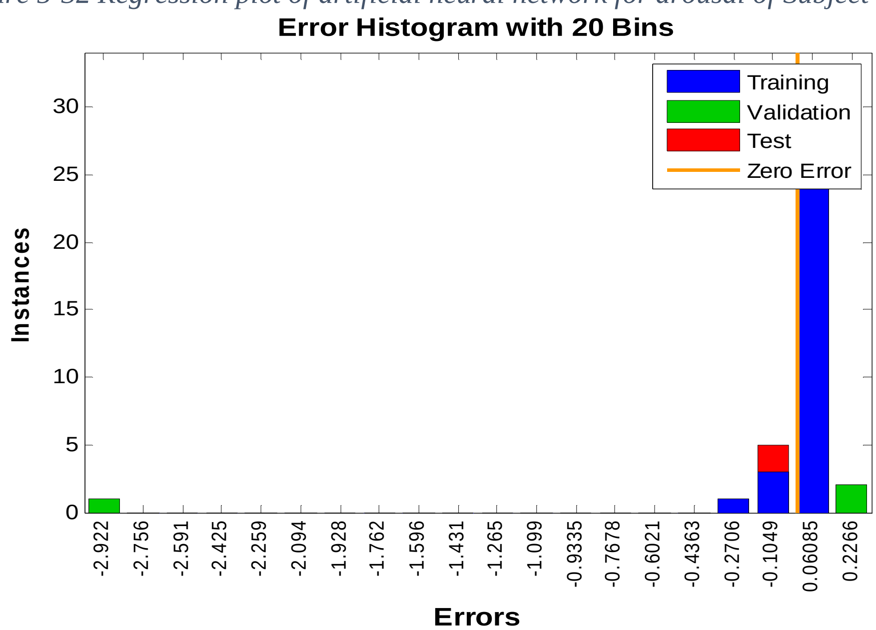

Figure 5-33Error histogram of artificial neural network for arousal of subject four.

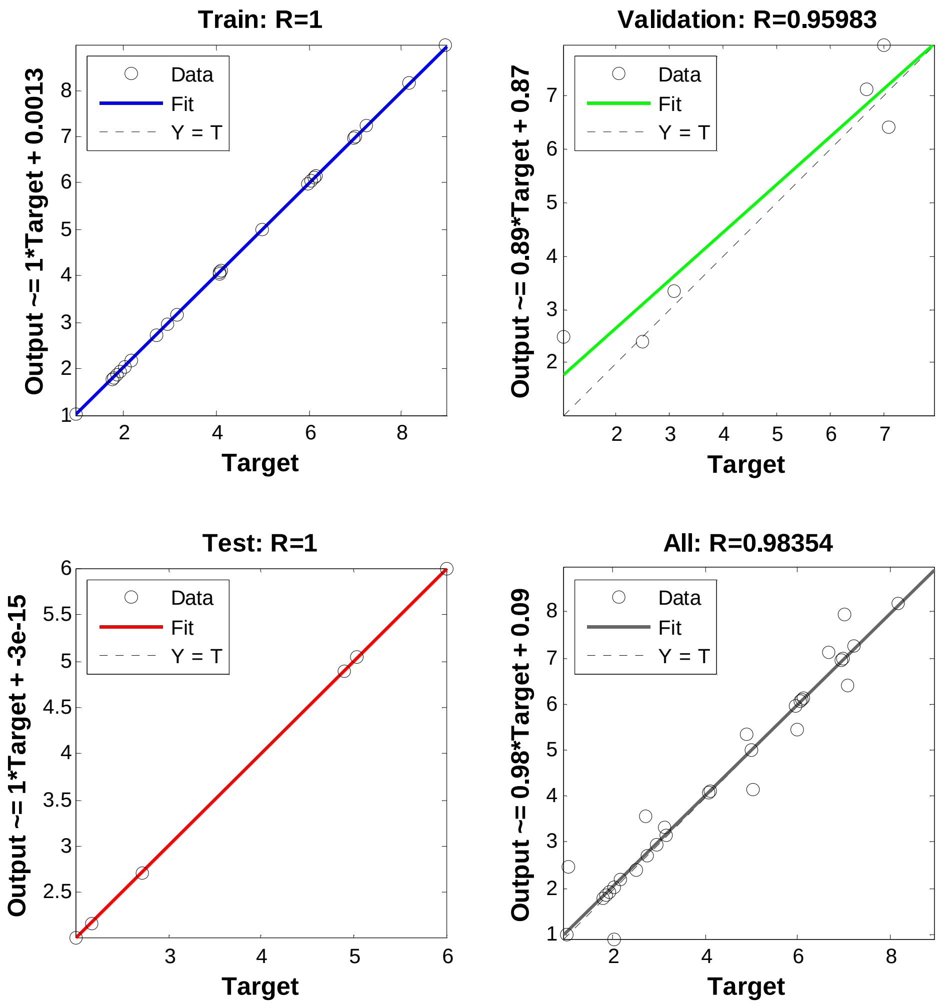

Figure 5-34Regression plot of artificial neural network for valance of subject four.

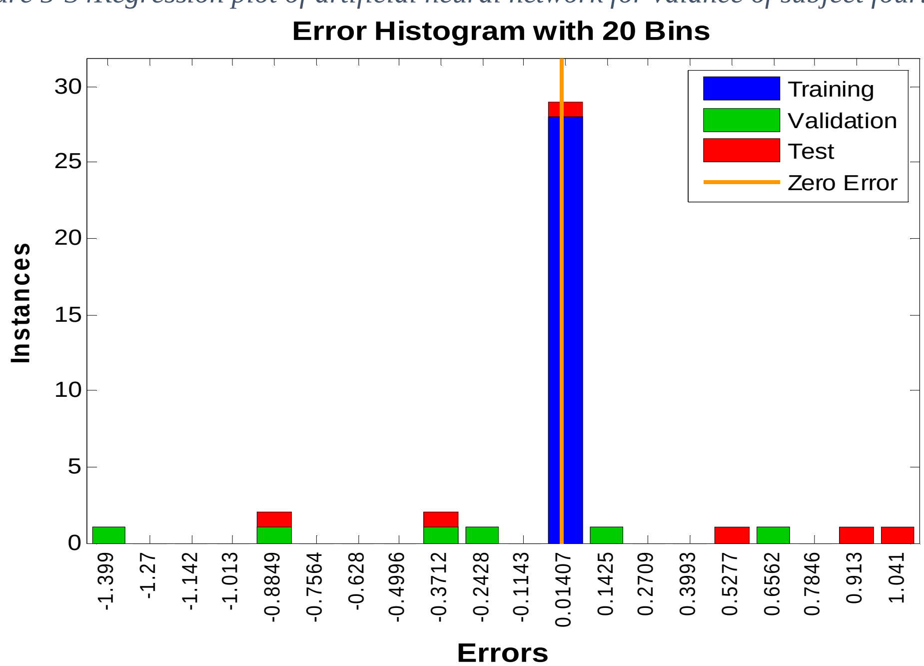

Figure 5-35Error histogram of artificial neural network for valance of subject four.

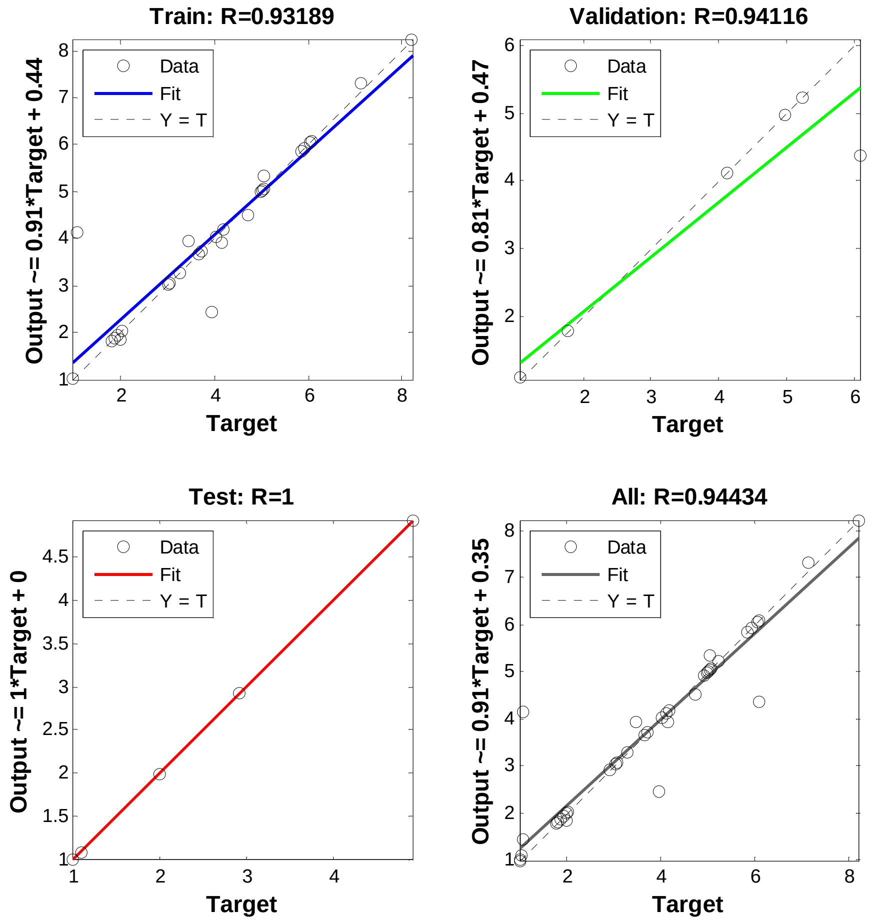

Figure 5-36Regression plot of artificial neural network for dominance of subject four.

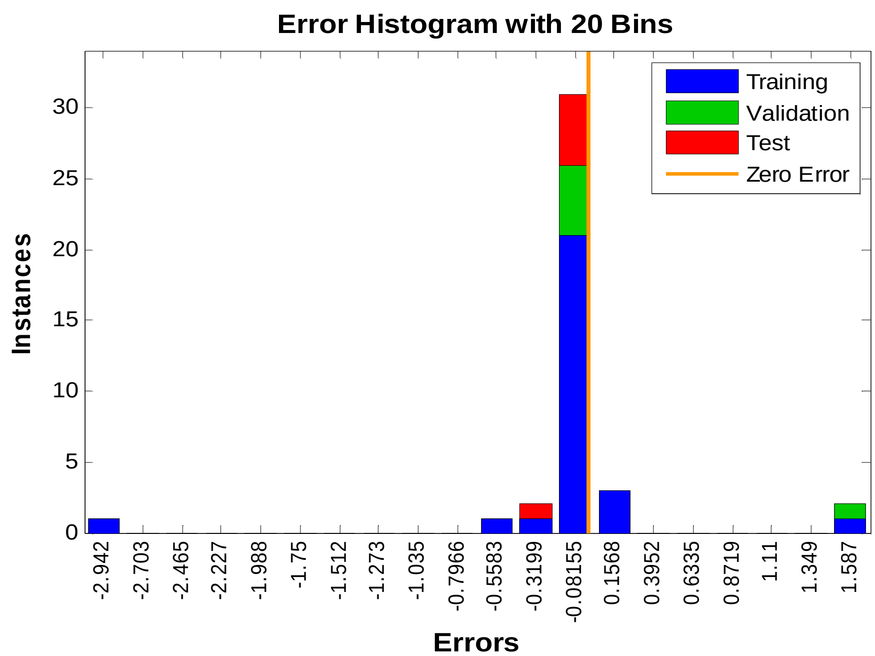

Figure 5-37Error histogram of artificial neural network for dominance of subject four.

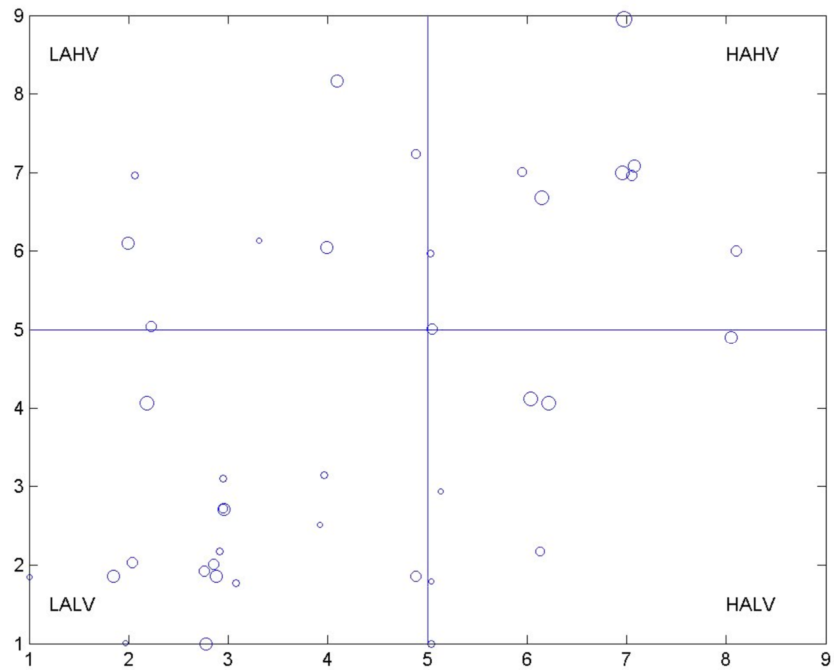

Figure 5-38Self-assessment Arousal-valance-dominance plot for subject four.

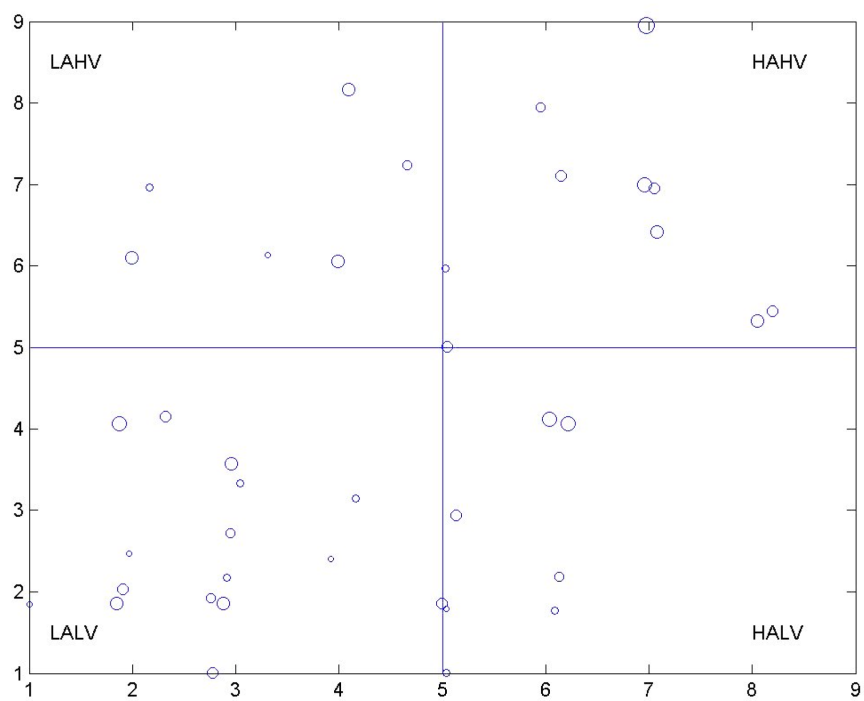

Figure 5-39Neural network model Arousal-valance-dominance plot for subject four.

5.6.5Subject Five

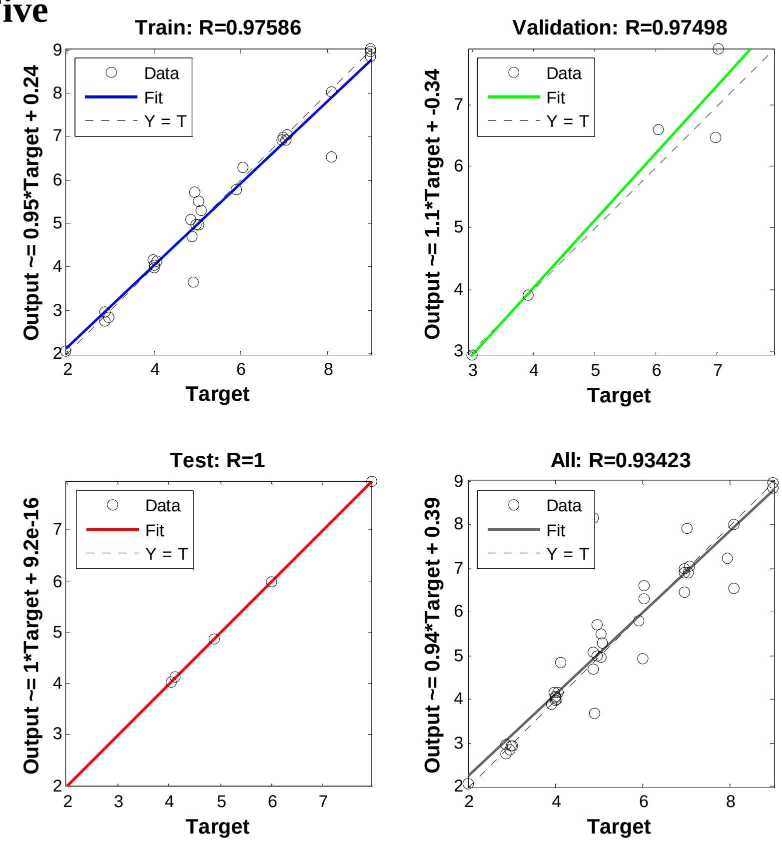

Figure 5-40Regression plot of artificial neural network for arousal of Subject five.

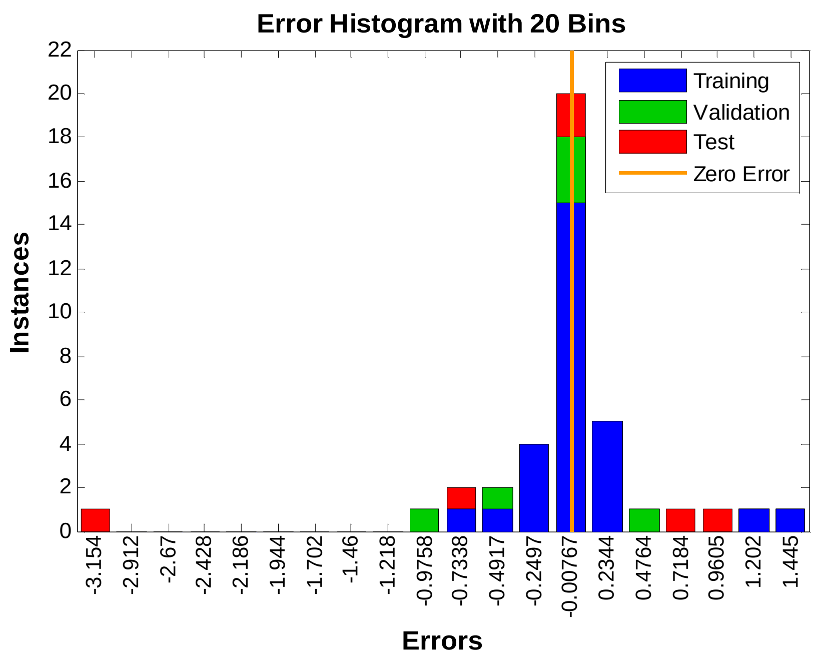

Figure 5-41Error histogram of artificial neural network for arousal of subject five.

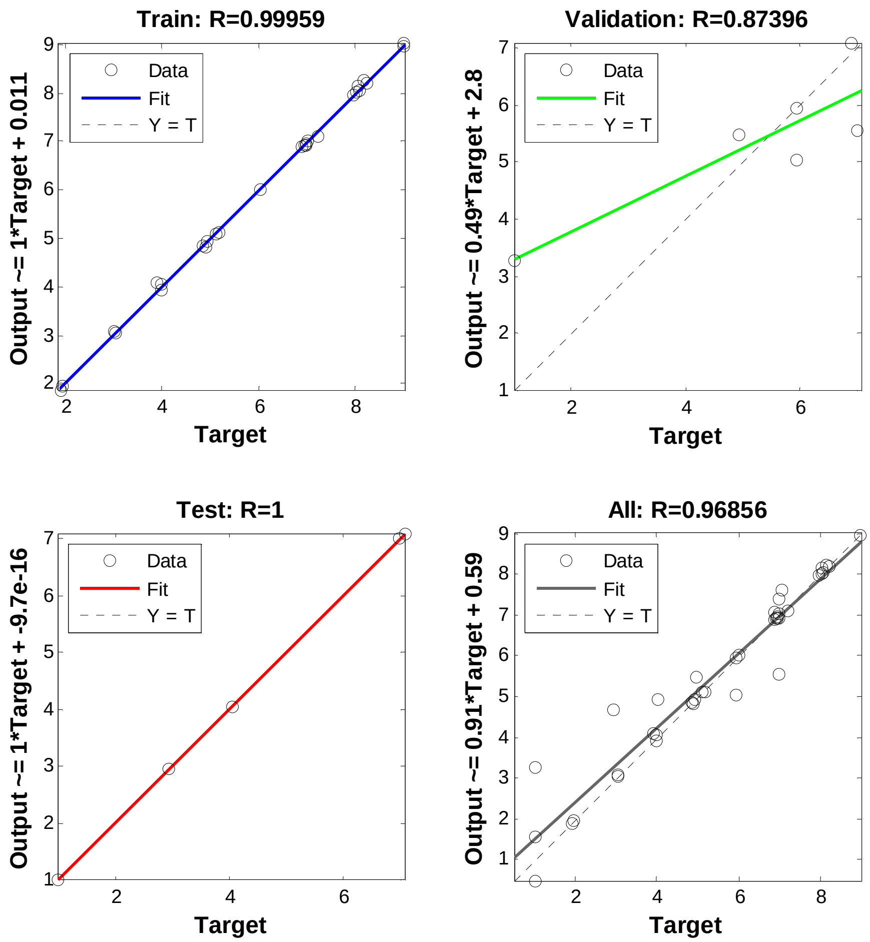

Figure 5-42Regression plot of artificial neural network for valance of subject five

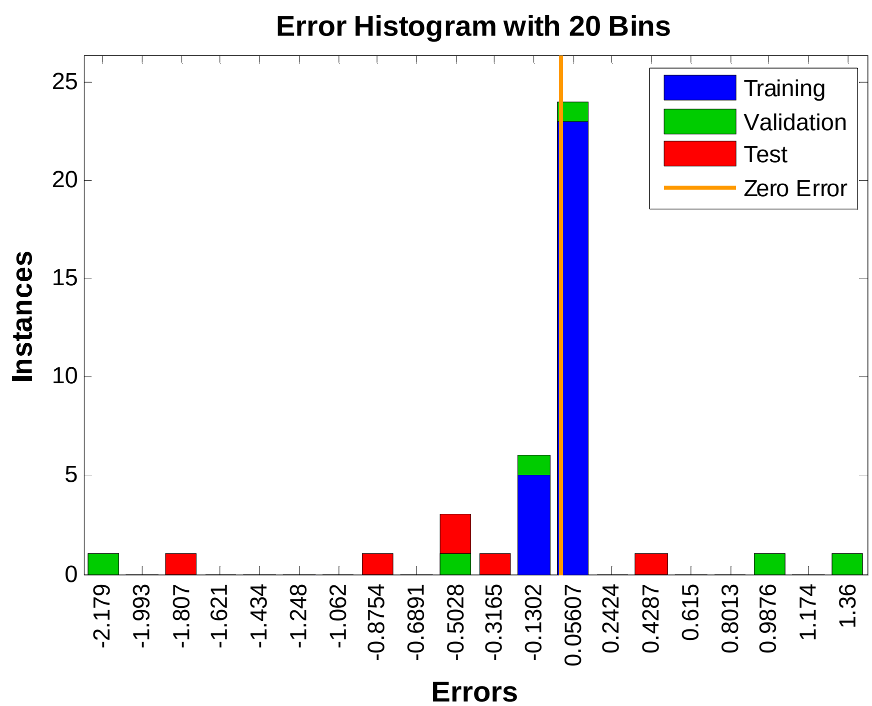

Figure 5-43Error histogram of artificial neural network for valance of subject five.

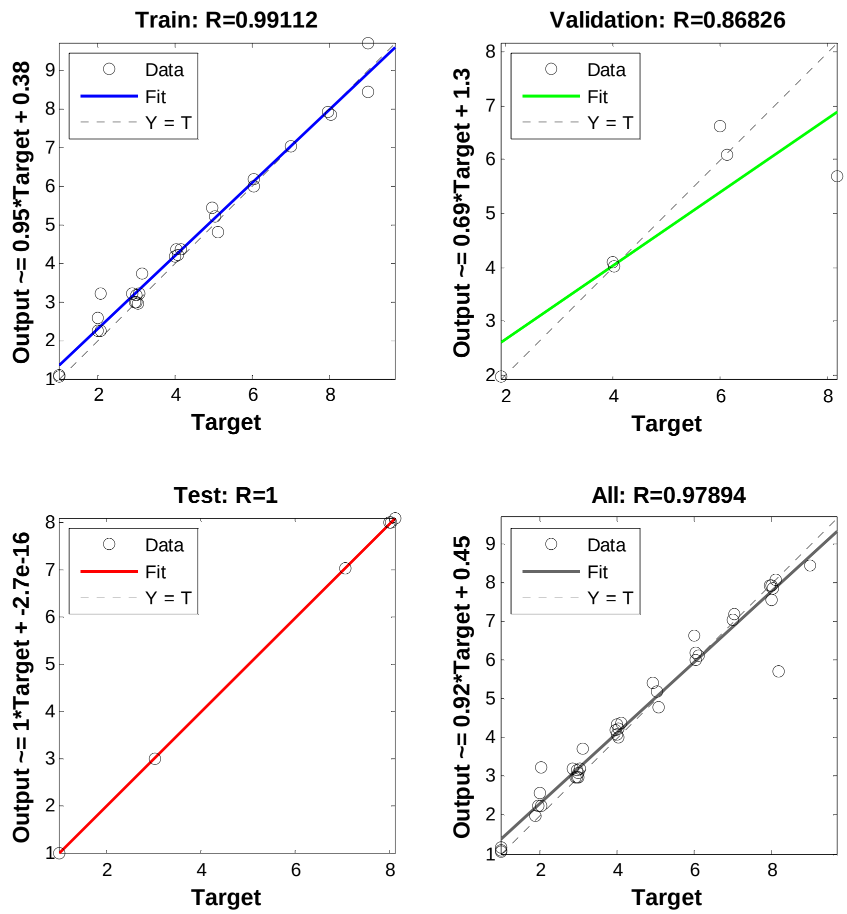

Figure 5-44 Regression plot of artificial neural network for dominance of subject five.

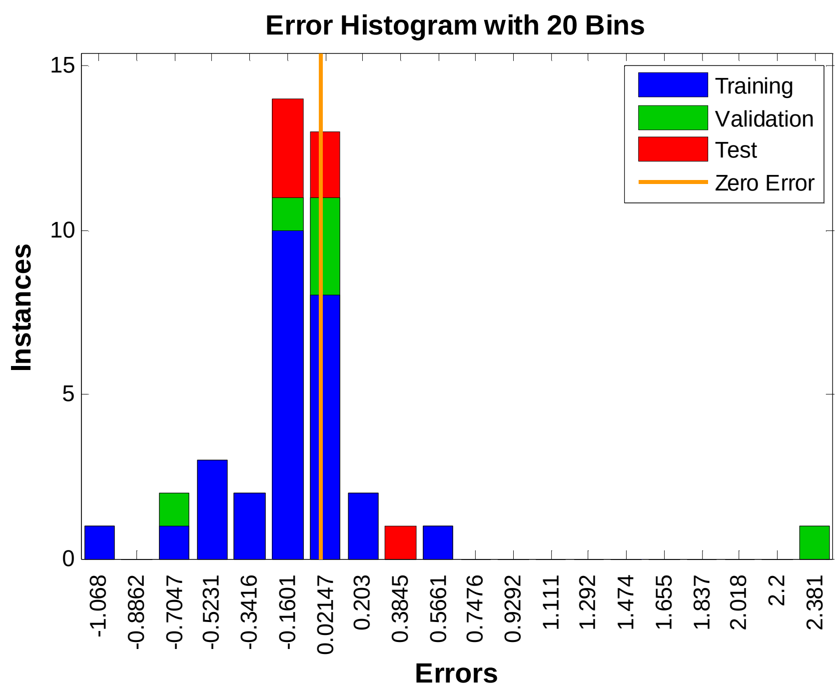

Figure 5-45Error histogram of artificial neural network for dominance of subject five.

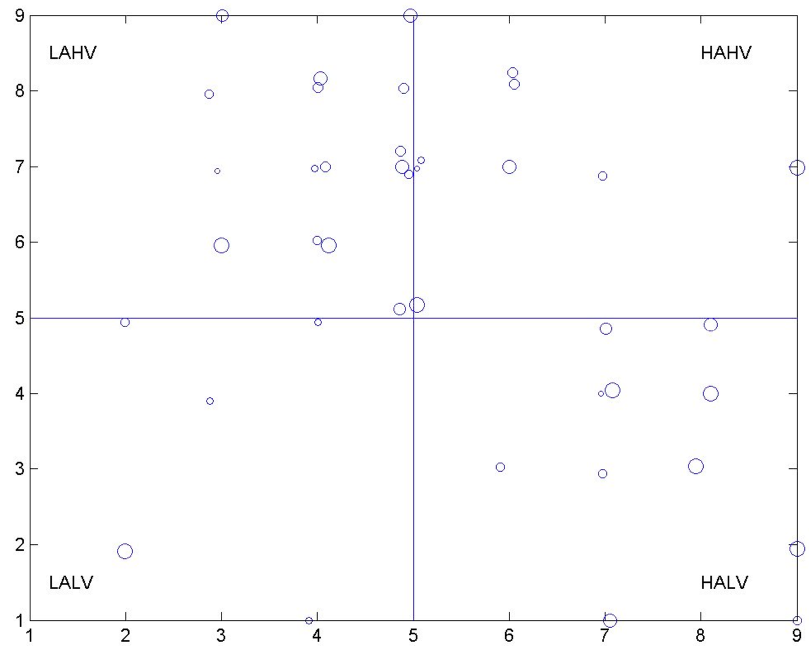

Figure 5-46Self-assessment Arousal-valance-dominance plot for subject five.

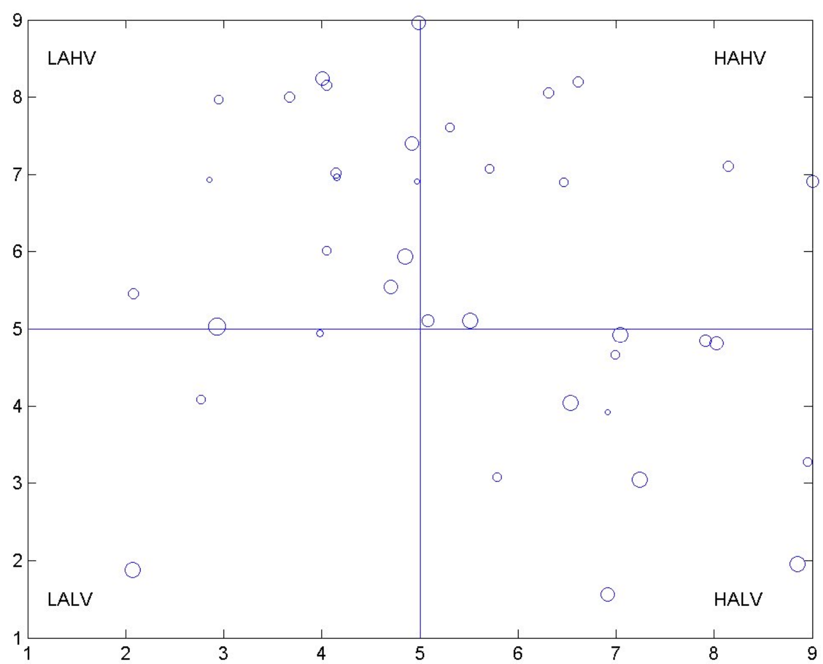

Figure 5-47Neural network model Arousal-valance-dominance plot for subject five.

5.7 Root Mean Square (RMS) Errors

Table 5-1 gives information about subject age, gender and root mean square error of artificial neural network of arousal, valance and dominance for each subject.

Table 5-1 Root Mean Square Error for all subject.

Participant	Age	Gender	Valance RMS Error	Arousal RMS Error	Dominance RMS Error
1	31	Male	0.5043	0.2297	0.3913
2	24	Female	0.7010	0.4477	0.7691
3	19	Female	1.3251	0.4164	0.3203
4	24	Female	0.4169	0.4822	0.6154
5	24	Male	0.5760	1.6975	0.5109
6	23	Male	0.0992	0.2310	0.7698
7	31	Male	0.3599	0.6226	0.0919
8	22	Female	0.3020	0.7061	1.0694
9	25	Female	0.3304	0.5627	0.1631
10	31	Female	0.6338	0.5450	0.7210
11	27	Female	1.5590	0.4607	0.5905
12	37	Male	0.4233	0.3937	0.5317
13	24	Female	0.6156	1.7316	0.2562
14	27	Female	0.1246	0.5900	0.6908
15	22	Female	0.6442	0.1592	1.2230
16	28	Male	0.6193	0.7766	0.7146
17	25	Male	1.6634	0.0569	0.2770
18	29	Male	0.6179	1.2157	0.4047
19	27	Male	0.4514	0.4091	0.1768
20	25	Male	0.5511	0.3372	0.2280
21	30	Male	0.0613	0.6102	0.0770
22	28	Female	0.4558	0.4329	1.0873
23	27	Male	0.6521	0.0295	0.5327
24	28	Female	0.0761	0.3626	0.2410
25	26	Female	0.0162	1.3831	0.6418
26	36	Male	0.4489	0.6147	0.7756
27	35	Male	1.7111	0.4089	0.2047
28	24	Male	0.5935	0.3008	1.4000
29	24	Male	0.4730	0.2567	0.4161
30	33	Male	0.3241	1.4836	0.0762
31	21	Female	1.5902	0.5061	0.3121
32	33	Female	0.3177	0.0096	1.3059

Conclusion

In this work, we have presented a novel method for emotion recognition induced by music videos. For this purpose we used EEG based event related topographs. We extracted pattern related features from this topographs. Then this features are used by artificial neural network for numerical prediction of Arousal, valance and dominance values. We obtained average root mean square error of neural network output of 32 subjects for valance is 0.6012, arousal is 0.5772 and dominance is 0.5495.

Future scope

In future it is expected to implement this work on hardware for real-time emotion recognition. Also some more features should extracted from topographic images to make the model more accurate and reliable.

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