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Article

A Novel Approach to Russell's Circumplex Model: 2D Quantification with Frontal EEG Theta and Gamma Asymmetry Indices

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Abstract: Background/Objectives: Quantifying emotions evoked by stimuli is a challenging task due to their subjective nature and the complexity of psychological states. Understanding how the brain processes emotions is critical, with applications in clinical, entertainment, and engineering fields. However, research on emotion processing in the brain is still in its infancy. This study focuses on quantifying emotions evoked by listening to slow-tempo musical stimuli (Raag Bhairavi), using Russell's circumplex model of emotion. The model utilizes the dimensions of valence and arousal to classify emotions. Frontal theta and gamma power asymmetry indices serve as key neurophysiological markers for emotion quantification, with participants categorized into Appreciators and Non-Appreciators based on their self-reported preferences for the musical stimulus. **Methods:** This empirical study employs Russell's 2D valence-arousal model to quantify evoked emotions. Electroencephalogram (EEG) data was recorded while participants listened to slow-tempo musical stimuli (Raag Bhairavi). **Indices Used:** Frontal theta and gamma power asymmetry indices were extracted to represent brain activity associated with emotional responses. **Labelling:** Participants provided self-reported responses to the stimulus, categorized as Appreciators (positive preference) or Non-Appreciators (negative/neutral preference). **Model Development:** Multiple models were created using frontal theta and gamma asymmetry indices. **Classification:** Support Vector Machine (SVM) was used for classification. **Performance** was validated using metrics such as accuracy and the Area Under the Curve (AUC); **Results:** The Total Gamma Theta (TGT) model achieved the best performance with a classification accuracy of 90.9% and an AUC of 90.74%. The Gamma Theta On 7 and 8 channel (GT78) model followed with an accuracy of 87.9% and an AUC of 89.28%; **Conclusions:** This study demonstrates the effectiveness of using EEG-based asymmetry indices for emotion quantification, providing a foundation for advancements in clinical, entertainment, and engineering applications.

Keywords: EEG; SVM; Raag Bhairavi

1. Introduction

The present article based on literature review article [1]. In which author analysed various related articles and discussed various gaps of existing articles the main aim of this article to address those gaps.

There are many methods to arouse the emotion; music is the splendid thriller and elicitor of emotion during listening unique music the physiological responses of subjects like shivering, rushing heart, goosebumps, laughter, lump in throat, sensual arousal, and sweating [2].

Tuning in to the music combines different psychological processes such as, perception, focused attention, multisensory combination, reviewing memory, syntactic processing, and social cognition [3]. Thus, music is a strong stimulus for evoking the feelings and investigating the processing functions of the human brain. Using the musical stimulus.

Indian Classical music has great heritage the origin of Indian classical music can found in *Vedas* (1500BCE) [4]. An full-size body of ancient Indian scripts belonging to the early centuries A.D. Have documented the emotions associated with ragas [5,6] . There are many of folklore, but very few scientific research studies using EEG modality.

1.1. Research Question and Hypothesis

The frontal spectral asymmetry power index, which is generated in the frontal lobe due to the potential difference between the two hemispheres during the processing of the *Raag Bhairavi* musical stimulus, can be applied to quantify the emotion evoked by the stimulus.

To decipher the research question the variables exerted refer Figure 1 the independent variable were spectral powers of EEG bands on the left (system 1) and right (system 2) hemispheres of the participants and dependent as self-response given to musical stimulus by the participants. The null and alternative hypothesis formulated as below.

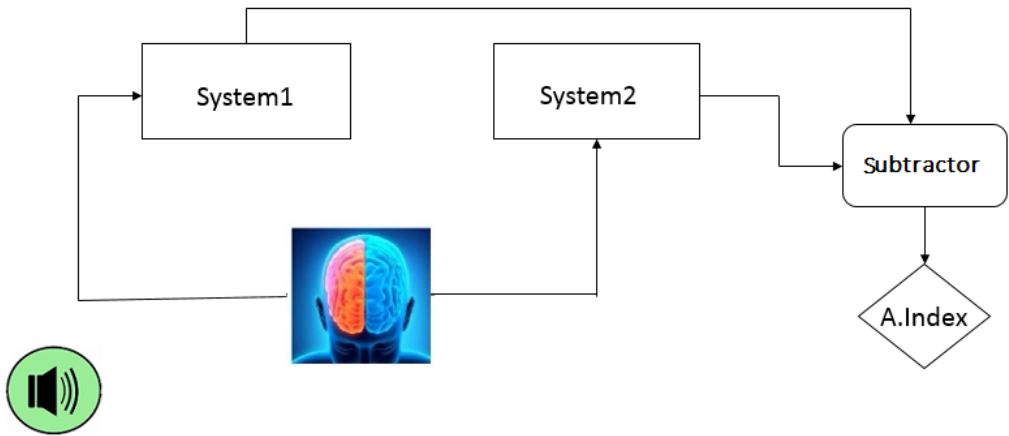


Figure 1. Asymmetry Index of evoked musical stimulus

H0: There are NO changes in Power of θ and γ while listening Instrumental *Raag Bhairavi* classical music on right and left hemisphere ($\mu_0 = \mu_1$)

H1: There are changes in Power of in Power of θ and γ while listening Instrumental *Raag Bhairavi* classical music on right and left hemisphere ($\mu_0 \neq \mu_1$)

The research is documented using Sec.-(1.2). deals with challenges and recommendations of research. Sec.-(2) covers theoretical frame work and proposed algorithm. Sec.-(3) covers approach adopted to decipher research question. Sec.-(4) deals with results analysis of proposed models. Sec.-(5) deals with discussion of the results. Sec.-(6) conclude the research.

1.2. Challenges and Recommendations

The author [7] documented the pitfall of such kind of research. Designing of particularly interdisciplinary studies very difficult. The researcher needs expertise in EEG technology, signal processing, mathematical modelling, experimental psycho physiology, neurophysiology, and machine learning. It is an big challenge for scientists to oversee the state of the artwork in a majority of these areas of expertise, and to combine it efficaciously of their research, or correctly choose the quality of studies accomplished by others. Author recommends six recommendation shown in Figure 2 to avoid the pitfall in such experiments

- R1: Define your state of interest with ground truth
- R2: Connect your state of interest with neurophysiology

- R3:Reduce confounding factor
- R4:Stick to good classification practice
- R5:Reason for the causes of classification success
- R6:Insight of added value using neurophysiology



Figure 2. Brouwer’s Recommendation R1-R6 adopted from [7]

1.3. Brouwer Recommendation as Bench Mark

All the existing literature analysed considering Brouwer’s recommendations as a benchmarks [8] shown in Table 1.

Table 1. Analysis on the basis of Brouwer’s recommendations.

Author	Year	R1	R2	R3	R4	R5	R6
Proposed	2025	✓	✓	✓	✓	✓	✓
[9]	2001	✓	✓	✓	×	✓	×
[10]	2002	✓	✓	✓	×	✓	×
[11]	2007	✓	✓	✓	✓	✓	×
[12]	2007	×	✓	×	×	×	✓
[13]	2008	×	✓	×	×	×	✓
[14]	2009	×	✓	×	×	×	✓
[15]	2010	×	✓	×	×	×	✓
[16]	2010	×	✓	×	×	✓	✓
[17]	2012	×	✓	×	✓	×	✓
[18]	2012	×	✓	×	×	✓	✓
[19]	2013	×	✓	×	✓	×	✓
[20]	2013	×	✓	×	✓	✓	✓
[21]	2013	×	✓	×	×	×	✓
[22]	2016	×	✓	✓	✓	✓	✓
[23]	2016	×	✓	×	×	×	✓
[24]	2016	✓	✓	✓	×	×	✓
[25]	2016	×	✓	×	×	×	×
[26]	2017	×	✓	✓	×	×	✓
[27]	2020	✓	✓	✓	×	×	✓
[28]	2024	✓	✓	✓	×	×	✓

✓ -Followed, × -Not Followed

The approach adopted to fulfil all recommendations

- R1:
 1. By involving music expert the music the stimulus selected which is unfamiliar as unfamiliar music suitable for the music recognition system [26].
 2. The participant selected from the unlike the population of different age As the accuracy of the depend on on the age [23]
 3. Clinical expert confirms the normalcy, handedness and psychometric tests to select the participant [29].
- R2:
 1. Models are created on the basis psycho-neurological findings. [1].
- R3:
 1. EEG recorded using artefact recording protocol as mentioned. [1,30].
 2. EEG recorded in three sessions before the stimulus , during the stimulus and after stimulus.
 3. Asymmetry checked on all four lobes.
- R4:
 1. Recorded EEG is preprocessed for different artefacts [1,30,31].
 2. Various statistical test conducted and results confirmed using post-hoc tests.
- R5:
 1. Different models are created using the spectral feature as mentioned. in Sec.-2.
- R6:
 1. Different applications implicated out of proposed study [29,32].

2. Theoretical Frame Work

After analyzing relevant and related articles mentioned in article [1].There is frontal asymmetrical EEG activity which modulated valence of emotion. An increased left frontal EEG activity for joyful music and more noticeable comparative right frontal EEG activity to unpleasant musical stimulus [9]. Intensity of asymmetry depends on as intensity of emotion [9]. The happy and sad emotions were evoked by pleasant and unpleasant musical stimulus [11]. Theta power modulate with evoked emotion [11]. δ , θ and α low-frequency bands are associated with evoked emotions are found [13,28]. β and γ band indicates arousal of emotion [17].

2.1. Proposed 2 D Models

Existing research shows that the frontal region is responsible for emotion processing when a subject evoked with positive emotion left hemisphere power high when a subject invoked with negative emotion subject is right hemisphere brain activity goes high to quantify the asymmetry frontal asymmetry models created. Theta power correlates the evoked valence of emotion frontal θ Some literature is suggesting high frequency gamma power correlates arousal of evoked emotion based on these findings 2-D model of emotion formatted using frontal theta power asymmetry index and gamma power asymmetry index and 2-D model of emotion based on theta and gamma asymmetry Table 2. TGT (Total Frontal channel Gamma and Theta asymmetry) comprises of valence variable Total Asymmetry Emotion Valence Theta Index (TAEVI $_{\theta}$) and arousal variable total Asymmetry Emotion Valence Gamma Index (TAEVI $_{\gamma}$). GT 7 8 (Gamma and Theta on channel 7 and 8) comprises Asymmetry Emotion Valence on Frontal 7 8 Theta (AEVIF78 $_{\theta}$). GT34(Gamma Theta on channel 3 and 4) comprises of valence variable Asymmetry Emotion Valence on Frontal 3,4 Theta (AEVIF34 $_{\gamma}$) and arousal variable Asymmetry Emotion Valence on Frontal 3 4 Gamma AEVIF34 $_{\gamma}$. GTFp12 (Gamma and Theta Fronto-Partial on channel 1 and 2) valence variable Asymmetry Emotion Valence on Fronto-Parietal channel 1 and 2 Theta(AEVIFp12 $_{\theta}$) and arousal variable Asymmetry Emotion Valence on Fronto-Parietal channel 1 and 2 Gamma (AEVIFp12 $_{\gamma}$).

Table 2. Proposed valence-arousal 2-D Models

Model	Valence Variable	Arousal Variable
TGT	TAEVI $_{\theta}$	TAEVI $_{\gamma}$
GT78	AEVIF78 $_{\theta}$	AEVIF78 $_{\gamma}$
GT34	AEVIF34 $_{\theta}$	AEVIF34 $_{\gamma}$
GTFp12	AEVIFp12 $_{\theta}$	AEVIFp12 $_{\gamma}$

3. Methodology

After having sufficient background about existing research, We have prepared methodology for our proposed study. The investigation proceeded after ethics committee approval from HBT Medical College and Dr R.N Cooper Hopital Total 33 right handed subjects participated in study 17 female and 16 males with average age 28.69 ± 11.69 all the subjects satisfied inclusion criteria all the participant most of the normal subjects were staff, faculty, doctors and relatives of patients of Dr Cooper Hospital and some are faculties of MPSTME. Handedness and normalcy of the subjects confirmed by an associated psychiatrist.

- Inclusion Criteria
 1. Right handed subjects
 2. Age 18-63

3. No medical condition and history of mental depression
- Exclusion Criteria
 1. Subjects under medication for mental depression
 2. Left-handed Subjects
 3. Subjects with suffering from neurotic diseases

To evaluate brain activity electrode cap of 8 electrodes placed on the scalp of participants in International 10-20 system using a non-invasive 32-channel EEG machine (Medicaid System, India). Electrode Placed on scalp at various location using referential montage FP2-A2, F8-A2, F4-A2, FP1-A1, F7-A1, F3-A1 After recording; participants were asked to rate the musical piece on a specially designed visual Analog scale of zero to four. This range specially designed to understand emotions evoked by musical piece. Zero is extremely negative or unpleasant emotions and four being extremely positive or pleasant emotions. The subject who rated 4 and 3 are clubbed as Appreciator while 0, 1, 2 called as Non-appreciator. The average spectral power computed for each electrode individually removing the artefact slots from recorded EEG using FFT in Nuromax software. Eq.-1 and Eq.-8 represent θ and γ power for all mentioned electrodes on right and left hemisphere of brain Eq-(4), Eq-(5), Eq-(6) and Eq-(7) represent valence variables and Eq-(11), Eq-(12), Eq-(13) and ,Eq-(14) represent arousal variable of model mentioned in the Table 2

$x(n)$, $n=0, 1, 2, 3 \dots N$ where is the raw sample of EEG signals at particular of frontal side power on left hemisphere and right hemisphere

$$x(\theta) = \sum_{i=1}^n x(n) e^{-\frac{2\pi i \theta n}{N}} \quad (1)$$

$$TF\theta PL = \theta P(Fp1A1) + \theta P(F7A1) + \theta P(F3A1) \quad (2)$$

$$TF\theta PR = \theta P(Fp2A2) + \theta P(F8A2) + \theta P(F4A2) \quad (3)$$

$$TAEVI_{\theta} = [\log_{10} TF\theta PL] - [\log_{10} TF\theta PR] \quad (4)$$

$$AEVIFp12_{\theta} = [\log_{10} \theta PF_{p1A1}] - [\log_{10} \theta PF_{p2A2}] \quad (5)$$

$$AEVIF78_{\theta} = [\log_{10} \theta PF_{7A1}] - [\log_{10} \theta PF_{8A2}] \quad (6)$$

$$AEVIF34_{\theta} = [\log_{10} \theta PF_{3A1}] - [\log_{10} \theta PF_{4A2}] \quad (7)$$

$$x(\gamma) = \sum_{i=1}^n x(n) e^{-\frac{2\pi i \gamma n}{N}} \quad (8)$$

$$TF\gamma PL = \gamma P(Fp1A1) + \gamma P(F7A1) + \gamma P(F3A1) \quad (9)$$

$$TF\gamma PR = \gamma P(Fp2A2) + \gamma P(F8A2) + \gamma P(F4A2) \quad (10)$$

$$TAEVI_{\gamma} = [TF\gamma PL] - [TF\gamma PR] \quad (11)$$

$$AEVIFp12_{\gamma} = [\gamma PF_{p1A1}] - [\gamma PF_{p2A2}] \quad (12)$$

$$AEVIF78_{\gamma} = [\gamma PF_{7A1}] - [\gamma PF_{8A2}] \quad (13)$$

$$AEVIF34_{\gamma} = [\gamma PF_{3A1}] - [\gamma PF_{4A2}] \quad (14)$$

4. Results and Analysis

Two-dimensional model created using Frontal Gamma asymmetry and theta asymmetry for the model total electrode F78, F34 and Fp12 created for the appreciator and non-appreciator. The scatter plots of all the models shown in the Figure 3. The scatter plot of Model Total Frontal Gamma and theta asymmetry and F78 gamma and theta asymmetry recognising appreciator and non-appreciator refer Figure 3 a) and b) whereas F34 and Fp12 model not recognising appreciator and non-appreciator Figure 3 c) and d).

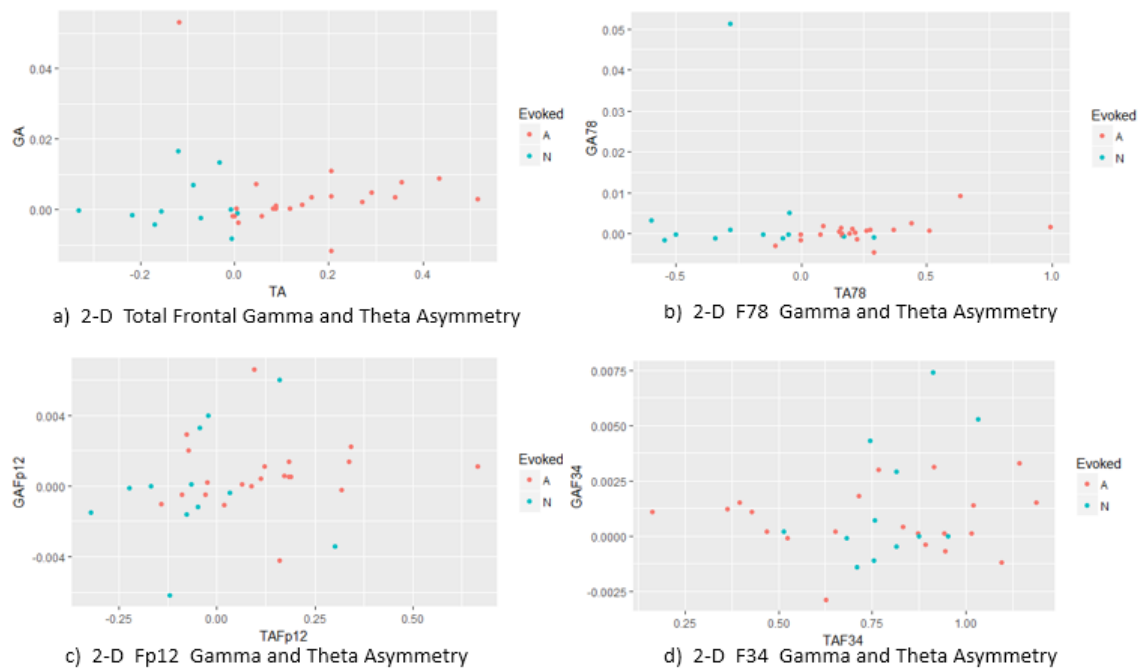


Figure 3. Two dimensional emotion model.

4.1. Total Gamma Theta

This model proposed using total Frontal Asymmetry Emotion Arousal Index (AEAI γ) on the Y-axis, total Frontal asymmetry emotion valence index (AEVI θ) on the X-axis. The SVM classifier with various kernel tricks used for classification. The classification for different kernel shown in Figure 4 Confusion matrices of all the kernels computed refer Eq. (15),Eq.(16),Eq.(17) and Eq.(18).The default cost for all kernel was 1 and gamma 0.5.The polynomial kernel with degree 3. The support vectors for kernels linear 15(8 7), radial 19(10,9), Polynomial 19(10,9) and sigmoid 16(8,8).

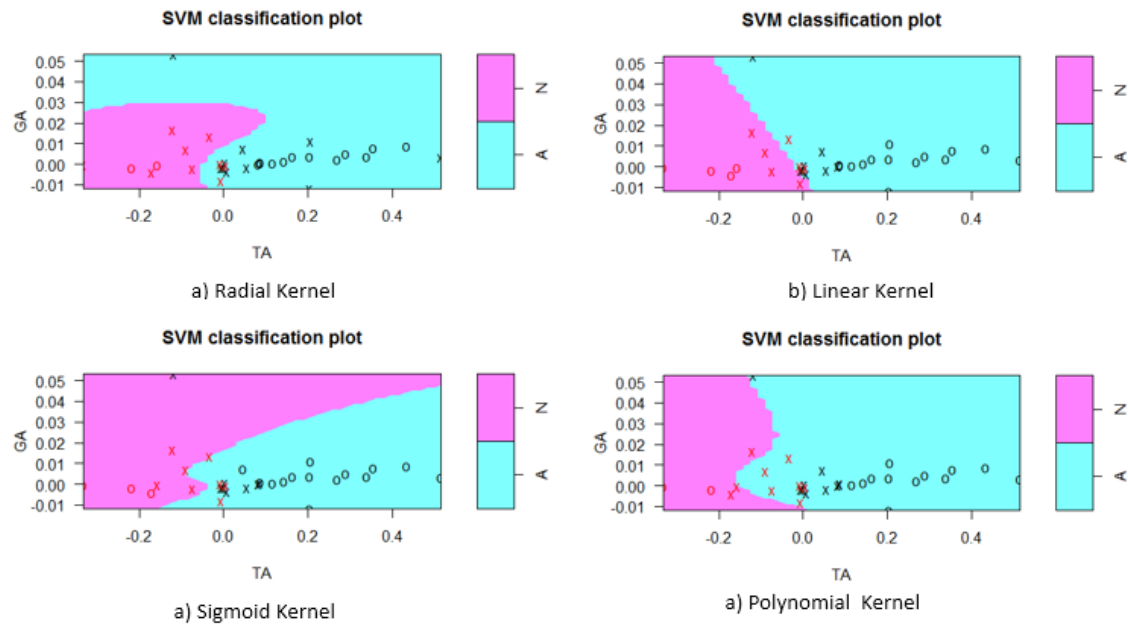


Figure 4. classification using various kernel for total GT asymmetry.

$$Cp(rad) = \begin{bmatrix} 21 & 3 \\ 0 & 9 \end{bmatrix} \quad (15)$$

$$Cp(lin.) = \begin{bmatrix} 21 & 3 \\ 0 & 9 \end{bmatrix} \quad (16)$$

$$Cp(poly) = \begin{bmatrix} 21 & 7 \\ 0 & 5 \end{bmatrix} \quad (17)$$

$$Cp(sig) = \begin{bmatrix} 19 & 3 \\ 2 & 9 \end{bmatrix} \quad (18)$$

4.2. Gamma and Theta on Channel 7 8

This model proposed using total Frontal Asymmetry Emotion Arousal Index (AEAI γ F78) on the y-axis, total Frontal asymmetry emotion valence index (AEVI θ F78) on the X-axis. The SVM classifier with various kernel tricks used for classification. The classification for different kernel shown in Figure 5. Confusion matrices of all the kernels computed refer Eq. (19), Eq.(20), Eq.(21) and Eq.(22).The default cost for all kernel was 1 and gamma 0.5.The polynomial kernel with degree 3. The support vectors for kernels linear 14(7 7), radial 20(10,10), Polynomial 16(8,8) and sigmoid 16(8,8).

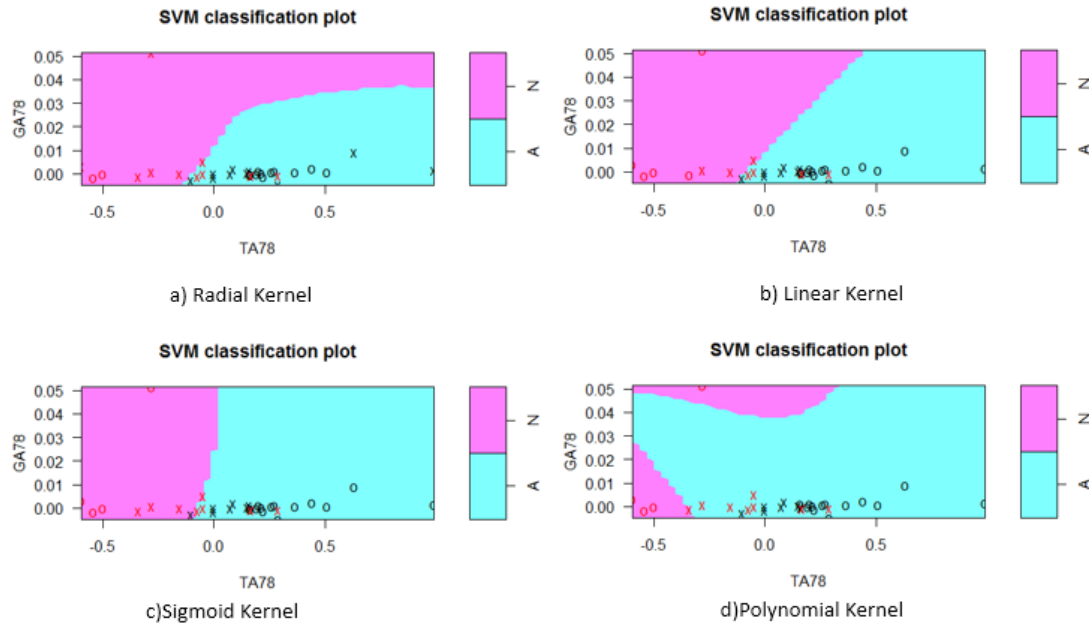


Figure 5. classification using various kernel for total GT78 Asymmetry

$$Cp(rad) = \begin{bmatrix} 21 & 4 \\ 0 & 8 \end{bmatrix} \quad (19)$$

$$Cp(lin.) = \begin{bmatrix} 20 & 4 \\ 1 & 8 \end{bmatrix} \quad (20)$$

$$Cp(poly) = \begin{bmatrix} 21 & 7 \\ 0 & 5 \end{bmatrix} \quad (21)$$

$$Cp(sig) = \begin{bmatrix} 20 & 3 \\ 1 & 9 \end{bmatrix} \quad (22)$$

4.3. Gamma Theta on Channel 3 4

This model proposed using total Frontal Asymmetry Emotion Arousal Index (AEAI γ F34) on the y-axis, total Frontal asymmetry emotion valence index (AEVI θ F34) on the X-axis. The SVM classifier with various kernel tricks used for classification. The classification for different kernel shown in Figure 6 Confusion matrices of all the kernels computed ref Eq. (23),Eq.(24),Eq.(25) and Eq.(26).The default cost for all kernel was 1 and gamma 0.5.The polynomial kernel with degree 3. The support vectors for kernels linear 26(14,12), radial 27(15,12), Polynomial 19(10,9) and sigmoid 23(12,11)

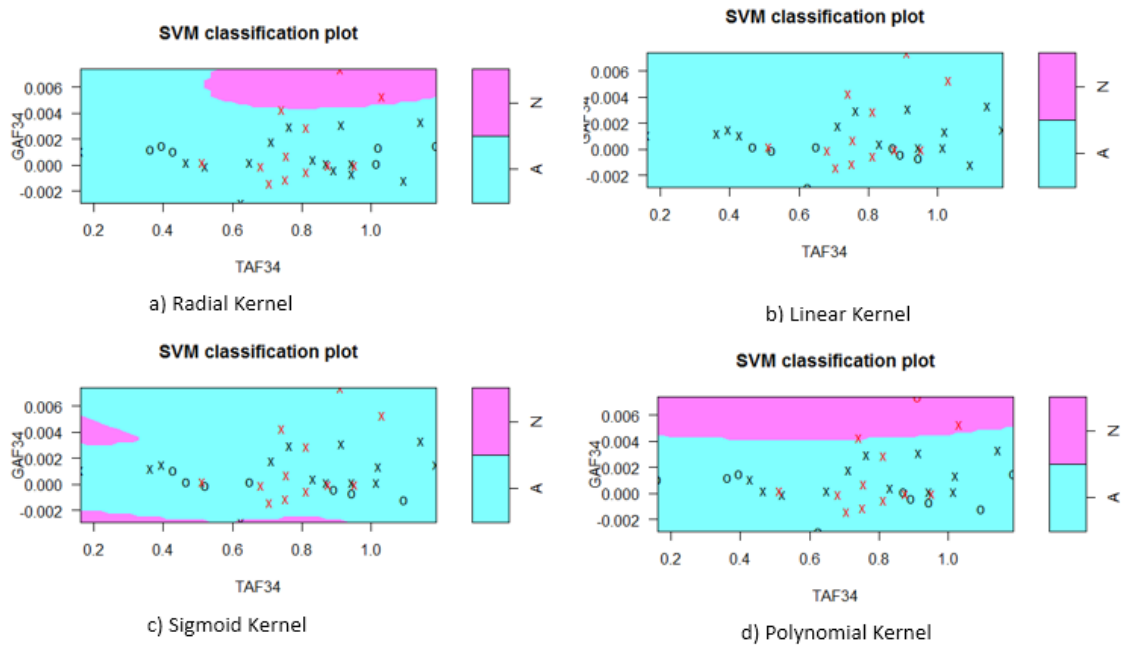


Figure 6. classification using various kernel for GT34 Asymmetry

$$Cp(rad) = \begin{bmatrix} 21 & 9 \\ 0 & 3 \end{bmatrix} \quad (23)$$

$$Cp(lin.) = \begin{bmatrix} 21 & 12 \\ 0 & 0 \end{bmatrix} \quad (24)$$

$$Cp(poly) = \begin{bmatrix} 21 & 9 \\ 0 & 3 \end{bmatrix} \quad (25)$$

$$Cp(sig) = \begin{bmatrix} 20 & 12 \\ 1 & 0 \end{bmatrix} \quad (26)$$

4.4. Gamma Theta on Channel Fp12

This model proposed using total Frontal Asymmetry Emotion Arousal Index (AEAI γ Fp12) on the y-axis, total Frontal asymmetry emotion valence index (AEVI θ Fp12) on the X-axis. The SVM classifier with various kernel tricks used for classification. The classification for different kernel shown in Figure 7 Confusion matrices of all the kernels computed refer Eq.(27), Eq.(28), Eq.(29) and Eq.(30).The default cost for all kernel was 1 and gamma 0.5.The polynomial kernel with degree 3. The support vectors for kernels linear 23(12,11), radial 25(13,12), Polynomial 22(11,11) and sigmoid 24(12,12).

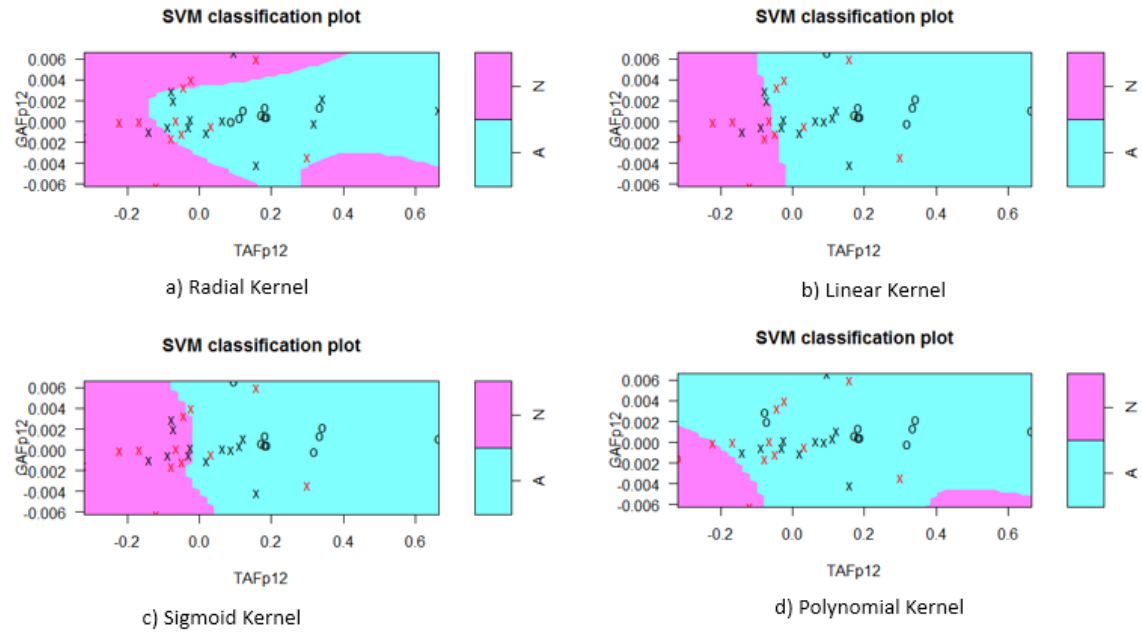


Figure 7. Classification using various kernel for GTFp12 Asymmetry.

$$Cp(rad) = \begin{bmatrix} 19 & 4 \\ 2 & 8 \end{bmatrix} \quad (27)$$

$$Cp(lin.) = \begin{bmatrix} 17 & 5 \\ 4 & 7 \end{bmatrix} \quad (28)$$

$$Cp(poly) = \begin{bmatrix} 21 & 9 \\ 0 & 3 \end{bmatrix} \quad (29)$$

$$Cp(sig) = \begin{bmatrix} 15 & 4 \\ 6 & 8 \end{bmatrix} \quad (30)$$

4.5. Best Performing Models

10-fold cross-validation of parameter tuning used to select the best model. The radial kernel was giving the best performance for all the models. For total Gamma and theta asymmetry model best performance achieved at the cost of 8 , gamma 0.5 and epsilon 0.1 with the number of support vector 14 (8,6) performance of SVM shown in Figure 8 a) The best model confusion matrix refer Eq.(31).

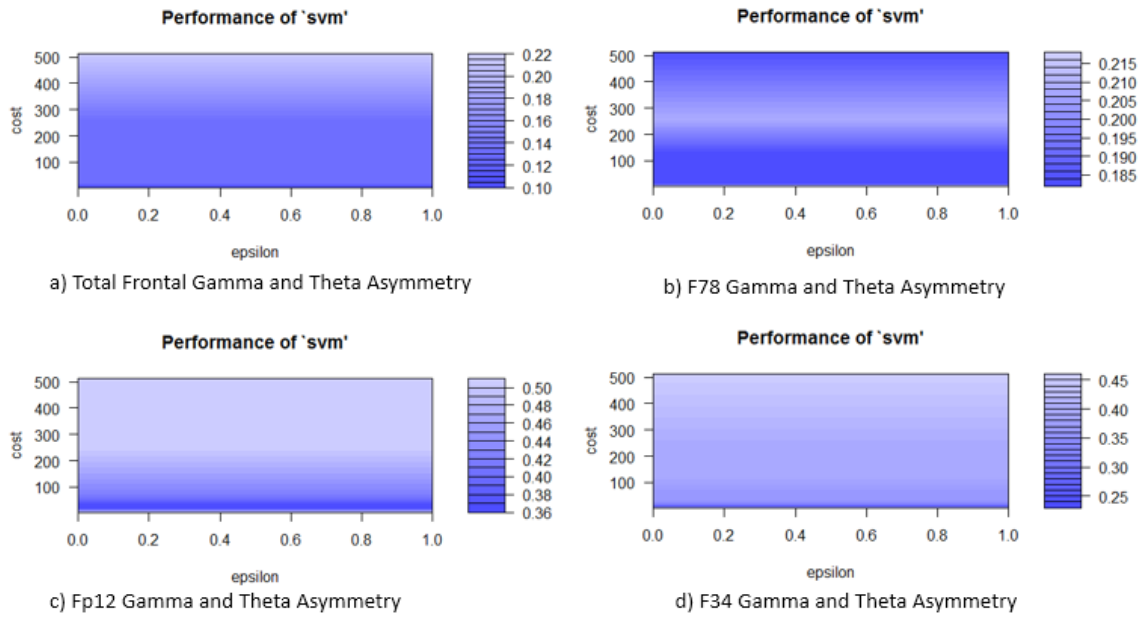


Figure 8. Performance of Model.

$$Cp(TGT) = \begin{bmatrix} 21 & 2 \\ 0 & 10 \end{bmatrix} \quad (31)$$

For F78 Gamma and Theta asymmetry model best performance achieved at the cost of 8 , gamma 0.5 and epsilon 0.1833 with the number of support vector 15 (8, 7) performance of SVM shown in Figure 8b) The best model confusion matrix refer Eq.(32)

$$.Cp(GT78) = \begin{bmatrix} 21 & 4 \\ 0 & 8 \end{bmatrix} \quad (32)$$

For F34 Gamma and Theta asymmetry model best performance achieved at the cost of 8, gamma 0.5 and epsilon 0.233 with the number of support vector 22 (11,11) performance of SVM shown in Figure 8d) The best model confusion matrix ref Eq.(33)

$$.Cp(GT34) = \begin{bmatrix} 20 & 5 \\ 1 & 7 \end{bmatrix} \quad (33)$$

For Fp12 Gamma and Theta asymmetry model best performance achieved at the cost of 16 , gamma 0.5 and epsilon 0.367 with the number of support vector 23 (13,10) performance of SVM shown in Figure (8c) The best model confusion matrix refer Eq.(34)

$$Cp(GTFp12) = \begin{bmatrix} 19 & 2 \\ 2 & 10 \end{bmatrix} \quad (34)$$

4.6. ROC of Models

The Figure 9 shows the ROC curves of the all 2-D models. The AUC of the models TGT 90.74% GT78 89.28% GT34 55.56% and GTFp12 75.39 %. The AUC verifying The models TGT and GT 78 performing adequately whereas GT34 and GTFp12 performance is poor

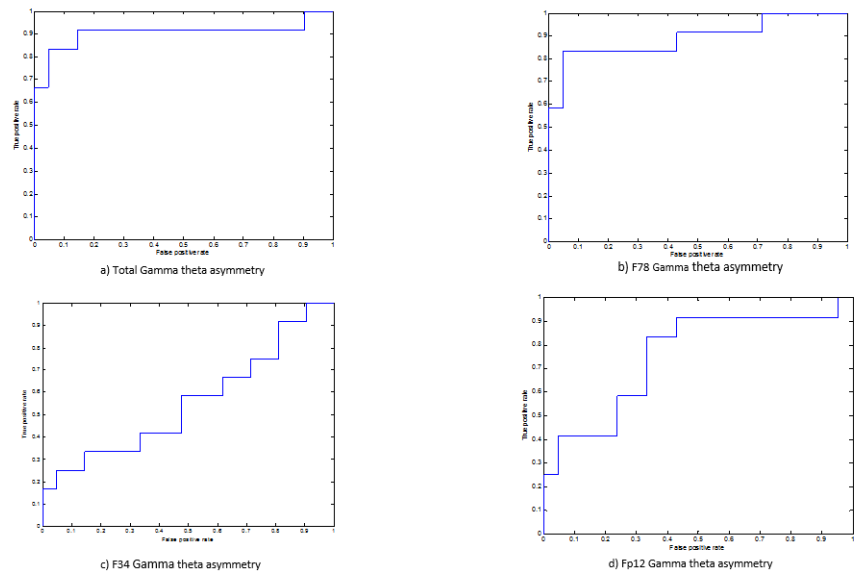


Figure 9. ROC of Gamma Theta asymmetry a) Total b) GT78 c)GT34 d)GTFp12

4.7. 2-D Model Performance

4.7.1. Tuned Model Performance

The performance attributes computed from the confusion matrix derived after tuning the parameters. All the model give their best performance in the radial kernel. The model GT have a very high accuracy 93.41%, upper TPR(100%), TNR(83.3%), F1(95.4%), and very high value of MCC(0.87), YI(0.83)markedness(0.91). Followed by the model GTF78 have a very high accuracy 87.9%, upper TPR(100%), TNR(66.7%), F1(91.3%), and very high value of MCC(0.75), YI(0.67), markedness(0.84). Followed by the Whereas the model GTFp12 performs accuracy 87.9%, upper TPR(90.5%), TNR(83.3%), F1(90.5%), and very high value of MCC(0.87), YI(0.73), markedness(0.91).

Table 3. Untuned Model Performance

Kernel	Model	TPR	TNR	PPV	NPV	FDR	FNR	FPR	ACC	F1	MCC	YI	Mark
Radial	GT	100	72.7	88	100	12.5	27.27	27.2	90.9	93.6	0.8	0.72	0.88
	GTF78	100	66.7	84	100	16	0	33.3	87.9	91.3	0.74	0.67	0.84
	GTF34	100	25	70	100	30	0	75	72.7	82.35	0.41	0.25	0.7
	GTFp12	90.5	66.7	82.6	80	17.4	9.5	33.3	81.8	86.3	0.66	0.57	0.62
Linear	GT	100	72.7	88	100	12.5	27.27	27.2	90.9	93.6	0.8	0.72	0.88
	GTF78	95.2	66.7	83.3	88.9	16.7	4.76	33.3	84.8	88.9	0.71	0.61	0.72
	GTF34	100	0	63.6	0	36.36	0	100	63.63	0	0	0	0
	GTFp12	80.9	58.3	77.7	63.6	22.7	19	41.6	72.7	79	0.5	0.39	0.41
Sigmoid	GT	86.36	81.8	90.4	75	9.5	13.63	18.1	84.8	88.3	0.77	0.68	0.65
	GTF78	95.2	75	86.9	90	13	4.76	25	87.9	90.9	0.77	0.7	0.76
	GTF34	95.2	0	62.5	0	37.5	4.7	100	60.6	75.47	0	0	0
	GTFp12	71.4	66.7	78.9	57.1	21	0	75	69.6	75	0.49	0.38	0.36
Polynomial	GT	100	41.6	75	100	25	0	58.3	78.7	85.7	0.55	0.41	0.75
	GTF78	100	41.7	75	100	25	0	58.3	78.8	85.7	0.55	0.41	0.75
	GTF34	100	25	70	100	30	0	75	72.7	82.35	0.41	0.25	0.7
	GTFp12	100	25	70	100	30	0	75	72.7	82.3	0.41	0.25	0.7

TPR(True Positive Rate), TNR(True Negative Rate), PPV(Precision) NPV(Negative Prediction Value), FDR(False Discovery Rate), F1score, FPR(False Positive Rate), FNR(False Negative Rate) ACC(Accuracy), MCC(Mathew correlation coefficient) YI (informedness(Youden index)), Mark(markedness)

5. Discussion

Investigating emotions is very quite challenging [34]. The affective expression has emerged as a growing area of studies in psychology, psychiatry [34] and computer science [35]. The emotions are adequately quantified using Russel’s circumplex model as shown Figure 10. This model put forward that emotions are disseminated in a two-dimensional circular space. Arousal represents the Y-axis and valence represents the X-axis, while the centre of the circle represents a neutral[33]. Emotions are mapped using angles like Pleasure(Like) (0°), Joy (45°), arousal (90°), distress(anger) (135°), displeasure(dislike) (180°) Emotion is generated from triggering inside unique neural pathways of the central nervous system (CNS) and each emotion is autonomous of the others in its behavioural, psychological, and physiological manifestations [36]. In our study, neuronal oscillations low-frequency theta (4 to 8 Hz) and high-frequency Gamma(30 to 99Hz) used as features. Theta asymmetry index and

gamma asymmetry index incorporated for the valence and arousal of evoked emotion. The uniqueness of *Raga Bhairavi* musical stimulus its slow tempo and tonality [29]. The tonality modulate arousal of emotion [37]. As *Raga Bhairavi* is unfamiliar music its most appropriate for model creation [36] [26]. In Non-musician participant there is increased frontal gamma power [19]. In our study the participant were non-musician. Refer the Figure 11 which is proposed model TGT for mapping evoked emotion in Russell’s circumplex model. In All Appreciator evoked with happy emotion evoked whereas in Appreciator(A1) euphoric Appreciator(A8) excited emotion were evoked, whereas in Non-Appreciator was evoked with upset emotion. In one Non-Appreciator(N15) tense emotion was evoked.

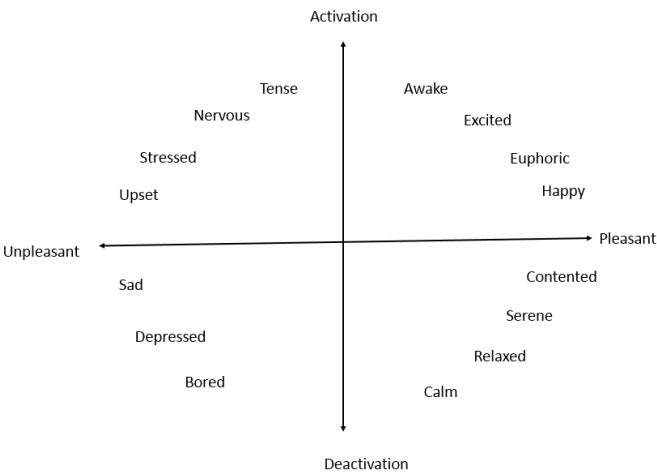


Figure 10. Circumpex model adopted from [33].

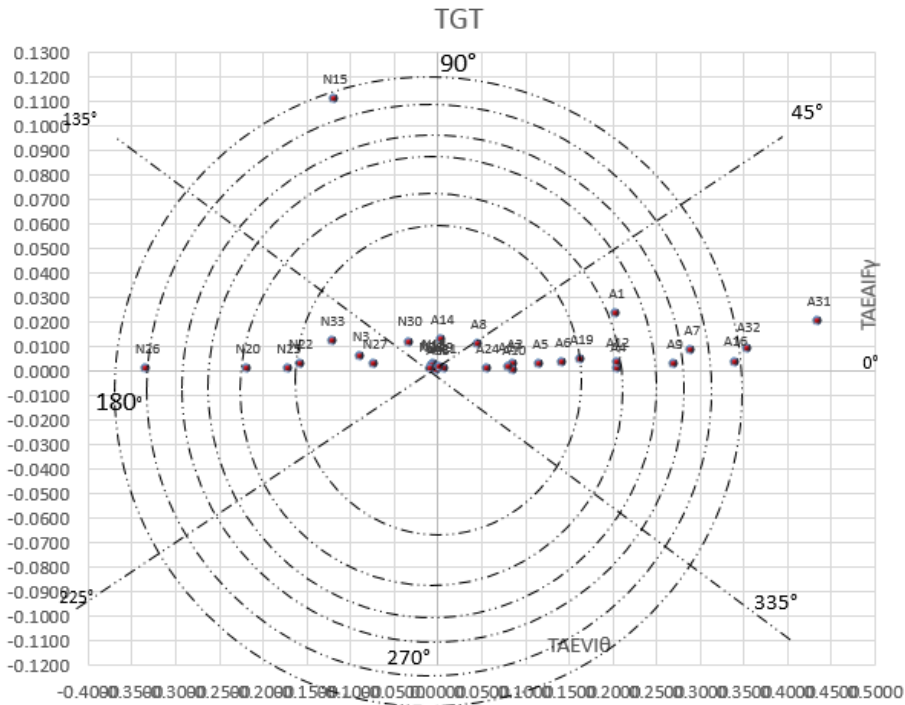


Figure 11. Emotion Mapping using TGT model

The reason for the high accuracy of TGT model may be due to all feature clubbed in that model might lead to over-fitting. The model GT78 giving high accuracy and AUC, all the appreciator and non-appreciator mapped for evoked emotions using Russel’s model Appreciator are evoked with happy

emotion the Appreciator (A1) evoked with serene emotion which evoked with excited emotion in TGT model whereas Non-Appreciators are evoked with upset emotions one of Non-Appreciator(N15) evoked with tense emotion refer the Figure 12. Neurological finding suggest that fronto anterior region is the epicentre for emotion processing [?].

Neurological acumen and machine learning performance attributes suggests model GT78 can be used for emotion as 2D emotion quantifier which give electrode reduced system for many clinical and non -clinical applications.

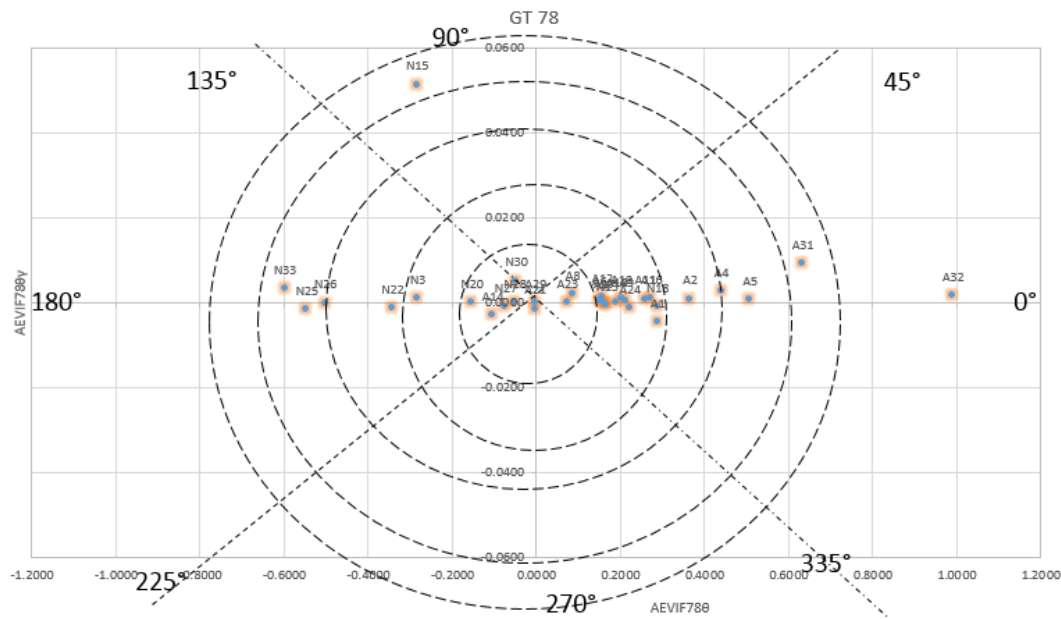


Figure 12. Emotion Mapping using GT78 model

6. Conclusions

The article is dedicated to investigating the research question of whether the asymmetry index can be used to quantify the emotion evoked by the instrumental musical stimulus *Raag Bhairavi*. To address the research question, we proposed several 2-D classification models and evaluated their performance using various SVM-based metrics. Support Vector Machine (SVM) proved to be a suitable supervised machine learning algorithm for classifying the proposed models the central gap of the previous research addressed creating a 2-D model by using gamma asymmetry index along with the frontal theta asymmetry index. The 2-D model TGT and GT F78 performing well. The 2-D models are quantifying valence and arousal of evoked emotion due to *Raag Bhairavi* in Appreciator and Non-appreciator.

7. Patents

This research work is based on the innovations described in the Indian Patent Application titled "MUSICALLY EVOKED EMOTIONS QUANTIFIER SYSTEM", filed under application number 202021004106. The patent has been filed with the Office of the Controller General of Patents, Designs & Trademarks, Government of India.

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