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Parameter Tuning for Enhancing Inter-Subject Emotion Classification in Four Classes for VR-EEG Predictive Analytics

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Abstract

The following research describes the potential in classifying emotions using wearable EEG headset while using a virtual environment to stimulate the responses of the users. Current developments on emotion classification have always steered towards the use of a clinical-grade EEG headset with a 2D monitor screen for stimuli evocations which may introduce additional artifacts or inaccurate readings into the dataset due to users unable to provide their full attention from the given stimuli even though the stimuli presentated should have been advantageous in provoking emotional reactions. Furthermore, the clinical-grade EEG headset requires a lengthy duration to setup and avoiding any hindrance such as hairs hindering the electrodes from collecting the brainwave signals or electrodes coming loose thus requiring additional time to work to fix the issue. With the lengthy duration of setting up the EEG headset, the user may expereince fatigue and become incapable of responding naturally to the emotion being presented from the stimuli. Therefore, this research introduces the use of a wearable low-cost EEG headset with dry electrodes that requires only a trivial amount of time to set up and a Virtual Reality (VR) headset for the presentation of the emotional stimuli in an immersive VR environment which is paired with earphones to provide the full immersive experience needed for the evocation of the emotion. The 360 video stimuli are designed and stitched together according to the arousal-valence space (AVS) model with each quadrant having an 80-second stimuli presentation period followed by a 10-second rest period in between quadrants. The EEG dataset is then collected through the use of a wearable low-cost EEG using four channels located at TP9, TP10, AF7, AF8. The collected dataset is then fed into the machine learning algorithms, namely KNN, SVM and Deep Learning with the dataset focused on inter-subject test approaches using 10-fold cross-validation. The results obtained found that SVM using Radial Basis Function Kernel 1 achieved the highest accuracy at 85.01%. This suggests that the use of a wearable low-cost EEG headset with a significantly lower resolution signal compared to clinical-grade equipment which utilizes only a very limited number of electrodes appears to be highly promising as an emotion classification BCI tool and may thus spur up open up myriad practical, affordable and cost-friendly solutions in applying to the medical, education, military, and entertainment domains.

Keywords: *Machine Learning, Electroencephalography, Emotion Classification, Virtual Reality, Wearable Technology*

1. INTRODUCTION

Although the human emotional experience plays a central part in our daily lives, our scientific knowledge relating to such human emotions are still rather limited. Additionally, progress in the affective sciences is crucial for the development of machine intelligence models that are able to understand the human psychology for the benefit and successful application of advanced technology to everyday human activities and human society in general. Humans have been evolving throughout the ages since the early times resulting in society becoming more and more complex as well as diverse. While emotions seem to have been imprinted into a human's innate being, both man and machine still struggle to decipher human emotions at times, the latter being significantly being more challenging. Because of the imprinted emotions that our body seems to depend on and hold on to, the notion here proposes that brain signals may be our key to solving emotion modelling and subsequently emotion recognition. To understand how our brain activity works, we require equipment that are sensitive enough to pick up the small signals that are transmitted throughout our central nervous system, in particular for regions around our brains. Medical technology has evolved rapidly in the last decade and devices are now capable of scanning our brain using functional magnetic resonance imaging (fMRI) (Mann, Janzen, Wu, Lu, & Guleria, 2016; Subramanian et al., 2018) or through picking up small electrical brain signals using non-invasive EEG headsets.

There are many attempts by researchers experimenting emotion classification using combinations of different medical-grade neurophysiological devices such as GSR (Shahnaz, Masud, & Hasan, 2017), ECG (Soleymani, Asghari-Esfeden, Pantic, & Fu, 2014; B. Zhang, Wang, & Fuhlbrigge, 2010), EMG and EEG (Tran, Thuraisingham, Wijesuriya, Craig, & Nguyen, 2014; Wang, Nie, & Lu, 2014) to detect the changes in our body function when a stimuli is presented to the user. The use of a 2D monitor to evoke the emotional responses have been greatly utilized thanks to the available open-source datasets such as DEAP (Koelstra et al., 2012), IAPS (Khalili & Moradi, 2008), IADS (W. Zhang, Shu, Xu, & Liao, 2017), ASCERTAIN (Subramanian et al., 2018), SEED (Yang, Wu, Zheng, & Lu, 2018) and SEED IV (T. H. Li, Liu, Zheng, & Lu, 2019). With the availability of these datasets, researchers have access to the contents used to stimulate the responses of the users and the recorded data of their physiological signals such as their heart rate, skin conductance, body temperature, and their brainwave signals.

Many of the researchers have extracted their raw recorded data of the physiological signals and attempted to improve the emotion classification rate through different methods such as pre-processing of the dataset, feature smoothing, feature selections, the types of classifiers used to classify the emotions and many others. Many of their studies showed some improvements to the accuracy of the classification while others have experienced reductions in their classification accuracy.

The collection of these recorded physiological signals does come at a cost such as the deployment time required for the researcher to collect the EEG signals from multiple channels required to be placed according to the international standards of the 10-20 system and the price of these systems per channel (Alotaiby, El-Samie, Alshebeili, & Ahmad, 2015; Portelli, Daly, Spencer, & Nasuto, 2011). The users have to withstand the lengthy time of setting up the EEG headset due to its sensitive and fragile electrodes that require trained personnel to attach them onto the participants while the wires hanging over the heads of the participants also weighs them down and causing further stress and fatigue on them which may introduce inaccuracies of the EEG signals during recording of the emotional responses. Furthermore, the contents that were presented to the participant may have some artifacts hidden within the recordings because of the shifted attention away from the monitor screen and this method of presentation for the user are not immersive which should be advantageous for stimulating strong emotional reactions in subjects.

To avoid the possibilities of the inaccuracy which may be caused from either the lack of stimuli, fatigue or lack of concentration or immersion to the stimuli, the proposed work then uses a head mounted device (HMD) such as a VR headset to provide an immersive experience (Freina & Ott, 2015) where the attention of the user are purely on the two screens within the HMD to stimulate the emotional reactions. Additionally, the use of a low-cost EEG headset could be the alternative solutions to the more expensive and sensitive clinical-grade EEG headset (Mheich, Guilloton, & Houmani, 2017). The portable EEG headsets would have no wires hanging over the participants head and would require almost no time to set up the headset and is worn over the head easily without any hindrance.

2. METHODOLOGY

2.1 Stimuli Preparation

The stimuli are prepared from collecting various virtual reality capable videoswould be able to provide the necessary stimulations according to the four-quadrant system from the arousal-valence space (AVS) model (Aguinaga, Lopéz Ramírez, & Rosaria Baltazar Flores, 2015; Bai et al., 2017). The model was used to generalized emotional gestures and it provides tags to the respective emotional states as provided by Ekman and Friesen (Ekman et al., 1987). The arousal scale ranges from calm to stimulated or excited emotion while the valence scale ranges from positive emotions to negative emotions (Verma & Tiwary, 2017). Fig 2.0 presents the model and its respective emotion tags. The collected VR videos are then stitched into 20-second clips with a total of 16 video clips where each quadrant has a total of four video clips presented to the participants.

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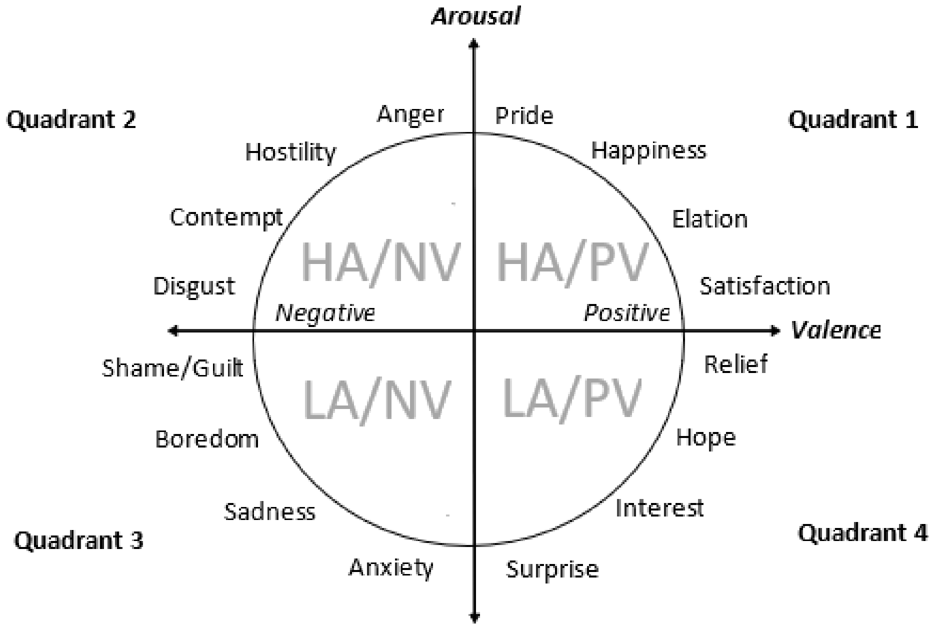

Fig 2.0: Arousal-Valence Space Model

2.2 Dataset Collection

The EEG dataset were collected over 31 participants from university students to young working adults with no health issues during the collection. The EEG dataset is collected through the use of a commercially-off-the-shelf EEG headset where the products are publicly available and is not sensitive equipment and is made portable and easy to setup (Kovacevic, Ritter, Tays, Moreno, & McIntosh, 2015; Z. Li, Xu, & Zhu, n.d.). The EEG headset used in this experiment is Muse 2016 EEG headset where it is capable of collecting sampling rate of 256Hz with four-channels concentrating on the frontal and temporal lobe (TP9, TP10, AF7, AF8) with a reference channel at Fpz (Hashemi et al., 2016). The electrodes are dry type and does not require extensive amount of time to set up thus making the process quick and easy. The dataset is transmitted over a Bluetooth connection to a smartphone installed with a Muse Monitor application that helps records the brainwave data and inertial movements (gyroscope and accelerometer data) and are then stored in an Excel spreadsheet file (CSV format) and saved over the cloud storage for ease of access to be later used for analysis.

Fig 2.1: Experimental Setup with EEG headset and VR Headset

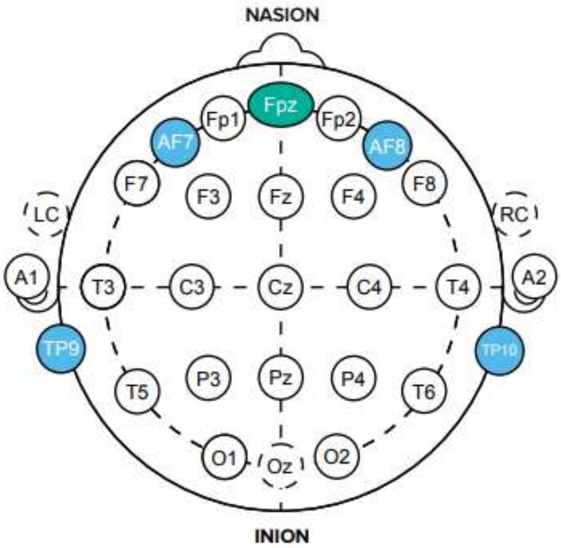

Fig 2.2: Electrode Positions from Muse EEG Headset

2.3 Classifiers

There are three classifiers which were used to conduct the emotion classifications, namely KNN, SVM and Deep Learning due to their prior success in emotion classification tasks (Ben & Wiem, 2017; J. Li, Zhang, & He, 2018). SVM was trained using kernel functions including Class Weights, Linear Kernel, Polynomial Kernel and three different Radial Basis Function Kernels (RBFK). These classifiers were compiled through the use of a statistical analysis platform called R with its sizable repositories of classification libraries which was accessed and programmed via its IDE called R Studio.

2.4 Overall Process

Fig 2.1 describes the overall process of the emotion classification from the collections of VR videos to the setup of EEG headset and training, testing and predicting the four-class emotion classification. While setting up the VR headset for the participants, it is important the users are able to view the videos comfortably by adjusting the interpupillary distance (PD) to achieve eye balance of left and right as well as the focus on the lens. During the setup of the EEG headset, it was paramount to check the connections of the dry electrodes obtaining the brainwave signals from the participants and making sure the participants were comfortable wearing the headset. Once the setup is complete, the stimuli videos are then shown to the participants and the brainwave sampling begins. Afterward, the collected brainwave samples are then passed over to the machine learning algorithms for emotion classification.

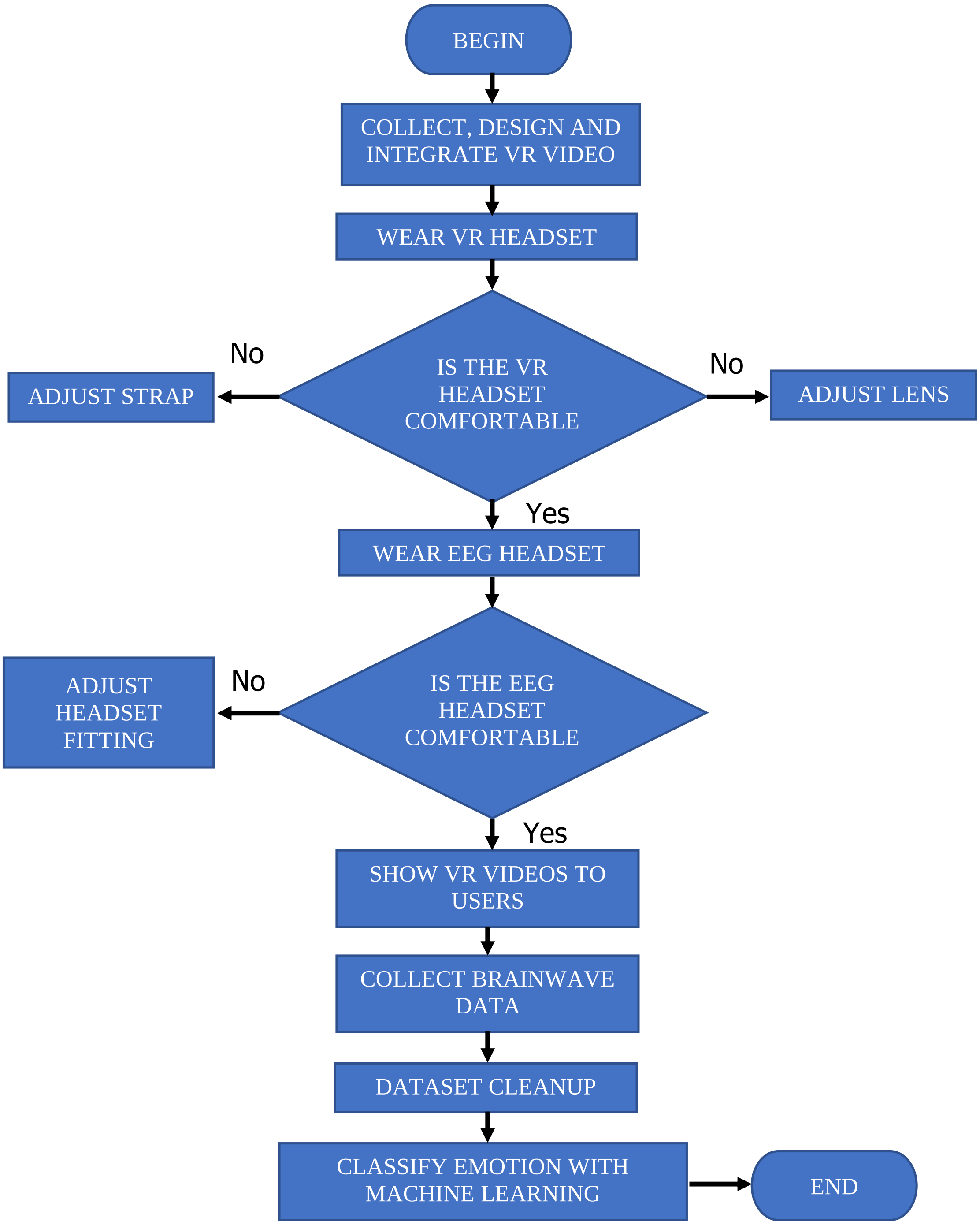

Fig 2.3: Overall Process of the EEG Emotion Classification Experiment

3. RESULTS AND DISCUSSION

According to Fig 3.0, it can be seen here that Deep Learning algorithms were performing the lowest at 34.62% in terms of accuracy while KNN performed better at 75.30% compared to Deep Learning. The best performing algorithm obtained prior to fine-tuning was from using the Class Weight kernel in SVM algorithms, where it obtained an accuracy of 77.36%. In order to see how much of an improvement the performance of an emotion classifier could be enhanced, the investigation then focused solely on the SVM kernels by fine-tuning its parameters.

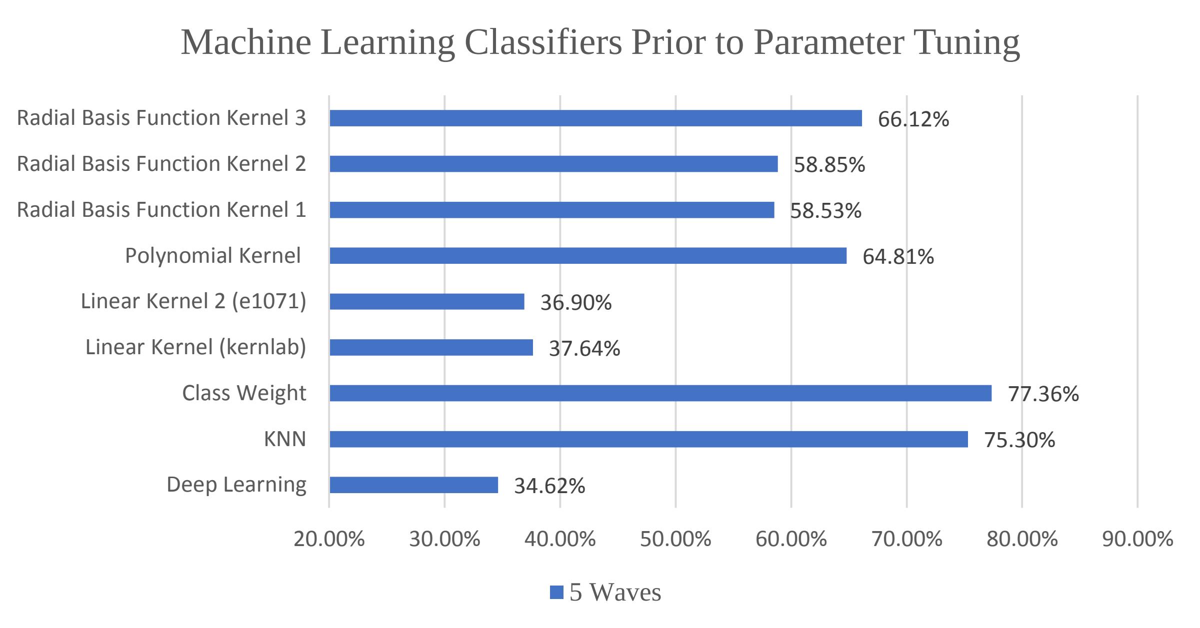

Fig 3.0: Results from machine learning algorithms (KNN, SVM and DL) prior to fine tuning

While working through the fine-tuning of the parameters for SVM, since it provided the most promising results from the initial findings in Fig 3.0, the results after parameter tuning are as shown Fig 3.1 where the Radial Basis Function Kernel 1 achieved a performance increase of up to 85.01% followed closely by Class Weight kernel at 84.80% and Radial Basis Function Kernel 3 at 84.44%. This shows that for a four-class emotion classification, a machine learning approach can properly predict emotions in a virtual reality environment given the correct stimuli is presented and an immersive experience is presented to the participant properly.

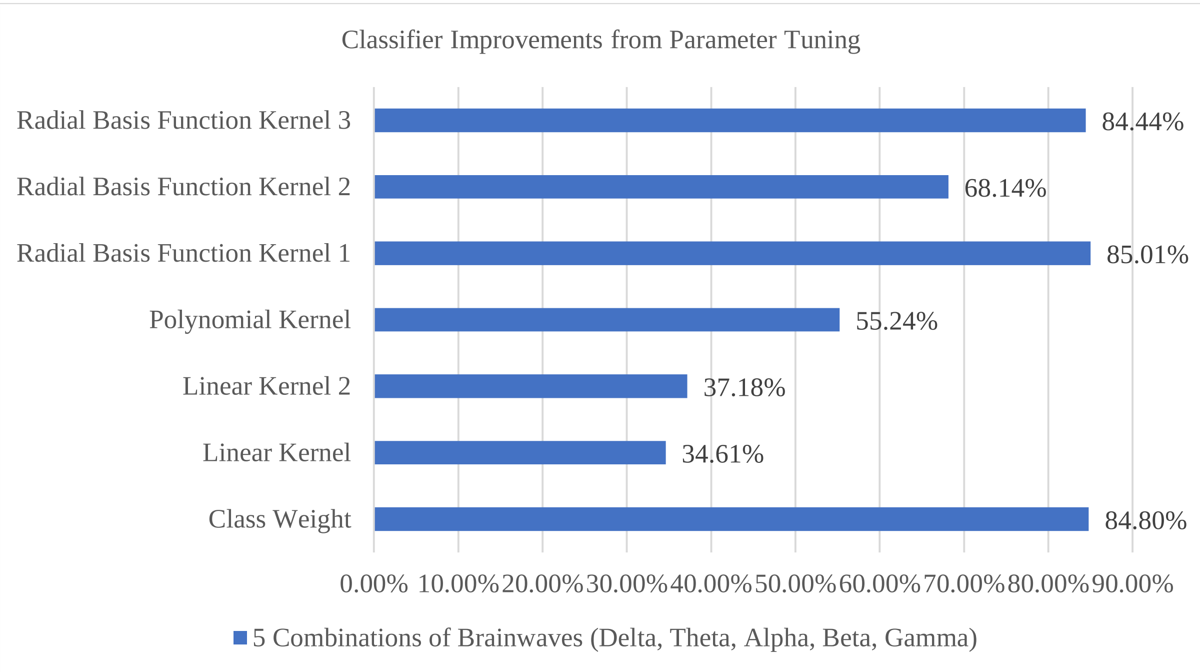

Fig 3.1: Tuned Parameters for Kernels from SVM Results.

To further justify whether the machine learning can truly differentiate the emotion classes, the Tables 3.0, 3.1, 3.2 and 3.3 show the confusion matrices for Class Weight and the three different Radial Basis Function Kernels. It can be seen that RBFK for overall performance was able to predict with good accuracy for calm, bored and angry emotions, while happy emotions were lower. The same pattern can be seen over the other 3 kernels as well except for RBFK 2 which seems to perform poorly on angry and happy emotions. However, as an overall output, happy emotions seem to have difficulty being predicted properly even though this happy emotion seemed to be the easiest to provoke. Looking back on Fig 2.0, a high arousal state and positive valence are required to provoke that specific happy emotion. It could be that the user was not aroused and may have been in the non-arousal state whereby it may have contributed to the higher accuracy state for calm and bored.

Table 3.0: Confusion Matrix Table for Five Band Class Weight Classifier in Inter-Subject Classification (After Tuning)

	Calm	**Bored**	**Angry**	**Happy**
Calm	416 (87.58%)	12	19	21
Bored	15	406 (85.12%)	13	32
Angry	30	31	417 (87.42%)	47
Happy	14	28	28	378 (79.08%)

Table 3.1: Confusion Matrix Table for Five Band RBFK Weight Classifier in Inter-Subject Classification (After Tuning)

	Calm	**Bored**	**Angry**	**Happy**
Calm	420 (88.42%)	6	18	15
Bored	20	425 (89.10%)	13	42
Angry	23	36	422 (88.47%)	67
Happy	12	10	24	354 (74.06%)

Table 3.2: Confusion Matrix Table for Five Band RBFK 2 Weight Classifier in Inter-Subject Classification (After Tuning)

	Calm	**Bored**	**Angry**	**Happy**
Calm	370 (77.86%)	38	96	40
Bored	31	365 (76.52%)	35	89
Angry	19	47	283 (59.33%)	63
Happy	55	27	63	286 (58.83%)

Table 3.3: Confusion Matrix Table for Five Band RBFK3 Weight Classifier in Inter-Subject Classification (After Tuning)

	Calm	**Bored**	**Angry**	**Happy**
Calm	418 (88.00%)	6	22	15
Bored	22	425 (89.10%)	14	44
Angry	24	38	419 (87.84%)	71
Happy	11	8	22	348 (72.80%)

4. CONCLUSION & FUTURE WORK

In this research, we have shown that we are able to do a four-class emotion classification on a virtual reality environment for emotional stimulations and using only a four-channel low-cost EEG headset. The experiments used KNN, SVM and Deep Learning for emotion classification and it was found that SVM is superior in emotion classification as is shown in the results and discussion section with the confusion matrix provided.

For future work, integration with the eye-tracker system may increase the accuracy of the emotion classification accuracy and assist in tracking the users' eye movements towards an object they are focused on. Furthermore, the combination of different electrode positions for classification such as frontal lobe electrodes only or temporal lobe electrodes only may present some evidence of where the emotional experience and reactions are processed and generated in the brain.

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