DAYANANDA SAGAR UNIVERSITY

KUDLU GATE, BANGALORE – 560068

Bachelor of Technology
in
COMPUTER SCIENCE AND ENGINEERING

Major Project Phase-II Report

EMOTION CLASSIFICATION BASED ON EEG SIGNALS: A COMPREHENSIVE STUDY

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CERTIFICATE

This is to certify that the major project phase II work titled **"EMOTION CLASSIFICATION BASED ON EEG SIGNALS: A COMPREHENSIVE STUDY"** is carried out by **ANIRUDH B M (ENG18CS0038), ARCHANA S NAIR (ENG18CS0044), PRATHYUSHA M (ENG18CS0214), SANJANA A G (ENG18CS0244),** bonafide students of Bachelor of Technology in Computer Science and Engineering at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2021-2022**.

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DECLARATION

We, **ANIRUDH B M (ENG18CS0038), ARCHANA S NAIR(ENG18CS0044), PRATHYUSHA M (ENG18CS0214), SANJANA A G (ENG18CS0244),** are students of the eight semester B.Tech in **Computer Science and Engineering**, at School of Engineering, **Dayananda Sagar University**, hereby declare that the major project phase II work titled **"EMOTION CLASSIFICATION BASED ON EEG SIGNALS: A COMPREHENSIVE STUDY"** has been carried out by us and submitted in partial fulfillment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2021-2022**.

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ABSTRACT

Emotion recognition is an important problem in the field of Brain Computer Interface. There are numerous ways for recognizing human emotions and one of them is through EEG signals. EEG signals are direct recordings of the subject’s electrical activity in the brain. Using feature extraction approaches such as Power Spectrum Density (PSD) and Discrete Wavelet Transform (DWT) and transferring these features to ML and DL models, this work aims to develop models that predict emotions from EEG data. In addition, the consequences of the above-mentioned feature extraction approaches are compared in this work. The proposed feature extraction methods and models are applied on the DEAP dataset.

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
DL	Deep Learning
EEG	Electroencephalogram
DEAP	A Database for Emotion Analysis; Using Physiological Signals
SVM	Support Vector Machine
KNN	k-Nearest Neighbours
DB	Database
FFT	Fast Fourier Transform
MLP	Multilayer Perceptron
PCA	Principal Component Analysis
SAE	Stacked Autoencoder
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
PSD	Power Spectral Density
DWT	Discrete Wavelet Transform

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CHAPTER 1

INTRODUCTION

1. INTRODUCTION

Emotions are an integral part of any social being. Emotional intelligence is what distinguishes us, humans, from animals. Emotion can be defined as "A strong feeling deriving from one's circumstances, mood, or relationships with others”. Since the advent of machine learning and Artificial Intelligence emotion recognition is a very hot topic in the field of Brain Computer Interface (BCI). Although, there are many biophysical signals given out by a person which can be used for emotion recognition (such as facial expressions, heart rate, perspiration, voice tempo etc.) EEG is the most prominent one. While signals like facial expressions and changes in voice tempo can be easily faked leading to wrong interpretation, electrical activity in the brain cannot be forged or tampered with. Hence, emotion recognition through EEG signals is a promising approach.

While, EEG signals make the most sense for emotion recognition, they are time-dependent, have a very high signal to noise ratio and require complex machinery to be recorded. These make feature extraction for machine learning and deep learning applications a trying task. To this end, there are two main feature extraction techniques: Power Spectrum Density (PSD) and Discrete Wavelet Transform (DWT). In our project, we perform a comparative analysis of the above-mentioned feature extraction techniques and their implications in machine learning and deep learning models namely, Support Vector Machine (SVM), Random Forest, K Nearest Neighbors (KNN) and Long Short Term Memory (LSTM).

The input variables for the machine learning models are EEG signals and the output labels are the emotions generated through the valence-arousal model. The valence arousal model, shown in Figure 1, is a two-dimensional model with valence on the horizontal axis and arousal on the vertical axis, proposed by James A Russell in 1980 [1]. Arousal is a degree of alertness to stimuli or a measure of how awake a person is to stimuli. It ranges from passive to active. Valence is a degree of aversion or attraction to a stimulus. It ranges from negative to positive.

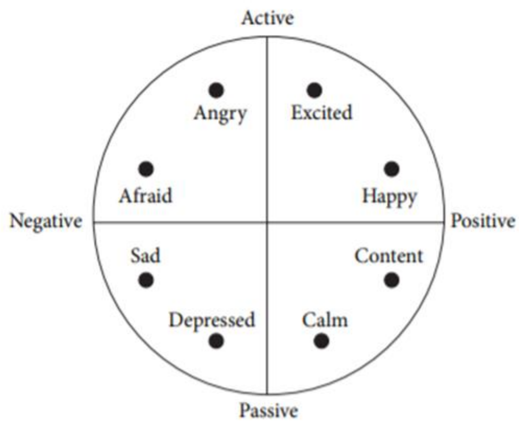

Figure 1-Valence arousal model

The valence arousal model allows us to quantify emotions and is perhaps the only innovative way to go about it. Further research has been done on the model giving us the 9-state model of valence arousal. [2]

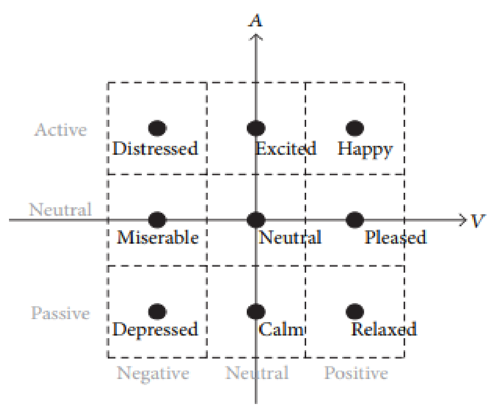

Figure 2-9 state model of valence arousal

Chapter 2

PROBLEM DEFINITION

2. PROBLEM DEFINITION

1. An extensive study on different feature extraction methods for EEG waves

2. Emotion Classification using Machine learning algorithms with different feature extraction methods.

CHAPTER 3

LITRATURE REVIEW

3. LITRATURE REVIEW

The DEAP dataset is a collection of EEG, physiological, and visual signals that can be used to analyze emotions. The description [3] provides a procedure for selecting stimuli, the experimental setup (explanation of the 10-20 system), self-assessment mannequins based upon valence, arousal, familiarity and dominance ratings, and the correlation between EEG frequencies and participant ratings. The results of [1] are contained in a database to examine spontaneous emotions, which contains psychological signals from 32 participants who watched and assessed their emotional responses to a 40 one-minute films.

A Brain-Computer Interface (BCI), also referred to as a Mind-Machine Interface (MMI) or a brain-machine interface (BMI), provides a non-muscular channel of communication between the human brain and a computer system [4]. BCI deals with how humans and machines interact and interface [5]. The research in this field tries to bridge the gap between humans and machines. Brain-computer interfaces, where computers can read and interpret signals directly from the brain, have already achieved clinical success in allowing quadriplegics, those suffering from the locked-in syndrome or people who have had a stroke to move their own wheelchairs or even drink coffee from a cup by controlling the action of a robotic arm with their brain waves [6].

Dreamer (A Database for Emotion Recognition through EEG and ECG Signals from Wireless Low-cost Off-the-Shelf Devices) dataset is used in [7] where all the signals were captured using portable, wearable, wireless, low-cost, and off-the-shelf equipment that has the potential to allow the use of affective computing methods in everyday applications. A baseline for participant-wise affect recognition using EEG and ECG-based features, as well as their fusion, was established through supervised classification experiments using support vector machines (SVMs). These findings further support the argument that the use of low-cost off-the-shelf EEG and ECG devices for affect recognition applications is a viable alternative to expensive and non-portable medical equipment, a fact that can facilitate the integration of affective computing methods into everyday applications.

[8] used algorithms like RNN, CNN and GRU to predict EEG abnormalities. Deep learning algorithms performed well, with an 86.7 percent testing accuracy in predicting EEG abnormalities.

[9] used algorithms like PCA for extracting the features and SVM, KNN and ANN were used for classification. SVM has 91.3 percent accuracy on ten channels. In [2] Principal Component analysis was used to extract the most important features, along with SAE. PCA based covariate shift adaption boosted the accuracy. The accuracy obtained was 49.52% and 46.03% (valence and arousal).

For arousal, the average and maximum classification rates were 55.7 percent and 67.0 percent, respectively, and for valence, 58.8 percent and 56.0 percent. [10], [11] uses the SVM technique as well. ASP uses data from both the left and right hemispheres of the brain. Valence and arousal had accuracy ratings of 55.0 percent and 60%, respectively.

[12], [13] ,uses artificial neural networks for emotion recognition through EEG signals. [14]uses wavelet energy to predict emotions through EEG signals.

Below table compiles some of the important works and their implications.

Table 1- Literature survey

Author and Paper Title	**Technology used**	**Results**	**Inference**
Sander Koelstra - "DEAP: A Database for Emotion Analysis using Physiological Signals."	Forty Electrodes were used to record EEG and 8 for physiological signals.	A DB for the analysis of spontaneous emotions, the DB consists of psychological signals of 32 participants where the emotional response of each participant watched and rated their emotional response to a 40-minute video.	In this paper, a description of the DEAP dataset is given. The stimuli selection procedure, experimental setup (description about the 10-20 system), Self-assessment mannequins-based valence arousal and dominance rating, and the correlation between the EEG frequencies and the participants ratings.

Stamos Katsigiannis- "DREAMER: A Database for Emotion Recognition through EEG and ECG Signals from Wireless Low-cost Off-the-Shelf Devices."	All the signals were captured using portable, wearable, wireless, low-cost, and off-the-shelf equipment that has the potential to allow the use of affective computing methods in everyday applications. A baseline for participant-wise affect recognition using EEG and ECG-based features, as well as their fusion, was established through supervised classification experiments using support vector machines (SVMs).	These findings further support the argument that the use of low-cost off-the-shelf EEG and ECG devices for affect recognition applications is a viable alternative to expensive and non-portable medical equipment, a fact that can facilitate the integration of affect computing methods to everyday applications.	EEG and ECG devices are good alternatives to expensive and non-portable devices. We can integrate affect algorithms to yield good results.

Xiao-Wei Wang - “EEG-Based Emotion Recognition Using Frequency Domain Features and Support Vector Machines.”	The classification algorithm used in this paperwere SVM, KNN, and MLP.	The SVM classifier performed much better than, KNN andMLP.	SVM is able to classify two emotional states with 87.5% accuracy..
Omid Bazgir et al - “Emotion Recognition with Machine Learning Using EEG Signals”	They have used algorithms like PCA for extracting the features and in classification, they have used, SVM, KNN and ANN	SVM have performed better than KNN and ANN.	SVM had an accuracy of 91.3% and the number of channels was 10.
Suwicha Jirayucharoensak - “EEG-Based Emotion Recognition Using Deep Learning Network with Principal Component-Based Covariate Shift Adaptation”	They have used algorithms like PCA and SAE.	PCA based covariate shift adaptation boosted the accuracy. Accuracy: 49.52% and 46.03% (valence and arousal)	To avoid overfitting of the data, Principal Component analysis was used to extract the most important features.

Subhrajit Roy - "Chrono Net: A Deep Recurrent Neural Network for Abnormal EEG Identification"	They have used algorithms like RNN, CNN and GRU.	This research has an 86.7% of testing accuracy in predicting EEG abnormalities	Deep learning algorithms have worked well.
Sander Koelstra - "Single-trial classification of EEG and peripheral physiological signals for recognition of emotions induced by music videos"	They have used algorithms like PSD and SVM.	The average and maximum classification rates of 55.7%and 67.0% were obtained for arousal and 58.8% and 76.0% for valence.	Power spectral density works well.
Dong Huang - "Asymmetric spatial pattern for EEG-based emotion detection"	They have used algorithms like PSD and SVM.	The accuracy rates for valence and arousal are 55.0% and 60%, respectively	ASP takes sources from the left-hemisphere and right-hemisphere of the brain.

CHAPTER 4

PROJECT DESCRIPTION

4. PROJECT DESCRIPTION

META STAGE

- Identifying and acquisition of reliable datasets
- Data cleaning

STAGE 1

1. Feature extraction:

- Determining the essential EEG channels out of the available 32
- Applying different feature extraction techniques.

STAGE 2

1. *Model building:*

- Building and comparing different ML and DL models.

2. *Training and Testing:*

- Based on precision, recall and F- measure.

4.1 DESIGN FLOW:

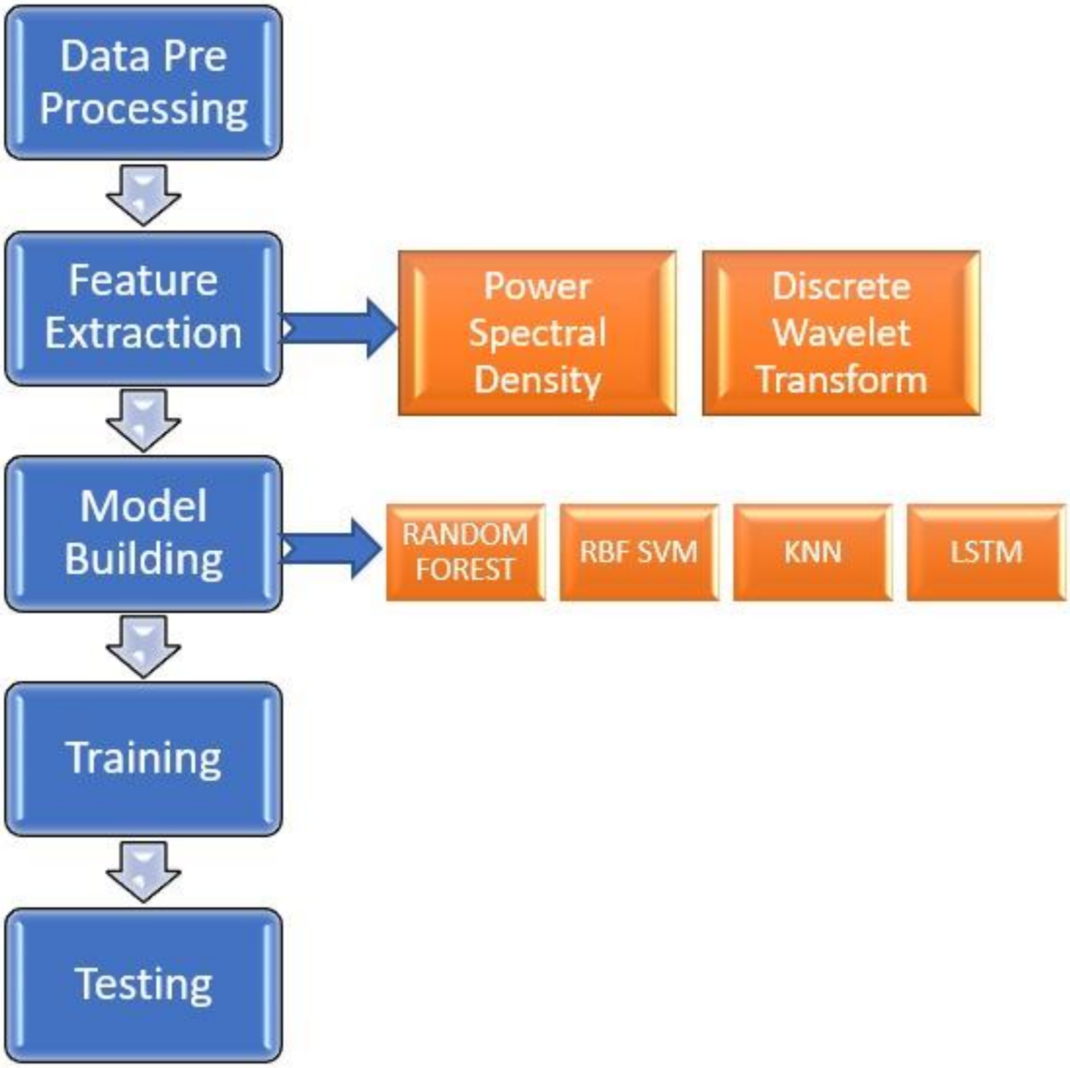

Figure 3- Design flow

CHAPTER 5

REQUIREMENTS

5. REQUIREMENTS

This section provides a detailed description of all inputs into and outputs from the system. It also gives a description of the hardware, software and communication interfaces and provides basic prototypes of the user interface.

5.1 Non-Functional Requirement

Non-functional requirements are requirements that are not directly concerned with the specified function delivered by the system. They may relate to emergent system properties such as reliability, response time andstore occupancy. The non-functional requirement related to this system is:

1. Finding datasets that fit the Valence Arousal Dominance model ofemotion classification.

5.2 Functional Requirement

1. An all-inclusive study on different feature extraction techniques.
2. A comparison of results from different machine learning models.
3. A model to predict emotions with a certain degree of accuracy.

5.3 Software Requirements

- Python - 3.8
- Anaconda
- Numpy, Pandas for data extraction and mathematical functions
- Matplotlib, Seaborn, Plotly for data visualization
- Scikit learn, Keras for Machine Learning models

5.4 Hardware Requirements

- RAM of 8GB or higher
- Processor i5 or higher
- CPU/ GPU which support CUDA

CHAPTER 6

METHODOLOGY

6. METHODOLOGY

In DEAP dataset, 32 subjects were exposed to 40, one-minute-long videos during which their EEG signals were recorded for 63 seconds with 3 seconds of baseline. 32 EEG channels and 8 physiological channels recorded the biophysical signals during the 63 second period. For the first 22 participants, facial videos are also available but not used in this work. The 10-20 system of electrode placement was used. After each video, subjects gave 4 ratings from 1 to 9: valence, arousal, dominance, and familiarity. The signals were denoised and down sampled from 512Hz to 128Hz.

In our work, we have selected 14 channels namely F3, FC5, AF3, F7, T7, P7, O1, O2, P8, T8, F8, AF4, FC6 and F4 which fits the Emotiv Epoch Plus model [7] which is a low cost off the shelf device EEG machine, in hopes that in future work the models developed can be used directly in connection with the EEG device. The electrodes F3, F4, AF3, AF4, F7 and F8 are used for neural activity imaging in the lobe's frontals of the subject's brain. Electrodes T7, T8, FC5 and FC6, are imaging the lobes temporals of the brain. The lobes parietalis is scanned by P8 and P7 electrodes. The neural activity of the lobes occipitalis is acquired by use of the O2 and O1 electrodes.

We make use of 4 second sliding window with an overlap of 0.5 second and divide the 60 second EEG signal to 112 data points for each trial. Therefore, for 40 trails for each patient we get 4480 data points.

The encoding of the valence arousal ratings into 9 emotional states was done as shown in Table2. The encoding of the states based on the division of ranges nullifies interpersonal emotional variance to some extent.

Table 2-Emotional states based on valence arousal rating

Emotional State	Valence Range	Arousal Range
Depressed	1 to 3	1 to 3
Calm	4 to 6	1 to 3
Relaxed	7 to 9	1 to 3
Miserable	1 to 3	4 to 6
Neutral	4 to 6	4 to 6
Pleased	7 to 9	4 to 6
Distressed	1 to 3	7 to 9
Excited	4 to 6	7 to 9
Happy	7 to 9	6 to 9

6.1 Power Spectral Density

Power Spectral Density (PSD) provides power in each of the bandwidths based on the frequency. Spectral analysis is a fundamental computational EEG analysis method that can provide information on power, spatial distribution, or event-related temporal change of a frequency of interest. PSD of the channels is extracted followed by training of different machine learning models. PSD provides the power in each of the spectral bins by computing the Fast Fourier Transform (FFT) and calculating its complex conjugate.

Mathematically, it is represented as

$$X(f) = F\{x(t)\} = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \qquad (1)$$

Where, x(t) is the time domain signal, X(f) is the FFT, and ft is the frequency to analyze.

6.2 Discrete Wavelet Transform

Discrete Wavelet Transform helps in extracting features from the time and frequency domain of EEG signal. A Wavelet is a wave-like oscillation that is localized in time. The basic idea is to compute how much of a wavelet is in a signal for a particular scale and location. In this work, Daubechies 4 (db4) is selected because its smoothing feature was suitable for detecting changes of the EEG signals.

A low pass scaling filter and a high pass wavelet filter are used in DWT to create a filtering mechanism. The lower and higher frequency portions of the signals are separated using this transform decomposition. The lower frequency contents provide a good approximation of the signal, whereas the high frequency contents contain the finer details of the fluctuation.

Entropy is a measurement criterion of the amount of information within the signal. Entropy measures quantify the uncertainty in EEG which roughly equates to the possible configurations or their predictability. The mathematical formula to calculate entropy using DWT is given as:

$$ENT_j = -\sum_{k=1}^{N} \left(D_j(k^2)\right) log \left(D_j(k^2)\right)$$

Wavelet energy reflects the distribution of the principle lines, wrinkles and ridges in different resolution. By summing the square of the wavelet coefficients over the temporal window, the energy for each frequency band is computed:

$$ENG_j = -\sum_{k=1}^{N} \left(D_j(k^2)\right) \;\; k = 1,2,\ldots,N.$$

Where j is the wavelet decomposition level (frequency band) and k is the number of wavelets coefficients within the j frequency band.

CHAPTER 7

EXPERIMENTAL SETUP

7. EXPERIMENTAL SETUP

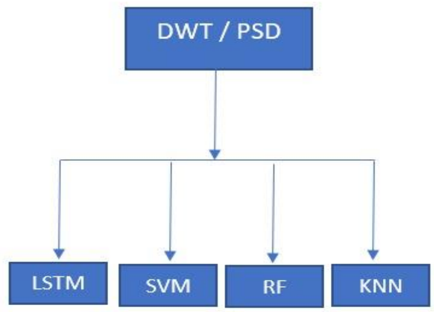

Figure 4- Experimental Setup

The selected algorithms are random forest, radial basis kernel support vector machine, k nearest neighbors and Long short term memory model. Random Forest, SVM and KNN algorithms were identified through literate review. In case of SVM, RBF kernel is used as it adapts to non-linearly separable data well [15]. The RBF kernel is a function which projects input vectors into a gaussian space. The generalization property makes RBF SVM insensitive to overfitting. LSTM model is used as it has high abstraction potential in case of time series data such as EEG.

The proposed LSTM model has five LSTM layers with 512 nodes in layer 1, 256 nodes in layer 2, 128 nodes in layer 3, 64 nodes in layer 4, 32 modes in layer 5. The final layer is dense layer with 9 nodes. The LSTM layers all have tanh activation function whereas the dense layer has SoftMax activation. After each epoch, batch normalization and a dropout of 0.3 is done to avoid overfitting. RMSprop optimizer is used to avoid vanishing gradient problem. The model is compiled with Mean squared Error loss. The below figure shows the proposed LSTM model architecture.

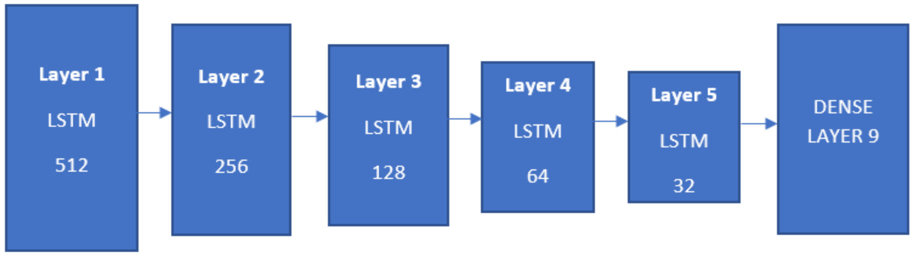

Figure 5- LSTM Model architecture

In the initial approach the entire dataset consisting of 32 subjects was combined and PSD and DWT features were extracted. Cross-Validation after training and testing gave inconsistent results. This was attributed to the interpersonal emotion variance which results in covariate shift in the dataset i.e., the intensity at which one person feels for the same emotion is different from other subjects. Hence, the approach was changed to individual subjects' emotion recognition. As shown in Figure 3, each subject's data was used to extract PSD and DWT features, trained on RBF SVM, RF, KNN and LSTM models separately.

The PSD and DWT were calculated in five frequency bins, namely Delta (4-7Hz), Theta (8-12 Hz), Alpha (13-16 Hz), Beta (17-25 Hz) and Gamma (26-45 Hz). These bins are associated with the most emotional activity. The window-size is chosen as 512[16].

The first three seconds, which were the baseline seconds, were removed for each subject after which, PSD and DWT were calculated. PSD technique gives a total of 70 features (14 channels * 5 bandwidths) whereas DWT gives a total of 140 (70 entropy and 70 energy) features. Following feature extraction, a standard scalar was used to perform normalization on the data, and 9 state emotion encoding was done.

CHAPTER 8

TESTING AND RESULTS

8. TESTING AND RESULTS

As described in experimental setup, PSD and DWT are computed subject wise by applying the parameters and stored. For each subject, PSD and DWT data are loaded separately. The labels corresponding to the data are then encoded into 9 emotional states. The data is normalized using standard scalar and split into test and training. The parameters such as number of estimators in case of random forest, C in case of RBF SVM, number of neighbors in KNN are all optimized using grid search algorithms. The optimum parameters obtained are n_estimators = 500, C=1e+10, n_neighbors=3.LSTM model was run for 100 epochs with batch size 100. Table 3 shows the testing accuracies for all 32 subjects for all four models with PSD feature extraction. Table 4 describes the same for the DWT feature extraction technique.

8.1 PSD

Table 3-Subject Wise PSD based Model Accuracies

Subject	RF results	RBF SVM	KNN	Accuracy
1	98.32	99.22	99.11	98.44
2	88.39	95.42	91.85	93.22
3	87.95	97.77	97.1	95.87
4	89.06	92.97	87.61	89.62
5	85.94	88.5	79.13	88.67
6	94.53	98.21	96.54	96.65
7	98.44	99.78	99.11	97.99
8	94.75	95.2	91.52	95.17
9	92.63	95.76	90.63	97.01
10	90.63	93.75	86.5	92.05
11	91.63	95.09	85.6	90.26
12	90.18	95.31	92.97	94.5
13	86.72	92.75	88.95	92.83
14	85.27	95.42	94.64	92.91
15	97.32	98.66	95.54	97.38
16	97.66	98.88	97.99	97.71
17	88.73	94.53	88.73	94.67
18	91.52	97.54	96.21	96.6
19	90.29	94.64	89.96	96.29
20	88.73	94.64	93.3	96.34
21	91.41	96.76	94.98	94.22

22	87.83	91.41	84.26	83.48
23	97.43	98.88	98.33	98.3
24	87.61	91.74	86.16	92.75
25	83.93	92.86	85.27	87.19
26	86.38	92.41	90.29	92.61
27	94.42	96.32	95.76	96.9
28	84.82	94.53	90.85	92.77
29	93.86	96.76	93.42	96.93
30	94.2	94.53	92.63	95.51
31	90.74	96.54	94.98	96.4
32	95.65	97.88	95.31	97.04
Mean	91.15	95.46	92.03	94.32

8.2 DWT

Table 4-Subject Wise DWT based Model Accuracies

Subject	RF result	RBF SVM	KNN	Accuracy
1	96.96	98.37	99.02	98.72
2	88.93	97.72	93.16	96.44
3	84.69	97.39	96.85	97.56
4	89.79	95.01	92.51	94.78
5	85.78	93.27	86.54	94.43
6	93.7	98.81	97.5	97.61
7	98.7	99.02	98.48	98.75
8	93.49	95.98	94.57	96.58
9	93.92	97.61	94.03	98.42
10	90.45	93.27	85.88	95.87
11	92.51	95.77	87.51	95.63
12	88.06	93.16	90.66	95.41
13	86.54	92.62	89.69	95.76
14	87.08	94.57	92.83	95.14
15	96.85	99.24	96.31	98.23
16	97.18	97.39	96.42	97.64
17	88.82	93.38	90.01	96.52
18	88.17	96.09	97.61	97.94
19	89.47	94.68	90.66	96.88
20	87.08	94.46	93.81	97.04
21	89.47	96.09	96.74	96.52
22	85.78	91.97	85.56	91.96
23	96.31	99.24	98.7	98.37
24	90.01	93.81	89.58	96.9
25	87.62	95.77	93.27	95.98
26	89.14	95.87	93.81	96.71

27	92.62	96.2	97.18	97.45
28	86.86	95.55	92.4	95.79
29	95.66	97.61	94.68	98.26
30	91.31	96.96	97.5	97.39
31	92.07	96.2	96.63	97.45
32	95.87	98.37	96.85	98.21
Mean	90.96	95.98	93.65	96.76

Table 5-Mean accuracies and Standard Deviations

	RF		SVM		KNN		LSTM	
	Accuracy	STD	Accuracy	STD	Accuracy	STD	Accuracy	STD
PSD	91.15	4.76	95.46	2.56	92.03	4.79	94.32	3.44
DWT	90.96	3.86	95.98	2.03	93.65	3.84	96.76	1.44

Table 5 shows the mean accuracies along with the standard deviations. LSTM model with DWT feature extraction has the highest mean accuracy and the lowest standard deviation. Since, DWT has both time and frequency features, LSTM performs well as compared to other models.

The mean accuracies with PSD feature extraction technique are 91.15 (Random Forest), 95.46 (RBF SVM), 92.03 (KNN) and 94.32 (LSTM). The mean accuracies for DWT are 90.96 (RF), 95.98 (RBF SVM), 93.65 (KNN) and 96.76 (LSTM). The accuracies of the four distinct models is visualized using a bar plot. Figure 6 shows the PSD mean accuracies. Figure 7 shows the DWT mean accuracies.

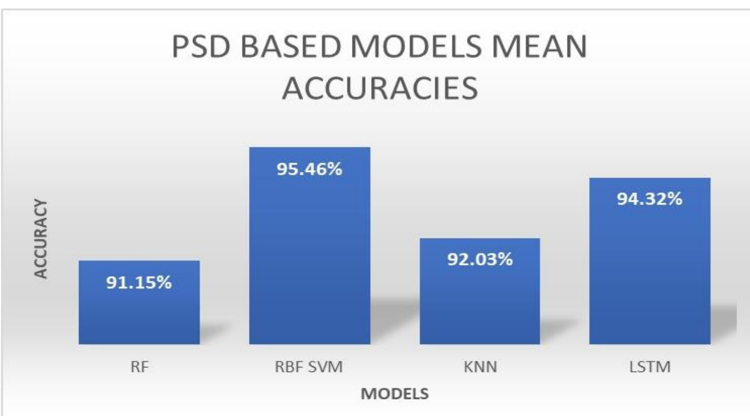

Figure 6-PSD Mean Accuracies

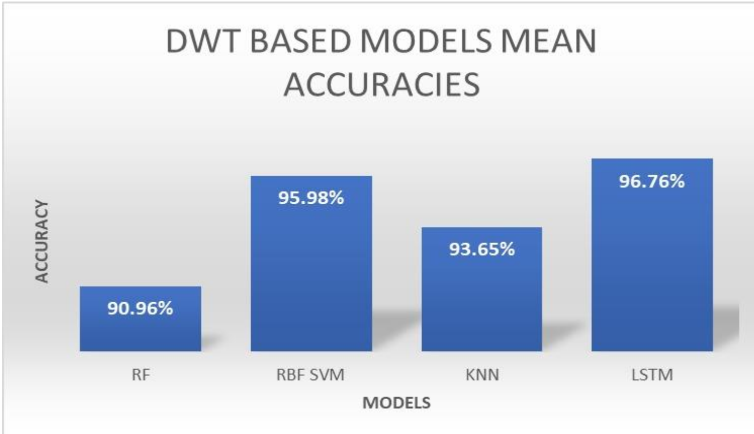

Figure 7-DWT Mean Accuracies

CHAPTER 9

CONCLUSION AND FUTURE WORK

9. CONCLUSION AND FUTURE WORK

In this project we have presented a state-of-the-art result for interpersonal emotion classification using EEG signals. The LSTM model developed can accurately classify the 9 basic emotions with only input from 14 channels. Through this research, we can conclude that it is unrealistic to develop a Unified Emotion Recognition model for every human being, but rather every person's emotions have to be trained individually to develop the model.

Future works include combing the models into a single algorithm and perform soft voting for better classification and to identify emotion activation process leading to emotion detection. Also, to develop an end-to-end algorithm, from collecting raw EEG signals through Emotiv Epoch Plus machine up till emotion detection and classification.

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