Analysis of Different Frequency Band in EEG Signals for Cognitive Based Specific Emotions

Sonu Kumar Jha [1], Pragya Gupta[2] and Harsh Chauhan [3*]

[1 2 3] School of Computer Science and Engineering, Galgotias University, Greater Noida, India
sonukumarjha1990@gmail.com,pragya.gupta7012@gmail.com,
harshachauhan3104@gmail.com

Abstract. A number of EEG frequency bands are studied in this work to classify-specific-based emotions using DEAP (Dataset for Emotion Analysis using Physiological Signals). The need for more precise and scalable solutions to recognize human emotional states is increasing, especially when it comes to understanding the mental state of those individuals that cannot effectively communicate their emotions (e.g., as, one with disabilities or cognitive impairment). EEG signals are excellent non-invasive signal media to record different brain wave patterns that are linked with different emotions. Specific cognitive states and affective states are linked with discrimination of such frequency bands, which means the success in detection of these bands is crucial for interpretation of neural correlates of said emotions. The goal of our work is to advance emotion recognition for real life applications and mental health monitoring. State-of-the-art machine learning algorithms such as the bi-LSTM are applied to EEG based emotion classification [5]. We incorporate the forward and backward dependencies of signals in order to increase recognition accuracy using Bi-LSTM, from which we obtained an accuracy rate of 85%**.**

Keywords: EEG, DEAP, Brainwave patterns, bi-LSTM, frequency bands.

1 INTRODUCTION

Emotions are a critical hallmark of human cognition, affecting decision-making, action and health. The ability to identify emotions is especially important in situations where it may be difficult, due to various reasons (people with disabilities or cognitive impairment), for individuals to express what they are experiencing. Facial emotion recognition can be an important source of information for understanding emotional states in individuals.

EEG based upon its ability to record the electric activity of brain regions in real-time has become one of the most powerful techniques for exploring neural origins behind emotions. EEG contains different frequency bands - delta, theta, alpha, beta and

P. Johri et al. (eds.), *Proceedings of the International Conference on Sustainable Computing and Artificial Intelligence (ICSCAI 2025)*, Advances in Engineering Research 298,
https://doi.org/10.2991/978-94-6239-674-6_24

gamma. The former also seem to correlate with certain cognitive and affective states. For example, Delta waves - deep sleep, unconsciousness and healing process, Theta waves - relaxation, drowsiness, meditation and light sleep state, Alpha waves - relaxed but not sleepy condition, Beta waves are related to active and busy thinking, learning/-thinking skills, intensity, motivation or excitement/mental stress or anxiety; and Gamma waves are associated with complex motor behavior and high-level consciousness. An EEG was used to follow brain electrical activity with electrodes. A standard steady-state positioning of EEG electrodes on the head for reliable and repeatable records. This system is fundamentally a 10-20 international system which relates the positions of electrodes to be located at either 10% or 20% of their distance in between two specific anatomical landmarks (.4 Nasion and Inion) on head as shown in Fig. 1. In our brain, the different regions like Frontal(F), Central(C), Temporal(T), Parietal(P) are as in Fig. 2. The number of electrodes employed ranges from 16, through 32 and to 64. Every electrode is associated with a number, odd numbers are located on the left side of the head (e.g., F3, P1), even numbers are placed to the right side of the head (e.g., F4, P2) and electrodes along midline are labeled with a Z (e.g., Oz, Pz).

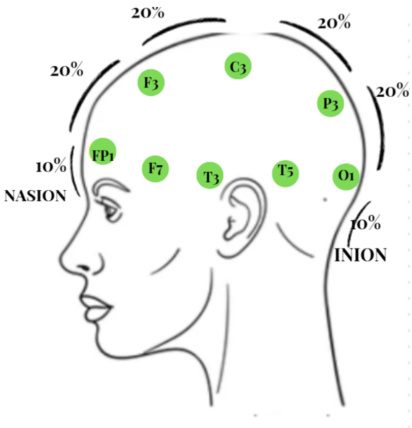

Fig. 1. EEG Electrode Placement 10-20 Interval

Spin has social, conversational and business applications: there is a certain pleasure in seeing how we could build up an idealized version of ourselves – say vastly more charismatic or amusing than we actually are. We are going to use Russell's Valence-Arousal Scale model to create how we will approach analyzing our emotion as it is a good well accepted tool for the categorization of emotions which has valence and arousal. Valence illustrates whether a model is positive or negative and Arousal demonstrates the strength of an emotion. Valence-Arousal representation by the mapping from emotions to valence and arousal, we are able to interpret EEG patterns relating to emotional states more precisely such as excitement (high arousal and positive valence) and sadness (low arousal, negative valence). In our research we use machine learning work-flow but consider the knowledge extraction on the DEAP dataset which is a well-known data collection that provides both, the EEG data and peripheral physiological signals like labels. Six different emotions are recognized based on model such as positive, neutral and negatives along with surprise, angry and fear. The process flow of our paper involves data collection, preprocessing feature extraction, emotion classification using valence-arousal model, validation and accuracy. In this work, we use Rus- sell's Valence-Arousal Scale and the rich EEG data set from DEAP to build a scalable system for high accuracy emotion detection. This system has potential to be applied in the context of brain computer interfaces (BCI), mental health monitoring and emotion- aware technologies.

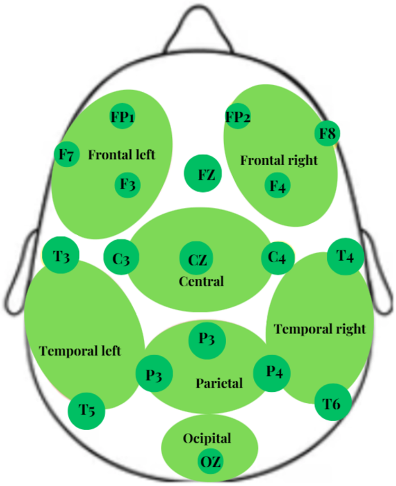

Fig. 2. Brain Regions

Background: To the best of our knowledge, we compare traditional machine learning algorithms (SVM, MLP and KNN) with the Bi-LSTM model for EEG-based emotion recognition over more than ever before. Through using frequency band-specific features analysis and taking advantage of the temporal model ability of Bi-LSTM, we hope to overcome the down-sides from previous methods and improve both accuracy and reliability in the emotion classification system.

2 LITERATURE SURVEY

In a recent paper [1], the ATDD-LSTM model has been proposed to allow recognition of EEG based on extracted features and outperform hand design feature-based method. The deep learning model combines an Attention based LSTM to catch spatial features as well as prioritize EEG channels related to emotions. In [2], the authors introduced an optimized deep CNN for emotion classification, based on a hybrid hunt optimization algorithm. The method modifies CNN hyper-parameters and picks the informative EEG electrodes, that depends on brain activity for better model accuracy. This optimized model not only obtained high accuracy of 96.60% and 95.80% on two datasets, but also a good robustness under the extraordinary circumstance. This paper demonstrates the effectiveness of hybrid optimization in the context of enhancing emotion detection by means of deep learning. If we talk about various frequency ranges and their specific features, they matter. Several investigations suggest that Delta is typically associated with slow-wave sleep and are also implicated in emotion regulation and cognitive function while awake. Study by Knyazev [3] showed that delta activity is related to motivation and emotional arousal. It has been correlated that the high delta wave is related to emotional states including sadness and calmness 3,4,5.

With respect to decision -making and self-regulation, delta wave activity has been shown to be influenced by them, emphasizing their role in emotional processing. When it comes to the theta frequency band, they are best recognized for their role in memory and learning. Research by Klimesch [4] showed that the theta activity grows who's the emotional regulation and the cognitive burden are required during use of the tasks. Theta band oscillations are important for linking emotional valence to cognitive processes. For example, Aftanas and Golosheykin study [5] demonstrated a high increase in the theta wave in sub- jects having a high emotional engagement, indicating that there could be a close relationship between theta waves and emotion-driven cognitive processing. Due to the alpha frequency band is mainly attributed to relaxation and cognitive rest, but also involved partly in emotional regulation. Research such as that by Coan and Allen [6] has indicated that the alpha asymmetry, particularly over frontal scalp region, is a robust marker of emotional states. In more detail increased right frontal alpha is associated with negative emotional states, and left- frontal alpha to positive emotions. This highlights the contribution of alpha waves in distinguishing emotional reactions. On the other hand, beta waves are associated with alertness, concentration and cognitive thought process, and will often rise in situations of high emotion arousal

.

Beta power was reported to be correlated with emotional arousal and anxiety by Ray and Cole [7]. Beta activity has been recorded to occur during the expression of emotional states such as happiness and anger, hence being important in understanding how strong are emotions and the alertness moments whilst experiencing an emotion. The fifth wave, gamma waves—essentially working at the highest frequency—are known to be critically involved in high-level thinking and are highly correlated with affective response. Research by Keil et al. [8] have reported that gamma oscillations are correlated with emotion arousal and attention, particularly in tasks which involve the integration of sensory and emotional stimuli. Task-related power in the gamma band also increases during emotive periods of high arousal, suggesting its importance for the examination of complex emotional states. In recent studies the aggregation of several frequency bands is often used for a more complete emotion recognition analysis. For example, Murugappan et al. [9] proposed an EEG emotion recognition system that trained delta, theta, alpha, beta and gamma to enhance the accuracy of classification. They found that certain combinations, in particular theta and beta, are having useful facts about the relationship between cognitive load and emotions.

Koelstra et al. [10] presented the DEAP dataset, a popular set for emotion analysis using physiological signals such as EEG and peripheral. The dataset contains video recordings of 32 participants watching 40 one-minute music videos. Emotions were rated with valence, arousal, dominance and liking scales while subjects had EEG signals recorded from 32 electrodes. The DEAP dataset is widely used as a benchmark for emotion recognition models, to compare and challenge algorithms of emotion analysis. Zhang et al. [11] presented a technique to recognize attention based on CNN using DEAP dataset and investigated the EEG processing. Although it is a study of attending, the result showed deep learning models have the potential to recognize cognitive states from EEG, and expand this approach on emotion recognition tasks.

3 METHODOLOGIES

In order to recognize and discriminate numerous emotions, the methods utilized in our research paper are focused on analyzing various frequency bands of EEG signal. We are looking into to analyze these signals and we target to be able to identify the emotions using Russell's valence-arousal dimension with the help of the diverse and popular dataset DEAP which includes several physiological signals. For classifying and predicting emotions according to their different states, in our case we will use machine learning based method and deep learning based approaches. Such techniques are composed of machine learning classifiers and bi-LSTM.
The Methodologies that we follow in our work are overviewed which comprise data preprocessing, feature extraction, classification, forecasting and model evaluation as shown in Fig. 3.

Pre-Processing of Data: For the implementation of our model processing at first, we require preprocessing DEAP dataset, with this pre-processing is the first process where raw EEG data are used to prepare for analysis and classification task. The data serving for reshaping and formatting into NumPy arrays as incremental in side-line artifact removals, in filtering to further support the right pre-operating process. From here on forward as a component of feature extraction the objective is to calculate the band power for each frequency band; that reflects the signal strength in this particular frequency range. After filtering the relevant voice features we will move, then in to step two, where we categorized our forensic emotional voice features into 4 groups of emotions HAHV, LAHV, HALV and LALV. These four categories are determined by the valence and arousal median split ratings. To classify emotions, we employ several Machine Learning (ML) classifiers such as SVM, KNN and MLP where these classifiers are trained on a portion of the data called training dataset to learn the pattern and context between pattern attributes (European extrapolated power features) and labels. 3.1 Analysis of the Pattern: After analyzing the pattern, we see KNN well suits for valence data (62%) and MLP is very suitable for Arousal data (68%) as it has temporal dynamics. [10] Bi-LSTM model: Can be a good choice for prediction because of its advanced techniques such as data processing in both the direction (left to right, right to left).

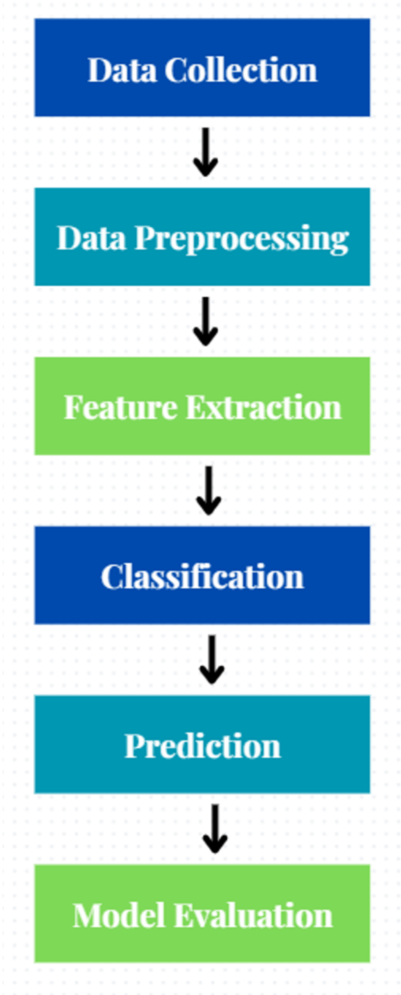

Fig. 3. Proposed Model

3.1 DEAP Dataset

DEAP is the abbreviation of "Dataset for Emotion Analysis using Physiological signals" [12]. It's an established high-quality dataset applied to a number of human emotional state studies based on the EEG and multiple peripheral physiological signals. EEG data is a subset of the DEAP. consisting of 32 subjects (16 men and 16 women, aged between 19 to 37 years). Each participant watched a music video created to elicit various emotional states. These responses are collected with the aid of electrodes (32 channels) distributed over the head in multiple locations (e.g., frontal and occipital sites), according to a 10–20 interval system. Residual signals are sampled at 128 Hz. 5 Now we will extract frequency bands for every trial utilizing bandpass filters. Frequency bands like delta, gamma, theta, alpha and beta as in Table. 2. We used half of the DEAP dataset in our study, with 5 subjects. The size of our data is presented in TABLE below. 1.

Table 1. DATA DIMENSION

LABEL	ENTIRE DATASET
(200,4)	(200,40,8064)

Table 2. FREQUENCY BANDS RANGE

S.NO	FREQUENCY BAND	FREQUENCY RANGE
1	Delta	0-5-4 Hz
2	Theta	4-8 Hz
3	Alpha	8-12 Hz
4	Beta	12-30 Hz
5	Gamma	30-60 Hz

3.2 BiLSTM

A variant of LSTM, bidirectional long short term memory (Bi-LSTM) net- work works on sequence data like LSTM, but it operates in both the forward and backward directions that help them to maintain future and past dependencies. [13] Bi-LSTM network consists of two parallel LSTM layers (forward LSTM and back- ward LSTM), as illustrated in Fig. 4. Forward LSTM reads from the start to the end of an input sequence, while backward LSTM computes it reversed way. Finally, the outputs of these two layers are concatenated at each time step and pooling steps bring a more comprehensive view of the in- put word by considering its entire context. Bi-LSTM is based on the Long Short Term Memory network, designed to operate on sequential data, and solve the vanishing gradient problem of regular RNNs. [14] The LSTM allows the network to learn and maintain long-range dependencies in sequences by introducing memory cell, three gates: forget gate, input gate and output gate handling information flow. The forget gate determines which information of input should be forgotten in past states(-cell-state), the input gate decides how much to accredit through new memory and output gate decides what part of data should be memories or passed to next time as depicted in Fig. 5. LSTMs are good at learning correlations over time, but can only learn in a forward direction. This reduces the power these models have to use context, particularly during tasks where meaningful information comes from future knowledge. By using the advantages of forward and backward LSTMs, Bi-LSTM solve this drawback. straight by processing the sequence bidirectionally.

Here is the mathematical intuition for Bi-LSTM.
In Forward Pass, let X be an input sequence$X = [x_1, x_2, x_3, x_4 \dots x_t]$,the input sequence is processed by the forward LSTM from t = 1to t = T. At each time step t.

Below $f_t^{forward}$ represents forget gate, $i_t^{forward}$ represents input gate, $O_t^{forward}$ represents output gate, $C_t^{forward}$ represents candidate memory(it stores potential important information which can be added to cell state), $C_t^{forward}$ represents cell state(long-term context) and $h_t^{forward}$ represent hidden state(short-term context) in forward LSTM.

$$f_t^{forward} = \sigma(W_t^{forward} \cdot \left[h_{t-1}^{forward}, x_t\right] + b_f)$$

$$i_t^{forward} = \sigma(W_i^{forward} \cdot \left[h_{t-1}^{forward}, x_t\right] + b_i)$$

$$C_t^{forward} = \sigma(W_C^{forward} \cdot \left[h_{t-1}^{forward}, x_t\right] + b_C)$$

$$C_t^{forward} = f_t^{forward} \cdot C_{t-1}^{forward} + i_t^{forward} \cdot C_t^{forward}$$

$$O_t^{forward} = \sigma(W_O^{forward} \cdot \left[h_{t-1}^{forward}, x_t\right] + b_O)$$

$$h_t^{forward} = O_t^{forward} \cdot tanh(C_t^{forward})$$

In Backward Pass**,** the input sequence is processed in reverse order by the backward LSTM.

Below $f_t^{backward}$ represents forget gate, $i_t^{backward}$represents input gate,$O_t^{backward}$represents output gate, $C_t^{backward}$ represents candidate memory(it stores potential important information which can be added to cell state), $C_t^{backward}$ represents cell state(long-term context) and $h_t^{backward}$ represent hidden state(short-term context) in backward LSTM.

$$f_t^{backward} = \sigma(W_t^{backward} \cdot \left[h_{t-1}^{backward}, x_t\right] + b_f)$$

$$i_t^{backward} = \sigma(W_i^{backward} \cdot \left[h_{t-1}^{backward}, x_t\right] + b_i)$$

$$C_t^{backward} = \sigma(W_C^{backward} \cdot \left[h_{t-1}^{backward}, x_t\right] + b_C)$$

$$C_t^{backward} = f_t^{backward} \cdot C_{t-1}^{backward} + i_t^{backward} \cdot C_t^{backward}$$

$$O_t^{backward} = \sigma(W_O^{backward} \cdot \left[h_{t-1}^{backward}, x_t\right] + b_O)$$

$$h_t^{backward} = O_t^{backward} \cdot tanh(C_t^{backward})$$

At last, while predicting the result of BiLSTM the output from the forward and backward LSTM are concatenated.

$$h_t^{BiLSTM} = concatenate(h_t^{forward}, h_t^{backward})$$

.Above $h_t^{forward}$ represents the output which we get from forward LSTM, $h_t^{backward}$ represents the output which we get from backward LSTM and h_t^{BiLSTM} represents what we get at the end as the result by concatenating both forward and backward LSTM output.

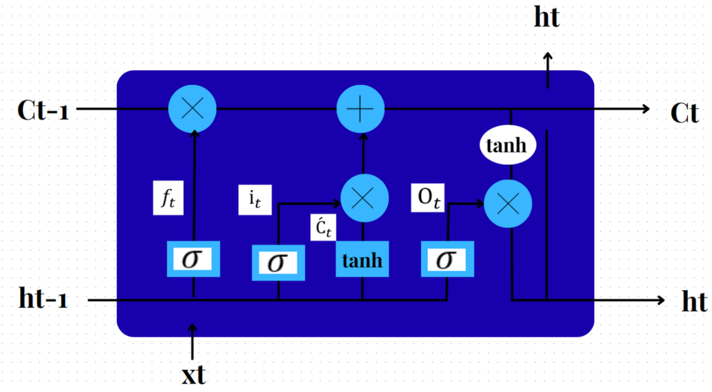

Fig. 4. Long-Short Term Memory Model (LSTM)

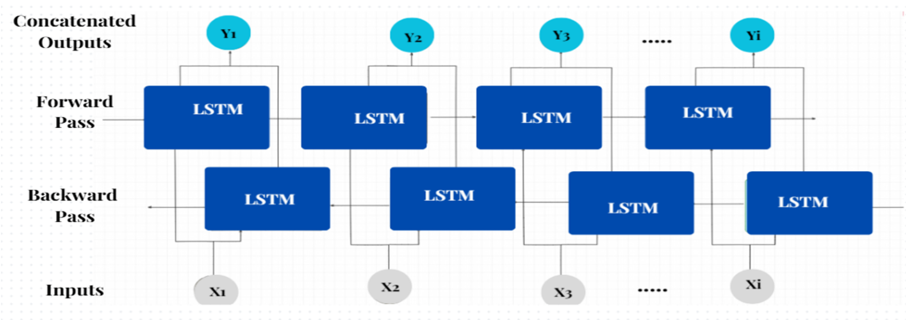

Fig. 5. Bidirectional Long-Short Term Memory Model (BiLSTM)

4 RESULTS

Performance evaluation demonstrates the effectiveness of the deployed models in EE-G-based emotion recognition. Due to its easy-to-use nature and power in finding local patterns, the K-Nearest Neighbors (KNN)model generation system achieved one of the highest accuracy results on valence classification, while MLP (Multi-Layer Perceptron) with ability of learning complex nonlinear relation-ships led other models when it comes to arousal level classification. Moreover, the BiLSTM successfully exhibited its capability to capture temporal dependencies in EEG data. Fitting performance of the model and comparison with different methods (cross-session) The training accuracy is 67% and testing accuracy is73%. 5 and Fig. 6. This analysis demonstrates the complementary nature of these models, as KNN provides interpretability, MLP deals well with non-linearity data and Bi-LSTM excels at learning temporal patterns.

The performance comparison of the three methods for EEG-based emotion recognition is displayed in Table. 3. We achieved 92% training and 85% testing accuracy which is the solid generalization of our model. The training accuracy of Huang et al. 's [15] paper is about 85%, while the testing accuracy is about 78%. It is the complexity of feature extraction [16] and challenges from inter-subject variability that make their study less accurate. The training accuracy of Zhu et al.'s (ZL) work [19] is about 83% while the testing accuracy is close to 77%. Barrett However, these numbers are lower than ours which is reason- able as their model architecture and also for our comparable problems in feature extraction differ. Though both those trials report encourage- learning results overall, they produce somewhat weaker results than ours. While the provided accuracy [17] [18] indicates that further feature selection and model adjustment might be required for better performance, especially on test stages, employing CNN, Bi-LSTM and attention mechanisms in their studies provide useful insights. Our improved testing accuracy by our method demonstrates that the feature extraction techniques and network architectures selected could equally are good when the EEG signals were processed for emotion recognition.

Table 3. RESULTS COMPARISION

METHODOLOGY	ACCURACY
Our Result	85%
Huang et al. (2023)	78%
Zhu et al. (2024)	77%

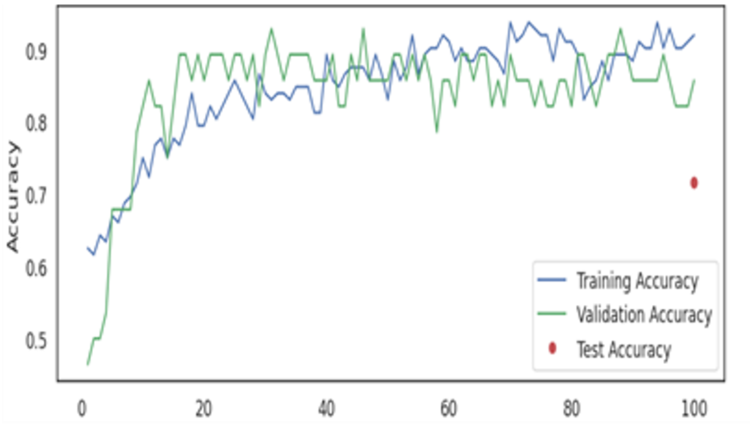

Fig. 6. Training, Validation and Test Accuracy

Fig. 7. Training, Validation and Test Loss

5 CONCLUSION

We adopt BiLSTM to explore EEG emotion recognition in this paper. Our model has ability to generalize very well across unseen data, accuracy on training sets were found 92% and that of testing set was recorded as 85%. A number of recent methods, such as the ones Huang et al. (2023) and Zhu et al. (2024) that reported a lower testing accuracy perform qualitatively worse than these results. The obtained results for emotion recognition indicate that the temporal dependencies in EEG signals can be modeled efficiently by computing coherence between paired electrodes. Notwithstanding these promising results, concerns such as subject specific variability and the complexity of EEG signal interpretation remain. More effective approaches of feature dimensionality reduction exploitation and model improving methods could lead to better performance in our framework, which will make it competitive with existing systems in practice for practical emotional recognition.

References

1. X. Du *et al.*, "An Efficient LSTM Network for Emotion Recognition from Multichannel EEG Signals," in *IEEE Transactions on Affective Computing*, vol. 13, no. 3, pp. 1528-1540, 1 July-Sept. 2022, Doi: 10.1109/TAFFC.2020.3013711.
2. S. B. Wankhade and D. D. Doye, “Hybrid hunt-based deep convolutional neural network for emotion recognition using EEG signals,” Compute Methods Biomech Biomed Engin, vol. 25, no. 12, pp. 1311–1331, Sep. 2022, Doi: 10.1080/10255842.2021.2007889
3. Mapelli, Alessia & Carini, Laura & Ieva, Francesca & Sommariva, Sara. (2026). A neighbor selection approach for identifying differential networks in conditional functional graphical models. 10.48550/arXiv.2601.02292.
4. Klimesch W. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Res Brain Res Rev. 1999 Apr;29(2-3):169-95. Doi: 10.1016/s0165-0173(98)00056-3. PMID: 10209231.
5. Luther L, Horschig JM, van Peer JM, Roelofs K, Jensen O, Hagenaars MA. Oscillatory brain responses to emotional stimuli are effects related to events rather than states. Front Hum Neurosci. 2023 Jan 18;16:868549. Doi: 10.3389/fnhum.2022.868549. PMID: 36741785; PMCID: PMC9891458.
6. J. A. Coan and J. J. B. Allen, "Frontal EEG asymmetry as a moderator and mediator of emotion," Biological Psychology, vol. 67, no. 1-2, pp. 7-49, 2004.
7. Martin T, Holliday E, Okhio C, Newman A, Latella L, McGinnis M, Požar R, Giordani B, Kavcic V. States, traits, and the resting state EEG task aftereffect. Int J Psychophysiol. 2025 Apr; 210:112523. Doi: 10.1016/j.ijpsycho.2025.112523. Epub 2025 Feb 9. PMID: 39933625; PMCID: PMC12317965.
8. Rieder MK, Rahm B, Williams JD, Kaiser J. Human γ-band activity and behavior. Int J Psychophysiol. 2011 Jan;79(1):39-48. Doi: 10.1016/j.ijpsycho.2010.08.010. Epub 2010 Sep 7.
9. V. G. Rajendran, S. Jayalalitha, K. Adalarasu and S. J. Mohammad, "Human emotional classification using EEG based on discrete wavelet transformation technique," *2023 First International Conference on Cyber Physical Systems, Power Electronics and Electric Vehicles (ICPEEV)*, Hyderabad, India, 2023, pp. 1-6, Doi: 10.1109/ICPEEV58650.2023.10391939.
10. S. Koelstra *et al.*, "DEAP: A Database for Emotion Analysis; Using Physiological Signals," in *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18-31, Jan.-March 2012, Doi: 10.1109/T-AFFC.2011.15.
11. F. Atilla and M. Alimardani, "EEG-based Classification of Drivers Attention using Convolutional Neural Network," *2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS)*, Magdeburg, Germany, 2021, pp. 1-4, Doi: 10.1109/ICHMS53169.2021.9582625.

12. S. Koelstra *et al*., "DEAP: A Database for Emotion Analysis; Using Physiological Signals," in *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18-31, Jan.-March 2012, Doi: 10.1109/T-AFFC.2011.15.
13. M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," in *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2673-2681, Nov. 1997, Doi: 10.1109/78.650093.
14. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," in Neural Computation, vol. 9, no. 8, pp. 1735-1780, 15 Nov. 1997, Doi: 10.1162/neco.1997.9.8.1735.
15. Huang, Zhentao, Yahong Ma, Rongrong Wang, Weisu Li, and Yongsheng Dai. 2023. "A Model for EEG-Based Emotion Recognition: CNN-Bi-LSTM with Attention Mechanism" *Electronics* 12, no. 14: 3188.
16. Jha, Sonu Kumar & Suvvari, Somaraju & Kumar, Mukesh. (2024). Maximizing Emotion Recognition Accuracy with Ensemble Techniques on EEG Signals. Recent Advances in Computer Science and Communications. 17. 10.2174/0126662558279390240105064917.
17. Jha, S.K., Suvvari, S., Kumar, M. (2025). Exploring the Impact of KNN and MLP Classifiers on Valence-Arousal Emotion Recognition Using EEG: An Analysis of DEAP Dataset and EEG Band Representations. In: Singh, M., *et al.* Advances in Computing and Data Sciences. ICACDS 2024. Communications in Computer and Information Science, vol 2194. Springer, Cham. https://doi.org/10.1007/978-3-031-70906-7_1
18. Jha, Sonu Kumar et al. "EEG-based Emotion Recognition: An In-depth Analysis using DEAP and SEED Datasets." *2024 11th International Conference on Computing for Sustainable Global Development (INDIACom)* (2024): 1816-1821.
19. Zhu X, Liu C, Zhao L, Wang S. EEG Emotion Recognition Network Based on Attention and Spatiotemporal Convolution. Sensors (Basel). 2024 May 27;24(11):3464. Doi: 10.3390/s24113464. PMID: 38894254; PMCID: PMC11174415.