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***Abstract*—This work aims to investigate the performance of the [redacted] ([redacted]) Model for [redacted]. For the experimentation, we use the publicly available DEAP dataset, which consists of pre[redacted]essed [redacted] and [redacted]. Our work limits itself to the study of only the [redacted] signals to have a scope for developing an efficient headgear model for real-time monitoring of emotions. In this study, we extract the band power, a frequency-domain feature, from the [redacted] signals and compare the classification accuracies for [redacted] and Arousal domain for different classifiers. The proposed [redacted] ([redacted]) model achieves the best classification accuracy of 94.69% and 93.13% for [redacted] and Arousal scales, respectively, illustrating a significant average inc[redacted]ent of 16% in [redacted] and 18% in arousal in comparison to other classifiers.**

[redacted]—[redacted] Data, Emotion, [redacted], DEAP dataset, Band power, [redacted]

[redacted]

[redacted] represents the state of mind of a person whether a person is happy or sad, angry or calm, stressed, or relieved. Emotions are the response to a particular stimulus. Studies suggest that emotion is a subjective experience: it varies from person to person, and because of this, it is one of the most challenging and exciting research fields in psychology [1]. Re[redacted] of emotion plays a vital role in daily life as it can help in enhancing one's psychological health which is equally important as maintaining physical fitness. Nowadays, a lot more people suffer from anxiety, stress, hypertension, and other mental health-related issues. So, [redacted] here plays a crucial role in improving the lives of people. For instance, when a game becomes too dull or too exciting, the level of the game can be modified depending on the exhibited emotional level of the person. Also, a computer can change the music or window background according to one's mood. There are various other [redacted] in the field of mental health where the knowledge of human emotion helps the psychologist to treat stress, tension, and anxiety issues.

Emotion is a phenomenon that is difficult to grasp, and for its better understanding, there are various models proposed by researchers like [redacted] and Arousal Model by Russell [2]. This model represents emotions on a 2-D circular space where arousal represents the vertical axis, and [redacted] represents the horizontal axis. The Circular space represents the neutral [redacted] and medium value of arousal. [redacted]. [3] proposed another model named Approach and Withdrawal Model or the vector model. It is also a 2-D model where the value of [redacted] determines the direction of emotion where a positive value of [redacted] shifts the emotion in the top vector. Likewise, the negative value of [redacted] would shift the emotion in the down vector. [redacted] and Tellegen [4] developed a Positive and Negative Model. In this model, the vertical axis represents low to high positive affect, and the horizontal axis represents low to high negative affect.

Earlier researches on emotions were done using facial expressions, speech [redacted]essing, and various other methods. However, since it is possible to fake this behaviour and techniques, the focus has now shifted on [redacted] using other [redacted] such as [redacted] ([redacted]), [redacted] (EMG), [redacted] ([redacted]), [redacted] (RR) and [redacted] ([redacted]) signals [5], [6]. [redacted] through [redacted] has vast [redacted] in the field of [redacted] ([redacted]), where the computer can adjust its behaviour according to user emotion. For the measu[redacted]ent of brain signals, [redacted] ([redacted]) device is used, which measures the electrical activity of the brain. [redacted] device contains a large number of electrodes that can be placed on [redacted]

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[redacted], according to the 10-20 International System. Since the understanding of the entire [redacted] signal at once is a complex task, the [redacted] signal is divided into various frequency bands. The different frequency bands are the [redacted] (0-4 Hz), Beta (4-8 Hz), Delta (8-13 Hz), Theta (13-30 Hz), and [redacted] (>30 Hz). Each band is associated with different activities taking place in the body. For instance, the Delta wave is related to deep sleep as well as the deepest level of relaxation. Similarly, the Theta wave is associated with [redacted] sleep, deep and raw emotions, and cognitive [redacted]essing. Likewise, in a drowsy state, the [redacted] wave comes into the picture. It is associated with relaxation and calmness. In a conscious state, the Beta wave is present during the thought [redacted]ess. [redacted] waves are current when a person tries to perceive two different senses at the same time as sound and sight. [redacted] signals have broad [redacted] ranging from [redacted] to diseases and disorders like Sleep Apnea, [redacted], and Alzheimer's disease.

Although various classification techniques have been reported in the literature [redacted] et al. [7] reports a classification accuracy of 85.65%, 85.45%, and 87.99% for valance, arousal, and liking, by using [redacted] model. Similarly, [redacted]. [8] employed [redacted] model achieving a mean accuracy of 76.6%. We compute the band power feature for each frequency band of the [redacted] signals and employ the machine learning methods, namely [redacted] ([redacted]), [redacted] ([redacted]), [redacted] ([redacted]), Decision [redacted] and [redacted]. Section II for Related Work presents a detailed description of the previous research work. In this work, we achieve a maximum classification accuracy of 94.69% for [redacted] and 93.13% for arousal using the [redacted] classifier, outperforming the other classifiers.

In the rest of the paper, Section II describes the related work. Section III contains the proposed methodology, and [redacted] includes the experimental results. Finally, we conclude the paper with section V with the conclusion and future work.

II. Related Work

There are various emotions like happy, excited, angry, afraid, sad, depressed, calm, and contentment and the proper classification of these emotions can be beneficial for the study. [redacted]. [9] have classified the emotional state as calm when the levels of arousal are below 4, and the level of [redacted] is between 4 and 6. Similarly, for stress, the levels of arousal should be greater than 5, and that of [redacted] should be less than 3.

In researches concerning the problem of emotion classification, the ability to classify emotions depends on two main factors:

1) Features extracted from the dataset.
2) Classifiers used for emotion classification.

The classification accuracy compared to the original dataset can be improved by extracting a wide range of features from the dataset. There are mainly three types of features :

1) Time-domain features.
2) Frequency domain features.
3) Time-Frequency domain features.

[redacted]. [10] have described several features and their relevance to [redacted] signals. Some of the features are statistical features like mean, standard deviation, power. [redacted] Features like activity, mobility, complexity. Frequency domain features include band power, higher-order spectra. The time-frequency domain features are [redacted] ([redacted]) and [redacted] (DWT). Recent researches have shown that frequency domain features are more useful in the analysis of [redacted] signals. A good number of papers have used [redacted], or [redacted]-based features generated from [redacted] signal datasets and achieved good accuracy to solve problems in the domain of [redacted] and classification. [redacted] also mentions the use of [redacted] for a myriad of analyses [11]. This motivates us to use frequency-domain features for extracting information from the [redacted] signals and explore various classification techniques.

This paper examines different classification techniques for [redacted] on the publicly available DEAP (Dataset for [redacted] using [redacted]) dataset [12]. We have also found [redacted] ([redacted]) being used in recent years to address the problem of [redacted] and classification effectively. We mention some of the prominent researches employing [redacted] model and other classifiers using DEAP dataset. However, all of them achieve accuracy less than the proposed model in this paper.

Dabas et al. [13] proposed a 3-D emotional model ([redacted], Arousal, and [redacted]) for classifying emotions using the DEAP dataset. They used machine learning algorithms like [redacted], Naive Bayes, and achieved an accuracy of 58.90% and 78.06%.

[redacted]. [14] has employed the DEAP dataset for classifying emotions and features like time-domain features (mean, power, standard deviation, higher-order crossings, fractal dimension, [redacted] feature), frequency domain features (power spectral density), time-frequency domain feature ([redacted]-[redacted]). Multi-electrode features (differential asymmetry and rational asymmetry, magnitude squared coherence estimate) are computed and uses maximum relevance minimum redundancy (mRMR) for feature selection. [redacted] and RF are employed as classification techniques with the highest accuracy of 66.17% for arousal using a magnitude squared coherence estimate as a feature.

[redacted] et al. [15] have experimented on the DEAP dataset using band power as the feature and [redacted] as classifier. The maximum accuracy achieved is 64.9% for [redacted] and 66.8% for liking while using the 3-dimensional emotion model. They have only used ten channels and have shown that performance accuracy is not improved even if 32 channels are employed.

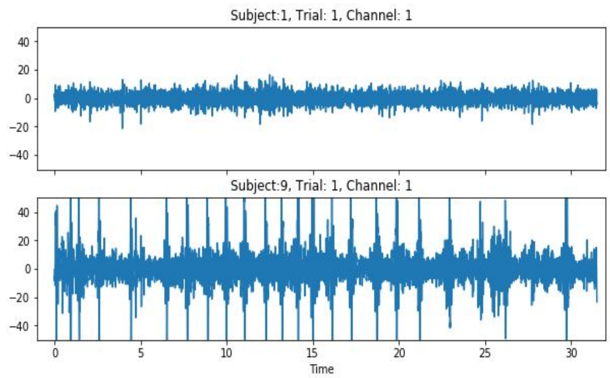
Salama et al. [16] designed a 3-dimensional convolutional [redacted] for [redacted] from [redacted] data. They have used the DEAP dataset for analysis and have achieved 87.44% and 88.49% accuracy for [redacted] and arousal classes.

[redacted] et al. [7] have proposed an end-to-end model employing the [redacted] classifier for emotion classification on the DEAP dataset. The average subject-independent accuracy achieved for arousal, [redacted], and liking is 85.65%, 85.45%, and 87.99%.

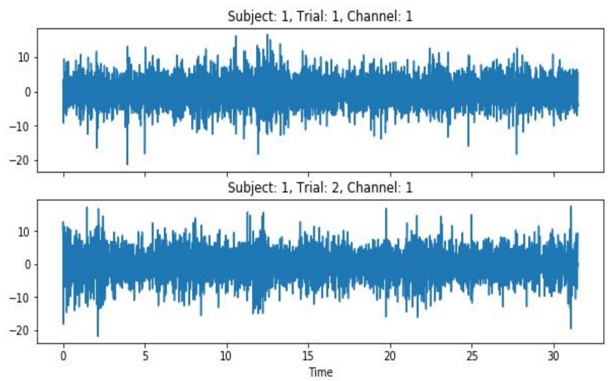
[redacted]. [8] have used [redacted] as a feature which represents frequency-space domain characteristics of the [redacted] signal. They have employed the [redacted] model on DEAP dataset and achieved a mean accuracy of 76.6%. [redacted]. [17] built Stack Autoencoder ([redacted]) for [redacted] signal decomposition and used [redacted] model for classification but still observed accuracy of 81.1% in [redacted] and 74.38% in arousal.

[redacted]. [18] propose a parallel combination of Convolutional [redacted] and [redacted] to extract features from the DEAP dataset and then use the softmax classifier for classification. This model obtained the mean accuracy of 90.80% and 91.03% for [redacted] and arousal.

Previous works in the [redacted] establish that the [redacted] models perform better than other classification techniques. Still, the reported work examines either the raw [redacted] signals or the time-domain features for training the [redacted] model. Here, we investigate the use of the band power, a frequency-domain feature for training the [redacted] model. To compare the performance of the proposed [redacted] model with other classifiers, we also train classifiers, namely [redacted], [redacted], Decision [redacted], and [redacted]. On contrasting the results, we observe a maximum classification accuracy of 94.69% for [redacted] and 93.13% for arousal using the [redacted] classifier, which is significantly better than other classifiers.



[redacted]. 1. [redacted] signal for Subjects:(1, 9), Trial: 1, and Channel: 1



[redacted]. 2. [redacted] signal for Subject:1, Trials: (1, 2), and Channel: 1

III. Methodology

A. Dataset Description

The DEAP dataset [12] is a multimodal dataset for the determination of human emotional states available for public access. For the creation of the database, experiments were performed where 32 participants were made to watch 40 one-minute-long excerpts of selected videos, during which the signals from 32 channels of standard [redacted] headset and [redacted] from 8 channels were captured. Equipment had a sampling frequency of 128 Hz. The data was pre-[redacted]essed, and artefacts were [redacted]oved. The participants rated each video on a scale of 0-9 in terms of [redacted], arousal, [redacted], and liking. These ratings become the benchmark for the classification of emotional states.

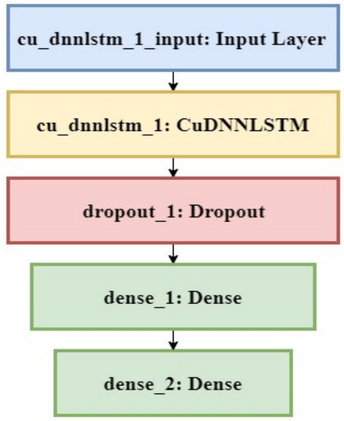
B. Pre-[redacted]essing

[redacted]. 1 illustrates the [redacted] signals for two subjects (1, and 9) subjected to the same trial. Both signals indicate differences in the magnitude and the pattern of activations of the brain for different individuals. Thus, it displays the uniqueness in the [redacted]essing of information in the brain for every individual.

[redacted]. 2 illustrates the [redacted] signals for a single person, subjected to two different trials. Both signals display similarity in the magnitude of the activation of the brain for the subject.

As inferred from [redacted]. 1 and [redacted]. 2, we conclude that [redacted] is to be done for each individual separately as the analysis displays no similarity in the activation of the signals recorded for different subjects in the population. Since every individual possesses unique consciousness and emotional limits, the prediction of emotion for an individual using the learning from any other individual will drastically reduce not only the accuracy in prediction but the model will also lose its credibility for the prediction of an unknown subject. But the analysis also shows that there does exist similarity amongst the signals, [redacted] and arousal values for the different trials of an individual. Hence, there is a possibility of finding a pattern for a certain emotion by understanding the signals obtained for that individual only. We exploit the results of this analysis to design a customized model for [redacted]. Although by increasing the size of data, it is possible to account for this diversity in the strengths of the [redacted] signals. This is demonstrated by the modern extensive Image Classification datasets such as [redacted] [19] which consists of more than 17 million images. Such a large dataset enables the [redacted] models to explore the hidden features of the dataset and account for the diversity in the sample population. But the DEAP dataset consists of only 32 subjects, so it is currently not possible to account for such variance in the [redacted] signals. Therefore this study limits its training and testing to independent subjects.

The original signals were recorded for 63s (3s prior and 60s for the video). The preceding signal recorded is not [redacted]oved as



[redacted]. 3. Proposed [redacted] Model

it does possess useful information regarding the state of mind of the individual before showing video trials. The band power for the different bands is calculated using the [redacted] method based on the [redacted] window. The window length here is 1s and the stride of 0.25s for the entire 63s, therefore, obtaining 249 band power values at different instances of time. Only the [redacted] data values are used for experimental purposes, as our long term goal is to develop a real-time emotion prediction model where we require a minimal amount of hardware so that it can be used in the daily lives of every individual, especially patients.

C. [redacted] Model

In this paper, we use the [redacted] as a useful tool for the prediction of the emotion of individuals. The [redacted]s are frequently used for handling sequential data such as paragraphs in [redacted] previous electricity load in the case of the electricity demand prediction. [redacted] cell possesses the ability to [redacted]ember the distant as well as recent events to accurately predict the target variable. This property of retention can turn to be useful for [redacted] as knowing about the past activations of the [redacted] signals can drastically affect the prediction of target variables and provide useful insights to the events leading to an appropriate response for the subject.

[redacted]. 3 shows the configuration of the Proposed [redacted] model. We implement the model in [redacted] the [redacted] Colab platform with [redacted] support for the [redacted]. The [redacted] layer has 40 nodes. Dense_1 layer has 10 nodes with 'tanh' activation function, and Dense_2 has a single node with 'sigmoid' activation function. We use a Dropout 25% between the [redacted] Layer and Dense_1 Layer. We use [redacted] Gradient Descent ([redacted]) optimizer (learning rate=0.01, learning rate decay constant=$1 * 10^{-5}$, and momentum constant=0.9) to minimize the binary-cross-entropy loss function.

Other than the customized [redacted] model, we also test the classification on the dataset using [redacted], [redacted], Decision [redacted], and [redacted]. We evaluate the performance of each classifier on the pre-[redacted]essed dataset. As expected from the previous studies, the proposed [redacted] model outperforms the other classifiers by a huge margin.

IV. Results

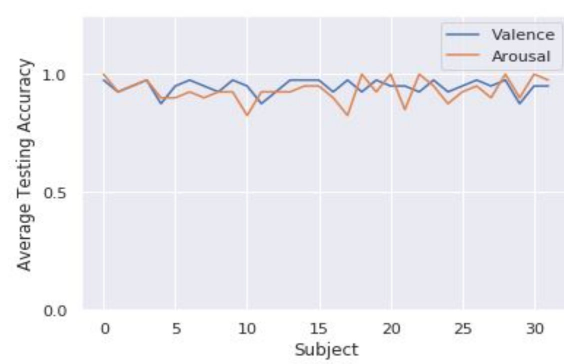
To verify the effectiveness of the proposed [redacted] model, we contrast the performance of [redacted], [redacted], Decision [redacted], [redacted], and [redacted] models for classification of the pre[redacted]essed dataset. We test models several times to ensure the significance of the results observed. Table I highlights the average prediction accuracies.

TABLE I
TESTING ACCURACIES

Model	[redacted]	Arousal
[redacted]	79.69	75.78
[redacted]	76.56	72.66
Decision [redacted]	77.34	74.21
[redacted]	80.46	77.34
[redacted]	**94.69**	**93.13**

On analyzing the results, we observe that the [redacted] model outperforms the other classifiers by a large margin. We observe a [redacted]arkable inc[redacted]ent of about 16% and 18% for [redacted] and arousal when comparing the [redacted] model with other classifiers. The highest inc[redacted]ent in average testing accuracy of 18% for [redacted] and 20% for arousal is observed when comparing the [redacted] classifier with the [redacted] model.

We compare our results with the results of [redacted]. [18] following similar experimental [redacted]edures with the [redacted] model. Here, we observe an inc[redacted]ent of 4% for [redacted] and 2% for arousal in average testing accuracies for all the subjects. Our proposed model notes a significant inc[redacted]ent of 9% in [redacted] and 7.5% in arousal for [redacted] et al. [7] and 14% in [redacted] and 19% in arousal for [redacted]. [17]. [redacted]. 4 illustrates the average testing accuracy for [redacted] and arousal of the 32 subjects.



[redacted]. 4. Average testing accuracy of 32 subjects for [redacted] model

V. Conclusion and Future Work

In this work, we evaluate power spectral density over the 32 channels of the DEAP dataset. We segregate them into five bands of frequencies, namely [redacted], Beta, [redacted], Delta, and Theta, to derive the band power of each band. We use band power as a feature for classifying [redacted] and arousal of the subject. We evaluate and compare using [redacted], [redacted], Decision [redacted], [redacted], and [redacted] as our classifiers. On analysis, we observe a minimum average inc[redacted]ent of 16% in the average testing accuracies and maximum classification accuracy of 94.69% for [redacted] and 93.13% for arousal using the [redacted] classifier, which performs better than the current state-of-the-art classifiers.

In future, we can use the proposed experimental setup to obtain useful information regarding the emotions of the subjects and extend it for real-time [redacted]. For further improvements, we can add more frequency domain features and test for their performance. As demonstrated by [redacted] and [redacted] [15], a subset of the channels for feature generation may perform better in terms of accuracy. The work may further be extended to include subject-independent models as well. The study can be also be extended to developing 3-D emotion models like the work of Dabas et al. [13].

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