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ANALYSIS OF DIFFERENT EMOTIONS WITH BIO-SIGNALS (EEG) USING DEEP CNN

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ABSTRACT
There is a wide range of feelings, thoughts, and behavior associated with emotions, as well as an outward manifestation of some of the more subtle aspects of human psychology. To feel an emotion is to experience the high-level psychological output of the human brain. It's an interdisciplinary field of study that draws from computer science, AI, neurology, healthcare, and other fields. People's personalities and mental health are greatly influenced by their emotional experiences. In order to overcome stress and other stress-related diseases, one must be able to recognize and name one's personal emotions. There has also been a lot of interest in the use of electroencephalogram (EEG) signals for emotion classification. In affective computing, EEG-based emotion recognition is a complicated and active research among researchers. The most important part in developing a highly effective brain-computer interface (BCI) system for emotion recognition using an electroencephalogram (EEG) are feature extractions and classifier selection. Recently, deep learning methods gained much importance for their better performance. In this paper, we propose a deep learning framework, Deep CNN for Emotion Recognition (DCNNER) that can detect human emotion with help of EEG signals. The use of principal component analysis (PCA) for feature selection and dimensionality reduction is also covered in this work. The suggested model uses principal component analysis (PCA) to minimize the dimensionality of the features and then feeds only the selected features to several classifiers. Different classifiers perform differently for pre-processed data and PCA applied data. Comparisons of different deep learning are discussed. The performance of the proposed system is measured with the model accuracy is 99% and model loss is 0.3.It is a 3-dimensional model which has valence, arousal and dominance for emotion detection.
Keywords: *EEG Signal, Stress, CNN, Deep Learning, PCA, Emotion Recognition, Accuracy*

1.INTRODUCTION
Emotion is defined as a mirror of one's mental states as well as its psycho-physiological manifestations [1,2].Emotion is significant in the fields of artificial intelligence and Brain - human interface (BCI) as well as in interpersonal language and emotional communication (HCI) [1].It is a multidisciplinary research area that involves computer engineering, cognitive computing, psychology, biology, and other field. The foundation of much earlier work on emotion detection is non-physiological cues, such as emotion recognition based on voice [3] and facial expression [2] analysis. However, because tone of voice and facial expressions can be purposefully concealed, the strategy based on them is manifestly unreliable. The EEG

signals are produced from the brain. The EEG signals directly reflect the psycho-physiological aspects of emotions. Many studies have come up in digital signal or brain signal processing with machine learning algorithms. The major problem in working with EEG signals for emotion recognition(ER) is non-linear behavior of the EEG signal Qiang Gao et al.(2020). The research in emotion identification using EEG signals in deep learning is gaining importance due to its performance. Deep learning is a part of machine learning which makes the work or analysis much easier. Using deep learning, convolutional neural networks (CNN) works well than other algorithms for emotions. The proposed model implements CNN with different layers Islam M.R. et al. (2019). Hence, the proposed model tries to identify the emotions which can be applied in different area such as product promotions, medical analysis, counseling the patients and social media analysis. This paper explains the pre-processing steps involved in the bio signals (EEG) and feature extraction where required features are extracted using different feature extraction algorithms. Feature selection plays a important role in deriving accurate output for emotions. The feature which is related to particular emotion is mapped and selected. The selected features are fed to the classifier DCNNER which is a deep convolutional neural network. The classifier classifies whether the person is stressed or not. Dataset is a real time dataset where 20 subjects' EEG signals are collected using an EEG recorder. The subjects are induced by different emotional videos and accordingly the EEG is recorded while they were watching the videos. The performance of the model is better as the accuracy is 99 for the real time data set.

The remainder of the paper is organized as follows: Section 2 describes the related works which were carried out in this research area previously. In section 3, the experimental setup, analysis, feature extraction, feature selection and classification approaches are all described in depth. The results as well as the discussion are explained in Section 4. The limitations and future works are discussed in the conclusion part.

2. RELATED WORK

Emotional recognition has gained a lot of interest in recent years. Identifying emotion is for various purposes such as product promotion, medical treatment, customer review and many more. EEG based emotion detection draws major at traction because the brain is where emotions begin and an EEG is a measure of human brain activity, EEG has a significant link with emotional state identification Rab Nawaz et al.(2020),S.K.B.Sangeetha et al(2021). Using EEG, the emotion identification is carried out with different features Gao, Q. et al.(2020). An algorithm is developed to understand the emotions of physically enabled people and Autism children using EEG signals with different convolutional neural network (CNN) Classifiers. Using EEG signals and facial expression, physically challenged people and Autism children's emotions were identified with CNN and LSTM for real time application Aya Hassouneh et al(2020).

CNN and RNN are a novel deep learning hierarchy that is designed to extract spatiotemporal features for emotion recognition from the EEG signals. In order to extract the temporal features, the RNN receives input from the CNN, which is utilized to extract the spatial information. Additionally, Chen et al.,(2019) used the Hidden Markov Model (HMM) as a classifier to recognize emotions from four physiological inputs, including EEG signals. They used Davies-Bouldin index (DBI) techniques and multimodal feature sets for feature selection. 216 EEG features were extracted by from 5 various frequency bands. These characteristics include the spectral power for 32 electrodes, the difference between the spectral powers of all the symmetrical pairs of electrodes, theta (4–8 Hz), slow alpha (8–10 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30+ Hz). Fisher's linear discriminant was used for feature elimination, and the Gaussian naive Bayes is used for classification. Study on emotion recognition using EEG signals and three classifiers -Neural Network, Neural Network voting, and SVM - addressed this issue. From the EEG waves, they recovered the same features as Koelstra et al., (2013) did.

RNN and the EEG signals were combined to extract temporal features by Alhagry et al.(2021). Their RNN is made up of two LSTM layers that are fully connected, a dropout layer, and a dense layer. Utilizing the SJTU Emotion EEG Dataset, Zhang et al.(2018) introduced a deep learning architecture termed spatiotemporal recurrent neural network (STRNN) to combine the learning of spatiotemporal characteristics for emotion detection (SEED). Even though the accuracy levels found in the aforementioned studies are respectively high, more advancement in the area of emotion recognition is still required.

The DEAP and DREAMER datasets are used to classify the emotions with deep learning techniques for multi-channel EEG signals and feature extraction with raw EEG signals Yu Liu. et al(2020). Spatial features of EEG signals were extracted to identify the emotion, whereas this paper proposes usage of wavelet features with scalogram for detection of emotion Divya Garg et al,(2020). A bimodal automatic encoder is proposed, first EEG signals are applied and the result is matched with facial expression to derive the output for emotions H. Zhang et al.(2020). Different neural networks are fused to derive a model to classify emotions. First layer is convolutional network and the second one is dense layer and the accuracy obtained is 92.58% and 90.63% for DEAP and SEED dataset respectively Z. Gao et al.(2021).

3. RESEARCH METHODOLOGY

The proposed model involves several steps from data acquisition to results. The proposed system DCNNER uses EEG signals to identify the emotions. The data is pre-processed with different preprocessing techniques such as different filters, removal of artifacts and noise. After that, techniques like wavelet entropy and statistical approaches are applied to the pre-processed data to extract useful features. Different features are extracted in this section. Extracted features are more in number and it is necessary to reduce the dimension to acquire the best results. Hence, the extracted data is passed through the feature selection process such as PCA. PCA reduces the dimensions of the features, so that it can give accurate results for emotion recognition. The DCNNER classifier receives the final vector from the dimensionality reduction section and the classifier classifies the emotions. In fig. 1, the architecture of the DCNNER is explained in a block diagram.

3.1 Preprocessing

EEG signals are filled with much noise due to movement of different body parts. When an EEG signal is recorded, eye blinking (Electrooculogram-EOG), movement of muscles (Electromyogram - EMG) and heartbeat (Electrocardiography -ECG) are also recorded. This creates a lot of noise in the raw EEG signal Hao Chao et al.(2020). The pre-processing step is compulsory for the EEG signals. Different filters are used to remove the noise and artifacts from the signal. The frequencies related to detecting the emotions are found below 40 Hz. Hence, frequencies above 40 Hz are removed with the help of different band filters Torres EP et al.(2020). The effect of pre-processing is explained in Figure 2 and artifacts are removed. The raw EEG signal is converted to a pre-processed signal and the same is given to the feature extraction module. The figure 1 explains the different types of EEG bands. The values of signal bands in Hz suits in which range the signal falls. Emotions basically come in the range 12-30 Hz. The Delta (0 – 4 Hz) is the range when people are in deep sleep. Theta is the range (4 – 7 Hz) where people are in dream or imaginary. Aplha (8 -12 Hz) is where human are relaxed. Beta is the range in which people think and be active. Hence, we work with this range of data.

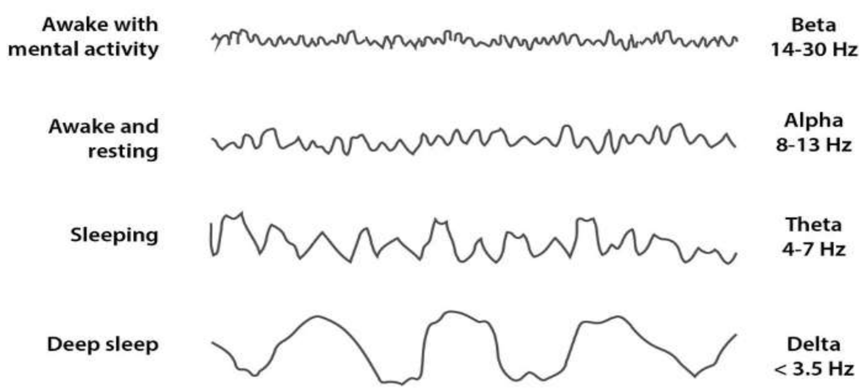

Figure.1 Types of EEG signals

3.2 Feature Extraction

The emotions can be plotted properly with the help of the significant features from the preprocessed signals. This can be achieved by extracting relevant features from the EEG signals. The EEG signals are non-stable and random in nature and it is very difficult to extract the features from these signals. Hence, less research has been carried out in this area Cho J et al.(2020). To the contrary, now many researchers are interested in working with EEG signals for emotion recognition S. K. Khare et al.(2021).

EEG signals provide more accurate results for detecting emotions. Different algorithms are used to extract the required features such as power and wavelet features. The important features which are very much suitable for classifying the emotions are extracted in this section. The result from this section is fed to the next module, feature selection. In the feature selection module, very important features are selected and given to the classifier.

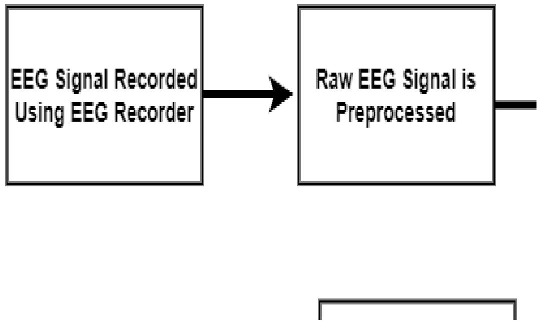

Figure 2: The Proposed Model Architecture (DCNNER).

3.3 Feature Selection - PCA

In this module, dimensionality reduction is done which is achieved by PCA. PCA is an unsupervised machine learning technique and a large set of variables are reduced to a smaller one which contains the same qualities. The prime objective of PCA is to identify principal components that can be used to characterize data points. Those data points help to plot the corresponding emotion. Hence, the principal components are identified and the same is selected to map the emotion using deep learning classifier. In this paper, dimensionality reduction for EEG signals is carried out with PCA because these signals have very high dimensions and the reduced output from PCA. The selected EEG channels AF3, AF4, F3, F4,F7, F8, FC5,

FC6, O1, O2, T7, T8, P7 and P8 are taken as input channels. These channels are the electrodes that are placed on the surface of the skull to record EEG signals with the use of an EEG recorder. The data channel has M=(M1,M2, M3. . . Mn) that can be applied to PCA, the output vector N is obtained from M by applying PCA Asghar et al.(2020).

N = E^T

where E^T is the eigenvector of the covariance matrix of M. Hence, the elements which are more important are selected using this process and those features that have high information are fed to the classifier.

The steps involved in PCA to reduce the feature are explained clearly in Figure 2 and the algorithm is explained in step by step below. The first step is the standardization of the datasets which involves normalizing the range of continuous input variables such that they all contribute equally to the analysis Z. Wen et al.(2017). The next step is computing the covariance matrix. With the help of the eigenvector and eigenvalue of the covariance matrix, the principal components are derived I.B.Rajeswari et al.(2014).

Steps involved in PCA algorithm:

- The data is split into two set of data such as training and validation data.
- Representing data into two-dimensional structure.
- Standardizing the data or normalizing the data.

- Calculating the covariance of the new matrix.
- Calculating the Eigen values and Eigen vector for the resultant matrix.
- Sorting the Eigen vector in descending order.
- Calculating the new values or principal components from the new matrix.
- Removing the insignificant features from the new dataset.

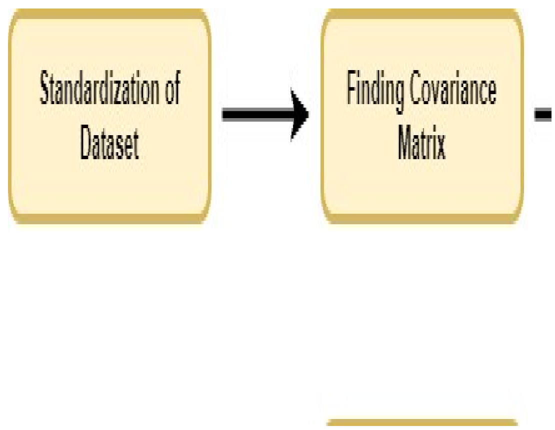

Figure 3: The steps involved in the PCA.

3.4 Feature Classifier - Deep CNN for Emotion Recognition (DCNNER)

In order to determine whether or not a person is stressed, we have employed the deep learning architecture known as a Deep Convolutional Neural Network (DCNNER), as shown in Figure 4. DCNNER is a classifier implemented using Keras library. DCNNER has different layers built together to achieve the accurate output. The DCNNER has two convolutional layers (input layer , activation layer) , next is the Maxpool layer, then flattening layer and finally activation and softmax layers of output Zhongke Gao et al.(2019).

The input layer receives the input from the previous section which is PCA Immanuel et al.(2022). The received input is sent to the convolutional ReLU layer where activation function is performed to activate the required features. Next layer is the max pooling layer that does the pooling operation with a 2 D filter to figure out the required information or the features. Y. Yang et al.(2018). In the next layer, the 1-D array of features is created by the process called Flattening. The output of the previous layer is taken as input and a 1-D vector is created. It is also linked to the final classification model, which is referred to as a fully-connected layer. The Softmax activation function is added to the final output layer.

The Softmax function uses decimal probabilities to activate the particular node which ranges between 0.0 to 1.0.This added constraint allows training to converge faster than it would without T. Song et al.(2020). The complete layout of the DCNNER is explained in Figure.4.Features retrieved from the EEG data via feature extraction and feature selection are fed into the proposed model DCNNER.We have trained the DCNNER model with the dataset which is split into training data and test data as 8:2 ratios accordingly. The figure 4 shows the different layers involved in the proposed model J. X. Chen et al.(2019).

```
Model: "sequential"

 Layer (type)                Output Shape
=============================================
 conv1d (Conv1D)             (None, 2539, 16

 conv1d_1 (Conv1D)           (None, 2537, 16

 max_pooling1d (MaxPooling1D  (None, 1268, 1
 )

 flatten (Flatten)           (None, 20288)

 dense (Dense)               (None, 100)
```

Figure 4: Different layers involved in DCNNER model.

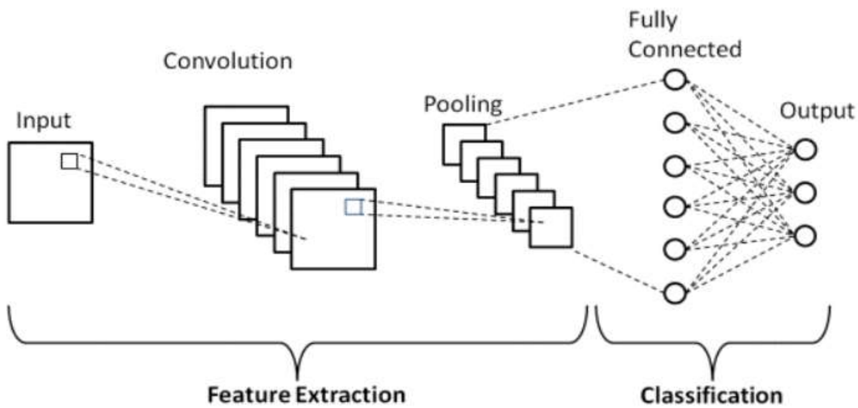

Figure 5: Architecture of DCNNER.

4. RESULTS AND DISCUSSIONS

4.1 Dataset

The data is acquired from 25 subjects in the EEG lab using an EEG signal recorder. The EEG signal is recorded from the subject when they were watching video clips related to different emotions Islam M.R et al.(2019). The international standard 10-20 system is used. Different emotion videos are played for them and EEG electrodes are connected to their scalp. The different electrical signals originating in subjects' brains for different emotions are captured and recorded in the system. Videos are of 1 minute and each subject is made to watch 10 videos respectively. The dataset is preprocessed with a band pass filter of range between 04 - 45 Hz.

4.2 Implementation

For this experiment, Keras library in TensorFlow is used to increase the speed of the execution of the proposed DCNNER model. The speed of the execution of the deep learning network is faster and easier with Keras. The model is properly trained with the dataset. The convolutional neural network is implemented with different layers.

CNNs are a subclass of Deep Neural Networks that are frequently used for visual image analysis and time series data. CNNs can identify and categorise specific features from images and signals. Their uses include natural language processing, image classification, video and image analysis for medical purposes, time series signals and image and video recognition.

Categorical-cross entropy is applied in this model which is suitable for multi-class detection. Moreover, Softmax activation function is used with categorical- cross entropy as they both work well together Haider Abdulkarim et al.(2021).The parameter can be controlled in the neural network with the help of Optimizer in deep learning. In this model, Adam optimizer is added to improve the performance of the DCNNER. Figure 5 shows that a comparison is made between train data and test data in terms of the model loss. Since the training is already complete with the train data, the loss for the test data is modest from the outset. As can be seen in Figure 7.The loss is eventually brought down to zero for the training data and 0.3 for the test data .

The model accuracy is described in Figure 6. Both the training data and the test data are used to draw a comparison on the model accuracy graph. On the X axis is the total number of epochs, while on the Y axis is the accuracy in percentage, from 0.0 to 1.0. The precision increases as the number of epochs grows Immanuel, Rajeswari Rajesh et al(2023).

The training data is indicated in blue line and the testing data is indicated in orange line in the figure 6 and figure 7.

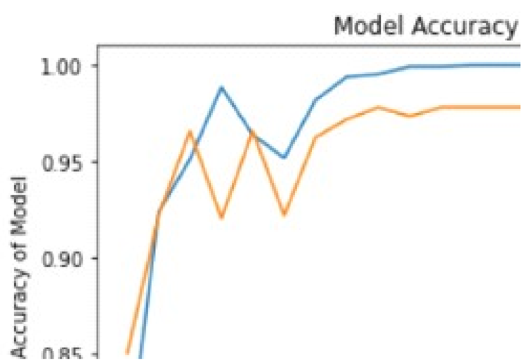

Figure 6:Accuracy of Model-DCNNER

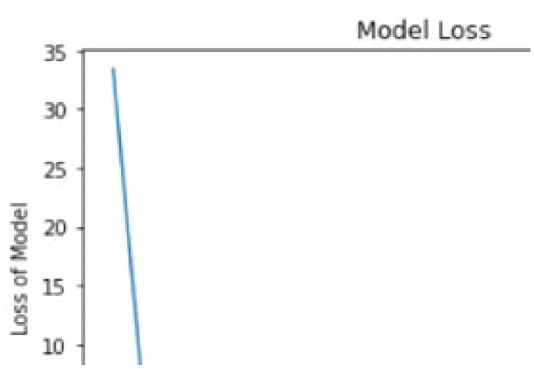

Figure 7:Loss of Model-DCNNER.

4.3 Comparison of Different Models

The proposed model's performance is compared with performance of other three different classifiers with the same datasets. The table 1 shows the performance of deep learning classifiers with DCNNER classifier. The performance metrics used in this study are accuracy and validation loss. The performance of DCNNER outperforms the other models. The graphical representation of the models displayed in figure.9.

The table 1 compares all the existing models with the proposed model for the same dataset. The table describes the validation loss and the accuracy of each model. The proposed model outperforms the other existing model in the accuracy for this real time dataset. The performance can be enhanced by including the cross fold validation and fine tuning the hyper parameters of the neural network.

Table 1: Comparison of Different Classifiers Performance

Classifiers	Validation Loss	Accuracy
RNN (Chowdary MK et al., 2022)	1.45	78.23
LSTM (Joshi, V. M et al., 2022)	0.9	81.86
DNN(Liu, W et al., 2022)	1.02	75.23
DCNNER (proposed model)	0.3	98.52

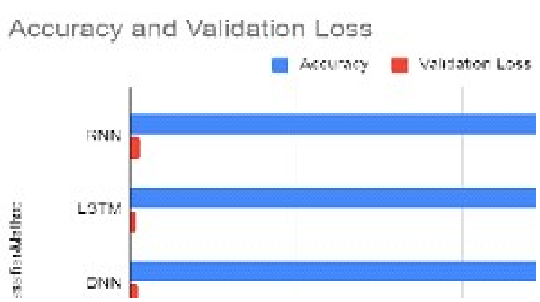

Figure 8:Graphical representation of accuracy and validation loss of the models

Figure 9: Accuracy of the models.

5. Conclusion

In this paper, the designed model (DCNNER) which uses Bio signal (EEG) to identify whether a person is stressed or not. This is achieved by implementing feature extraction, feature selection - PCA with the real time dataset. PCA is used to derive the significant features from the extracted features. The signals are preprocessed and which will help to obtain high accuracy emotion recognition. The accuracy obtained from this model is 99% and the loss of the model is 0.3%. For future work, the same model can be improved to recognize different emotions with different intensity.

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