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IDENTIFYING DIFFERENT EMOTIONS OF HUMAN USING EEG SIGNALS USING DEEP LEARNING TECHNIQUES

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ABSTRACT

Emotions encompass a wide range of feelings, thoughts, and behaviors, reflecting the complex output of the human brain. This interdisciplinary field draws from computer science, AI, neurology, healthcare, and more to study emotional experiences. Understanding and labeling one's emotions are crucial for mental health and well-being, especially in managing stress-related conditions. Emotion classification using electroencephalogram (EEG) signals has gained interest, particularly in affective computing.Developing an effective brain-computer interface (BCI) system for emotion recognition through EEG involves key components such as feature extraction and classifier selection. Deep learning methods, known for their superior performance, have recently garnered significant attention in this domain. Our paper introduces the Deep CNN for Emotion Recognition (DCNNER) framework, utilizing deep convolutional neural networks to accurately detect human emotions from EEG signals.To enhance the model's efficiency, we employ principal component analysis (PCA) for feature extraction(FE) and dimensionality reduction. By feeding only the selected features to various classifiers, we compare their performances on pre-processed and PCA-applied data. The proposed system outperforms existing approaches, achieving a remarkable model accuracy of 99% and a model loss of 0.3. The model employs a 3-dimensional representation, encompassing valence, arousal, and dominance for emotion detection.Our research showcases the potential of deep learning in EEG-based emotion recognition, promising advancements in affective computing and its applications in various domains, including mental health and well-being.

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 .Emotion is significant in the fields of artificial intelligence and Brain -human interface (BCI) as well as in interpersonal language and emotional communication (HCI) .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 and facial expression 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. 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 [1]. 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[2]. 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 FE algorithms. FE 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.Real-time EEG signals were gathered from 20 subjects using an EEG recorder to create the dataset.

The subjects are induced by different emotional videos and accordingly the EEG is recorded while they were watching the videos. On the real-time dataset, the model performs admirably with a remarkable accuracy of 99%. EEG signals are non-linear, which makes it difficult to reliably identify emotions from them. In light of this, this research analyzes various techniques for extracting distinctive features to enhance emotion identification and illuminates the non-linear nature of EEG signals.

The rest of the paper is organized as follows: Section 2 describes the related works that have been done previously in this research area and also provides an overview of the existing systems. Section 3 details the experimental setup, analysis, feature extraction, feature selection, and classification. The results of different models and the proposed model are compared and the discussion is explained in Section 4. Limitations and future work are discussed in the concluding section.

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 [3],[4]. Using EEG, the emotion identification is carried out with different features [5]. 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 [6].

RNN and EEG signals were integrated by [7] to extract temporal characteristics. Their RNN design consists of a dropout layer, a dense layer, and two fully connected LSTM layers. The SJTU Emotion EEG Database is used by [8] to train a deep-learning framework called SEED, which

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learns spatiotemporal properties for emotion identification. Although both experiments had high levels of accuracy, more work needs to be done in the area of emotion identification.

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 [9]. 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 [10]. 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 [11]. 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 [12].

Convolutional neural networks (CNNs) have made significant advancements in the processing of images, videos, and sounds due to their capacity to learn small stationary structures and develop them into multi-scale hierarchical patterns. However, CNN's benefits also place restrictions on its capacity to analyze data that can be organized using graphs but is irregular or from non-Euclidean domains. By fusing spectrum theory and convolutional neural networks, graph convolutional neural network (GCNN) extends the capabilities of the conventional convolutional neural network (CNN). The graph convolutional neural network has an advantage over the standard convolutional neural network when it comes to extracting discriminative features from signals in the discrete spatial [13].

3. RESEARCH METHODOLOGY

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 [14]. 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 [15]. 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.

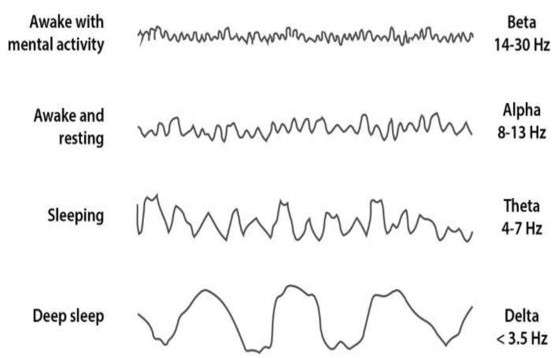

Figure.1 Types of EEG signals

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 [16]. To the contrary, now many researchers are interested in working with EEG signals for emotion recognition [17].

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.

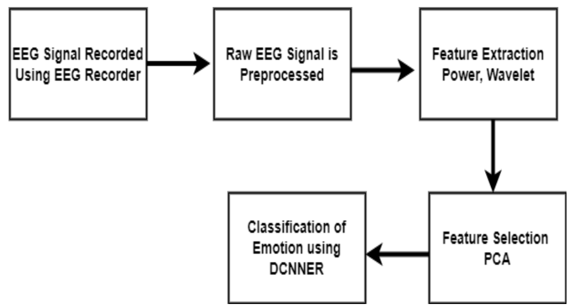

Figure 2: The Proposed Model Architecture (DCNNER).

3.3 Feature Selection - PCA

In this module, dimensionality reduction is done which is achieved by PCA [18]. 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. The channels mentioned represent electrodes positioned on the skull's surface to record EEG signals via an EEG recorder. The data channel, denoted as F=(F1, F2, F3, ..., Fn), can be subjected

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to Principal Component Analysis (PCA). PCA to obtain the output vector N from F.
Mathematically, N = F * Ψ, where Ψ represents the eigenvector of the covariance matrix F. This process helps select the most important features, retaining those with high information content, which are then fed into the classifier [18].

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 [19]. 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 [20].

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.

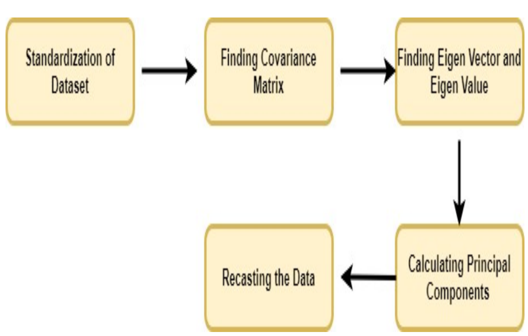

Figure 3: The steps involved in the PCA.

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 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 [21].

The input layer receives input from the previous section which is PCA [22]. The received input is sent to the ReLU convolutional layer, where an activation function is performed to activate the desired functions. The next layer is the maximum pooling layer, which performs a pooling operation using a 2D filter to find out the desired information or features. [23]. In the next layer, a 1-D array of features is created by a process called Flattening. The output of the previous layer is taken as input and a 1-D vector is created. It is also connected to the final classification model, which is referred to as a fully connected layer. A 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 [24]. The complete layout of the DCNNER is explained in Figure.4.We trained the DCNNER model using a dataset that is divided into training data and test data in a ratio of 8:2. Figure 4 shows the different layers included in the proposed model by [25].

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 2539, 16)          176

 conv1d_1 (Conv1D)           (None, 2537, 16)          784

 max_pooling1d (MaxPooling1D  (None, 1268, 16)         0
 )

 flatten (Flatten)           (None, 20288)             0

 dense (Dense)               (None, 100)               2028900

 dense_1 (Dense)             (None, 3)                 303

=================================================================
Total params: 2,030,163
Trainable params: 2,030,163
Non-trainable params: 0
_________________________________________________________________
```

Figure 4: various layers involved in DCNNER model.

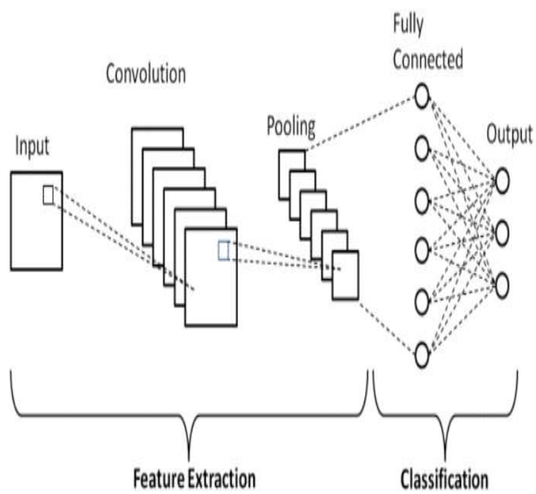

Figure 5: Architecture of DCNNER.

4. RESULTS

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 [26]. 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 of the Model

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

CNNs are a subclass of deep neural networks that are often used for visual analysis of image and time series data. CNNs can identify and categorize specific features from images and signals. Their uses include natural language processing, image classification, medical video and image analysis, time series signals, and image and video recognition.

Categorical cross-entropy is used in this model, which is suitable for multi-class detection. Additionally, the Softmax activation function is used with categorical-cross-entropy because both work well [27]. A parameter can be controlled in a neural network using the Optimizer in deep learning. In this [28] model, the Adam optimizer is added to improve the performance of DCNNER. Figure 5 shows that a comparison is made between the train data and the viewpoint test data. 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 accuracy of the model is described in Figure 6. Both the training data and the test data are used for comparison in the model accuracy graph. The Xaxis is the total number of epochs, while the Y-axis is the accuracy in percent, from 0.0 to 1.0. Accuracy increases with increasing number of epochs [29].

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

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.

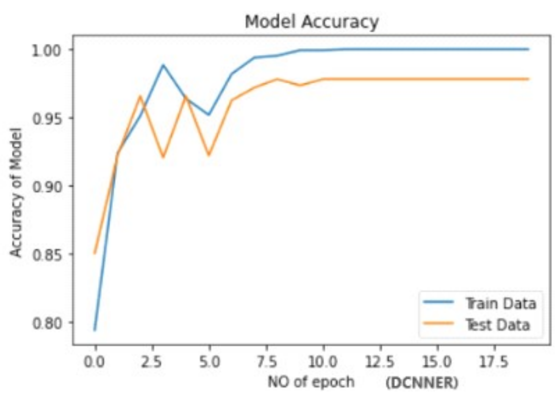

Figure 6:Accuracy of Model-DCNNER

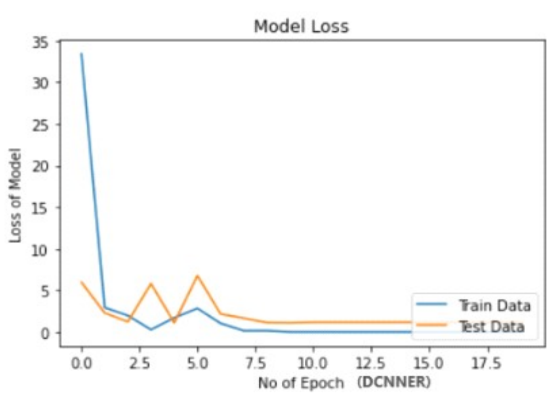

Figure 7:Loss of Model-DCNNER.

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 [30] 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[31].

Table 1: Comparison of Different Classifiers Performance

Classifiers	Validation Loss	Accuracy
RNN [4]	1.45	78.23
LSTM [14]	0.9	81.86
DNN [22]	1.02	75.23
DCNNER (proposed model)	0.3	98.52

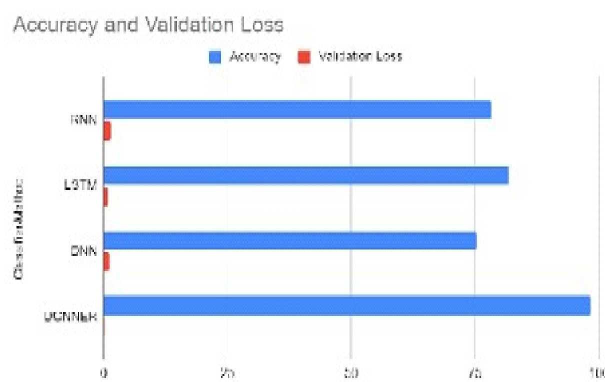

Figure 8:Graphical representation of accuracy and validation loss of the models

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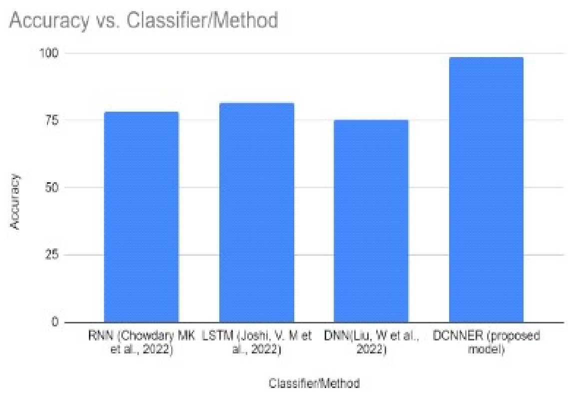

Figure 9: Accuracy of the models.

5. CONCLUSION

In this paper, the designed model (DCNNER) which uses biological signal (EEG) to identify the human emotion. This is achieved by implementing feature extraction, feature selection - PCA method with the real time dataset. Important features are emotions are derived using feature exaction method. 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.The future work can be improved by adding many channels of EEG signal and identifying more accurate results.

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