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Robust EEG-Based Emotion Recognition using CNN: A High-Accuracy Approach with Differential Entropy Features and Spatial-Frequency Domain Analysis on the SEED Dataset

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Abstract

The area of Human Emotion Recognition using EEG signals is rapidly evolving its dimensions at a more excellent pace and with time, it has become an important area of research for affective computing in the field of neuroscience. Neuro-computing has also shown its potential applications in the domain of mental health monitoring, brain-computer interface, and adaptive learning systems. The deep learning models have shown significant progress in producing effective results when implemented in analyzing different EEG signals. In this study, the efficiency of Convolutional Neural Network (CNN) models for emotion categorization is investigated on an EEG-based SEED dataset. Differential Entropy (DE) characteristics derived from five important EEG rhythms—delta, theta, alpha, beta, and gamma—are used as inputs to CNN classifiers. To enhance the performance, the model uses a two-dimensional (2D) tensor representation of the input, which allows the network to learn and use spatial correlations between different EEG channels. Experimental results show that the proposed CNN-based strategy outperforms previous methods with an average accuracy of 94.09 %. These findings highlight the potential of CNNs in developing robust and scalable solutions for EEG-based emotion recognition, providing a path for more intuitive and adaptive systems in future applications.

Keywords: Emotion Recognition; SEED; Differential entropy; Deep learning; CNN.

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1. Introduction

Emotions are part and parcel of human life. They are compounds that help control our bodies and minds, assisting us in overcoming the challenges of interacting with people, making decisions, and navigating life. The modern concept of emotion was first introduced in the English language in the 1830s, but Thomas Brown coined the term "emotion" in the early 1800s. Emotion is a set of feelings, sensations, and perceptions that are associated with a set of thoughts and behaviors. Emotions are inevitable in everyone's day-to-day life. According to Paul Ekman's widely accepted theory of fundamental emotions and how they manifest, there are six basic emotions that humans experience. Sadness, surprise, happiness,

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fear, anger, and disgust are among them [1]. For broad emotional reactions, Robert Plutchik offered a psycho-evolutionary categorization technique. Accordingly, there are eight fundamental emotions: sadness, anger, fear, disgust, anticipation, surprise, joy, and trust [2,3] (Fig. 1). Plutchik considers that these eight basic emotions can give rise to all other emotions. EEG is proving to be a useful tool to study human emotions and cognitive processes from the perspective of its potential capabilities. The domain of affective computing, which tries to comprehend human mental states, is gaining prominence. As a result, the research on EEG signals is highly correlated with emotion. Since speech and facial expressions can be manipulated it poses many difficulties in creating real responses to a specific emotion. Therefore, they are considered ineffective predictors of emotion. It is evident from various studies that humans have no control over the automatically produced EEG signals which leads to creating a trust among the scientists working in this field that EEG signals for emotion detection are more accurate and reliable. After analyzing EEG-based data, it has been observed that it is possible to achieve better classification accuracy for emotion detection even if there are situations that react faster to mood changes. Emotions are omnipresent and they are a necessary part of our lives. A person's actions can significantly affect how they communicate and how they go about their everyday lives. As a result, examining EEG signals for emotion classification is more trustworthy and effective. Although the EEG signal on the scalp has a limited spatial resolution, its high temporal resolution (in milliseconds) allows it to record both gradual and fast changes in brain activity. As a result, both temporal and spatial EEG correlation must be addressed when extracting characteristics associated with particular brain emotion dynamics. Due to the remarkable potential of end-to-end self-learning of complicated high-level feature representation, deep learning technology has made significant strides in identifying tasks in a variety of fields, including bioinformatics, computer vision, natural language processing, and automated speech recognition. Deep learning models have become a popular and effective approach for emotion recognition using EEG signals [4,5]. These models are good at automatically extracting complex features and patterns from raw EEG data, eliminating the need for extensive manual feature engineering. Transfer Learning models can also be used for feature extraction in the classification of Nematodes Species [6].

To classify different emotions, we employ the CNN model on the SEED Dataset, which has a greater accuracy value. The remainder of the study is organized as follows: In Section 2, the associated work is described. The materials and suggested techniques are outlined in Section 3. Results and comparison with the other works are summarised in Section 4. Section 5 provides the conclusion and future scope of the work.

2. Related Study

With the help of different EEG signals, authors have detected four human dispositions such as crying, anger, happy, and sad by using machine learning algorithms. The Hidden Markov Model (HMM) classifier that uses the wavelet transform is employed to measure statistical characteristics based on features like mode, mean, median, skewness, etc., the study is carried out to address the computing complexity and low efficiency of the SVM and KNN classifiers. By applying electrodes to human brain scalps for the disposition description approach, the database collects data from healthy males and girls between the ages of 20 and 25.

Fig. 1. Plutchik's eight basic emotions.

The different EEG signals recorded are contaminated with noise and to produce effective results they are filtered with the help of a low pass and notch filter. Due to the non-stationary behavior of EEG signals, the method adopted for feature extraction is Wavelet Transform which extracts features utilizing frequency as well as time domain technique. The Hidden Markov Model's Manhattan distance matrix approach determines the distinction between the trained and tested signals with an accuracy of 88.50 %, [7] identifies the subject's true disposition. EEG provides useful information for Ambient Assisted Living (AAL) by identifying the mental state of individuals who might need particular care. People who suffer from depression generally have worse physical and mental health than those who do not suffer from this deadly stage of human life. To detect the emotions of a patient, several features have been extracted from the EEG signals using the combination of wavelet energy, wavelet entropy, discrete wavelet transform, and other statistical features. Three distinct classifiers support vector machines, k-nearest neighbor, and quadratic discriminant analysis [8] are employed to create an effective emotion recognition model that achieves an accuracy of 60.78 %, 75.53 %, and 83.87 % respectively. Some researchers proposed a wavelet and scalogram transform-based pre-processing approach for recording multi-channel neurophysiological signals into grid-like frames that depict 2D frame representation. The study is carried out [9] with the primary goal of creating a hybrid deep learning model for emotion categorization using multi-channel EEG signals by combining CNN and RNN. The proposed model also holds the capability of predicting at each time step, which plays an extremely important role in current-time emotion assessment situations. The study used EEG signals from the DEAP dataset to propose two distinct neural models for user emotion classification. The deep neural network has four completely connected layers, with 500 and 1000 nodes after the first neural layer with 5000 neurons. All these layers employed the Rectified Linear unit as an activation function. The last neural layer reduces these 1000 inputs to the final output of two or three classes. In the last layer, Softmax serves as the activation function, and its dropout probability is taken as 0.5. The second model effectively classifies pre-processed EEG data given in 2D format using a 2-dimensional CNN model. The CNN architecture involves 2 convolutional layers, 1 max. Pooling layer and a soft plus layer. Finding the best activation function and optimizer combination to apply for improved outcomes is the primary task in the convolutional neural network model.

Additionally, the study also compared CNN and deep neural networks and found that CNN outperformed by showing better performance. The models [10] show classification accuracy of 81.41% and 73.35 % for two classes and 66.79 % and 57.58 % for three classes while taking into consideration valence and arousal. The deep neural network records the classification accuracy as 75.78 % and 73.12% for two classes and 58.44 % and 55.70 %, respectively, for three classes again in the case of valence and arousal.

Deep learning models are prevalent in the research world and some researchers proposed a model that is developed using a recurrent neural network or long short-term memory which learns its characteristics from raw EEG data and to identify the emotions, the dense layer is utilized for classification. [11] uses the DEAP dataset for validation, has an average accuracy of 87.99 % for liking classes, 85.65 % for arousal, and 85.45 % for valence respectively. It compares the suggested model's output with the other four models that have made use of the DEAP dataset. The overall accuracy produced by the developed model is very promising. In neurology and psychiatry, automated real-time emotion detection based on multi-channel EEG data is becoming an essential computer-aided tool for diagnosing emotion disorders. Yang *et al.* [12] proposed a neural network that is hybrid integrating CNN and RNN to categorize human emotions in a single framework. To extract spatial information from data frames, CNN is applied, and to extract temporal information from an EEG sequence, an RNN is employed. Following the CNN and RNN processing, the spatial and temporal information are fused using a feature fusion approach. For valence and arousal classification tasks, the suggested models produced high accuracy of 90.80 % and 91.03 %, respectively. By applying machine learning and signal processing techniques, authors investigate the feasibility and effectiveness of employing EEG signals for emotion recognition tasks. Using the SVM Classifier, Jha *et al.* [13] showed noteworthy valence accuracy at 76.00 % and significant arousal efficiency at 70.88 %. The use of electroencephalography signals for more reliable and accurate emotion analysis has been the subject of increasing interest in recent years. Aslan and his group [14] examined three distinct data sets, and the brain regions were used to measure how well each dataset performed in emotion recognition. For the DEAP, SEED-V, and GAMEEMO datasets, the corresponding accuracy were 64.01 %, 57.42 %, and 82.83 %. The state-of-the-art in EEG-based emotion recognition is advanced by these contributions, which handle important issues including high dimensionality and variability. With classification accuracy values of 90.04 % for arousal, 89.97 % for valence, 87.73 % for dominance, and 90.84 % for liking, the proposed approach by Henny *et al.* [15] showed remarkable performance in four-category emotion classification.

In this experimental study, the CNN model is used to classify the emotions of 15 participants into neutral, positive, and negative. The computation of CNN classifier is carried out on Google Collaboratory, a cloud-based Jupyter notebook service that requires no setup and offers free access to computing resources, including GPUs. The CNN model is implemented using Python, TensorFlow framework, and the Keras API.

3. Materials and Methodology

3.1. *Dataset and pre-processing*

This paper presents the publicly available EEG Dataset, SEED [16,17] published by Shanghai Jiao Tong University's BCMI Laboratory, and it includes EEG signals collected from 15 people (7 males and 8 females) while watching Chinese films expressing positive, neutral, and negative emotions. Every participant takes part in three distinct recording sessions executed on different days. The participants saw 15 Chinese cinema snippets during each session and each session lasted for about 4 minutes. These clips were carefully chosen to create three different emotional states: positive, neutral, and negative. The signals from an EEG are recorded using a 62-channel system that utilizes an original sampling frequency of 1000 Hz and then down-sampled to 200 Hz for further analysis. The dataset includes pre-processed features including Differential Entropy (DE), which are derived from five different EEG frequency bands. The DE characteristics are arranged in such a manner that the spatial layout of the 62 electrodes remains intact. Due to its 1-second non-overlapping epochs, each trial can be used for in-depth temporal analysis of emotional reactions. The EEG data are broken down into EEG rhythms in the current work using a filter called Butterworth of order 3. Five EEG rhythms are extracted from the SEED dataset's EEG signals called delta (1-4 Hz), theta (4-8 Hz) alpha (8–14 Hz), beta (14–31 Hz), and gamma (31–51 Hz. Each subject has an overall 3394 epochs after segmentation.

3.2. *Proposed methodology*

3.2.1. *Feature extraction*

A metric that measures the complexity or uncertainty of continuous random variables is called Differential Entropy (DE), and it comes from information theory [18]. Because DE extends the idea to continuous domains, as opposed to standard entropy, which pertains to discrete variables, it is especially well-suited for analyzing physiological signals like EEG, which are by nature non-linear and non-stationary. DE is used in EEG-based recognition of emotions to record variations in signal energy within specified frequency bands such as alpha, beta, delta, theta, and gamma. These characteristics provide an accurate depiction of brain activity, allowing for good distinction between emotional states. DE is calculated by calculating the signal's probability density function and incorporating its logarithmic representation in "Eq. (1)" which is defined as:

$$H = -\int_{-\infty}^{\infty} p(x)\log p(x)\,dx \qquad (1)$$

The p(x) denotes the signal's probability density function. DE is a reliable and discriminative characteristic for emotion classification tasks due to its capacity to characterize the complexity and energy distribution of EEG signals. Differential Entropy (DE) is a feature used in this work to categorize different emotional states [19]. DE has proven to be useful in analyzing non-stationary and non-linear signals, including EEG, and it evaluates the complexity of the signal effectively. DE offers a reliable representation for classifying emotions by collecting energy differences between low and high frequencies. Five different EEG rhythms are used to calculate DE features for the SEED dataset. The final feature matrix obtained for each person and session has dimensions of (3394, 62, 5), where 5 stands for the five EEG rhythms, 62 represents EEG channels, and 3394 for the total number of epochs obtained from the 15 trials. Fig. 2 displays the overall methodology for the recommended procedure.

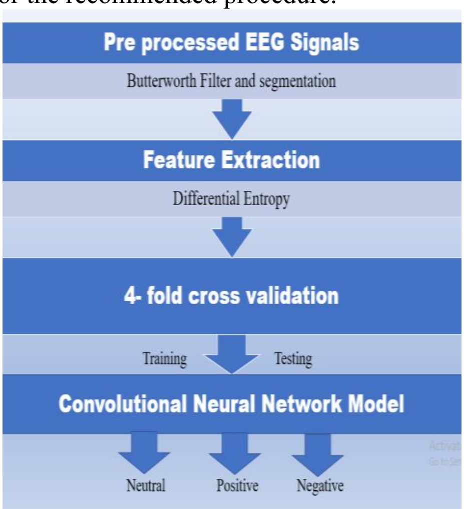

Fig. 2. Proposed methodology.

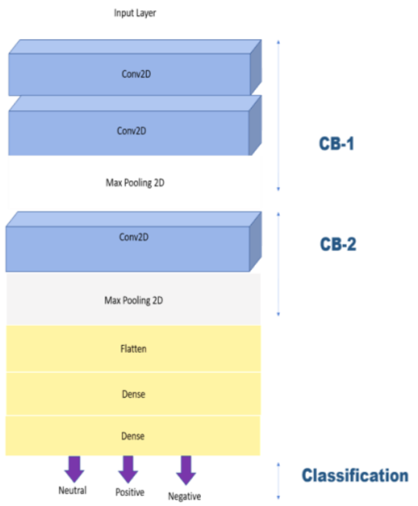

Fig. 3. Proposed CNN architecture.

3.2.2. *Convolution Neural Network model*

In the current era of data analytics, Convolutional Neural Networks (CNNs) are recognized as one of the most effective deep learning architectures for analyzing EEG signals due to their powerful tendency and capacity to automatically identify, extract, and learn spatial and temporal properties out of the complex information. EEG signals, which are non-linear, non-stationary, and have a multi-channel structure, can be represented as spatially organized inputs that reflect electrode layouts or as spectro-temporal properties determined from frequency analysis [20]. CNNs take advantage of this structure by using convolutional layers to capture localized patterns across channels of EEG or frequency bands, pooling layers to reduce dimensionality and improve computational efficiency, and fully connected layers to incorporate high-level features for classification tasks. When used for emotion recognition with EEG, CNNs may successfully capture spatial dependencies between electrodes as well as hierarchical trends within neurons that correspond to various emotional states. CNNs can learn spatial correlations as well as frequency-specific patterns by organizing differential entropy characteristics from numerous EEG frequencies (e.g., delta, theta, alpha, beta, and gamma) in a spatial manner that corresponds to electrode placements. This capacity allows CNNs to manage the complexities of EEG inputs, making them ideal for emotion recognition tasks where subtle and dynamic patterns in brain activity are crucial. CNNs' automatic feature extraction reduces the need for traditional feature engineering, which increases their application in EEG-based research [21]. To represent the spatial layout of the electrodes, the CNN classifier organizes the Differential Entropy (DE) feature matrix in a two-dimensional feature space [22]. The suggested CNN model is divided into two different convolutional blocks, CB-1 and CB-2, each of which is intended to gradually extract relevant features from the input data. CB-1 uses two convolutional layers (CLrs) with 256 filters and a kernel size of 5×5, capturing spatial relationships between input features. Following these convolutional layers, a max-pooling layer reduces spatial dimensions while maintaining important characteristics, hence increasing computing efficiency. To further improve the feature extraction process, CB-2 has a single convolutional layer with 128 filters of size 4×4. Higher-level spatial patterns in the data can be captured by this layer due to its tendency to carry out optimization. The max-pooling layer in CB-2, which is similar to CB-1, down-samples the feature maps while preserving the key representations by employing a stride of 2 and a filter size of 2×2. To use it as an input to a dense layer, the result of the last pooling operation in CB-2 is subsequently flattened into a one-dimensional feature vector. This dense layer, which has 64 units, is in charge of learning intricate feature pairings and producing a brief summary of the features that were retrieved from the data. The architecture's last layer is a classification layer with a softmax activation function that allows multi-class classification by mapping the learned representations to the target classes' probability distribution. The diagrammatical representation of employed CNN architecture is given in Fig. 3.

4. Results

The study uses a 4-fold cross-validation approach to evaluate the model's performance. The average of the four phases is used to get the final classification accuracy. Each subject's performance is evaluated independently. As evident from the literature and continuous execution of our hypermeter tuning to the model, the CNN classifiers fixed to the maximum of 100 training iterations and a batch size of 128 [23] to improve upon the efficiency of the model. The classification model is implemented using the Keras library, and the network is trained using its default learning rate using the Adam optimizer. The Rectified Linear Unit (ReLU) activation function adds nonlinearity to the network by applying it to all layers except the final classification layer. The output layer calculates the probability distribution in the emotion classes using the softmax activation function. Fig. 4 displays the mean training and validation accuracy curves. The training accuracy is recorded higher as compared to the validation accuracy and the curves demonstrate the same leading to no overfitting. Fig. 5 shows the validation accuracy of 4 folds on 100 epochs. Fig. 6 displays the confusion matrix for subject 1 (session 1) and shows how well the model performed across the three emotion classes. The class labels are represented as 0, 1, and 2, corresponding to neutral, positive, and negative emotions, respectively. In particular, 284 samples were accurately identified as positive, 273 samples as negative, and 256 samples as neutral by the CNN model. Table 2 represents the classification result of the CNN Model. The efficiency of the suggested CNN-based method for subject 1 for emotion recognition tasks is demonstrated by the average accuracy of 96 %. This depicts how the proposed model can remain accurate in a variety of emotional states. Table 1 summarizes the comparison of the proposed model with existing work on the same dataset for emotion classification.

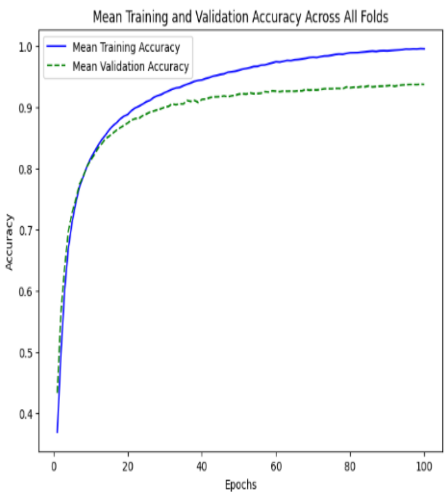

Fig. 4. Mean training and Validation Accuracy.

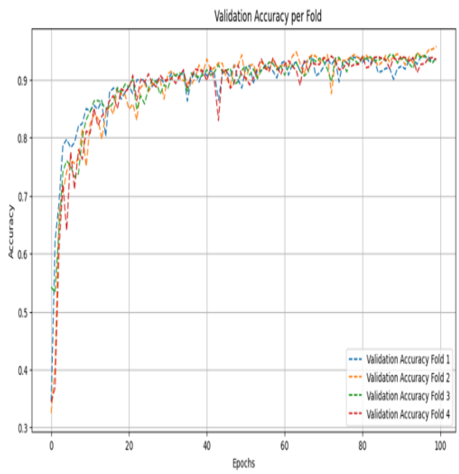

Fig. 5. Validation Accuracy of each fold.

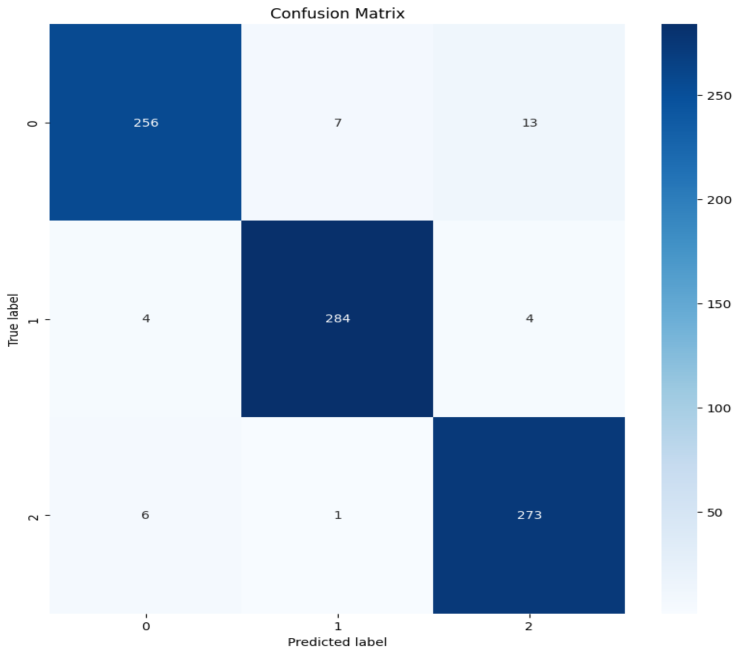

Fig. 6. Confusion matrix.

Table 1. Comparison of the proposed model to classify emotions.

Authors	Method	Accuracy (%)
Fu *et al.* [20]	cGAN	82.14
Asa *et al.* [21]	RFE with SVM	93.10
Joshi *et al.* [22]	LFDE and BiLSTM	80.64
Cheah *et al.* [23]	ResNet	93.42
Shen *et al.* [24]	4D-CRNN	94.74
Sidharth *et al.* [25]	ResNet	93.1
Our Proposed Model	CNN	94.09

Table 2. Classification result of CNN model.

Model	Mean Accuracy	Mean Standard Deviation	Mean F1 Score
CNN	94.09	3.18	0.94

5. Conclusion

This paper evaluates a classification technique using Convolutional Neural Network (CNN) models to analyze a classification strategy and assess how well they perform on the publicly accessible SEED EEG emotion dataset. The classifiers are fed Differential Entropy (DE) characteristics, which are obtained from different EEG rhythms called alpha, beta, delta, theta, and gamma. In comparison to state-of-the-art methods, experimental results show that the CNN-based approach performs better on the SEED dataset when compared to all the existing studies conducted on the said dataset. The efficiency of the suggested CNN-based method for emotion recognition tasks is demonstrated by the average accuracy of 94.09% on the SEED dataset. The CNN classifier improves accuracy by using tensor (2D) input to better learn spatial relationships between EEG channels. In future work we plan to focus on cross-dataset validation, in which the suggested CNN model will be examined using several EEG datasets, such DEAP, DREAMER, or AMIGOS, in order to assess its generalisability across various participants. Additionally, we will also look into hybrid deep learning models that combine CNNs with RNNs, LSTMs, or Transformer architectures to improve feature extraction by efficiently identifying temporal and spatial dependencies in EEG signals. These developments will enhance the reliability, effectiveness, and practicality of EEG-based emotion recognition systems.

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