CNN Brain Label-Maker: Computer Vision Based ICA Rejection EEG based System Architecture

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Abstract

The electroencephalogram (EEG) is a practical and reasonably applied tool for researching brain disorders and behavior changes. EEG offers a minimally restricted and non-invasive method, where the significant difficulties in utilizing EEG in studies on cognitive development are in the temporal resolution, the outbound signal sources, and the EEG Artifacts. Automated IC category classification of ICs can be achieved sufficiently accurately, which expedites the analysis of large-scale EEG research and permits the use of ICA decomposition in near-real-time applications. Thus, this work presents an automated convolution neural network-based brain activity labeling for ICA rejection using the data from the well-used and widely utilized by neurologists and Scientists such as ICLabel MATLAB, EEGLab tools, etc. Replacing the manual task via an atoms system, which makes the proposed system reduces the processing time by $7200\times$ and accuracy of 89.45%. The proposed system was trained, verified, and tested using CCHMC clinical data, using a 128-channel HydroCel electrode net (Magstim EGI, Eugene, OR) and an EGI NetAmp 400 at a $1000Hz$ sampling rate.

Introduction

Electroencephalography (EEG) remains a fundamental tool for studying brain activity, capturing the electrical signals generated by neuronal populations [Khoshnevis and Sankar2019]. Independent Component Analysis (ICA) has proven effective in separating mixed signals into independent components, revealing distinct neural sources. In this paper, we present a novel technique that leverages graphical representations derived from EEG-ICA to label specific brain activities, enhancing the interpretation ability and utility of EEG data, shown in Fig. 1.

EEG monitors the electrical potential between two electrodes on the scalp, with evidence indicating the origin of this electrical signal [Pizzagalli et al.2007]. The EEG signal is context-dependent but spontaneous; the EEG produced during calm rest differs quantitatively from the EEG produced during cognitive functioning. The temporal resolution of the EEG signal is milliseconds. Postsynaptic alterations are instantly reflected in the EEG, which makes this technology exceptional for monitoring sudden changes in brain activity [Lukatch and MacIver1996]. The robustness of electrical signals recorded at the scalp and the ease of use and non-invasive nature of the techniques used to obtain them make them valuable for research with younger people. On the other hand, getting high-quality signals usually takes a lot of training.

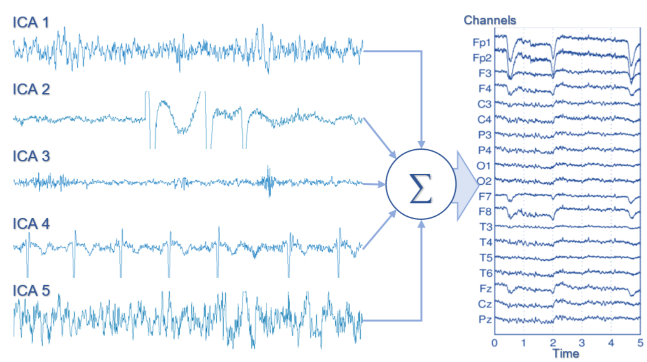

Figure 1: A portion of an EEG recording of ISO (10-20) with (5) dominant ICA Components.

The literature currently has several techniques for removing EEG artifacts, and earlier research has focused chiefly on the manual or automatic identification of one or more different kinds of EEG artifacts. Independent Component Analysis (ICA) based techniques are frequently utilized in conjunction with other suggested ways to identify the artifacts [Naik and Kumar2011] effectively.

To obtain useful information from complicated neural signals and progress both basic and clinical neuroscience research, IC labeling of EEG recordings is essential for better knowledge of how the brain functions. IC labeling of EEG recordings holds significant importance in nonscientific research and clinical applications, especially for source separation, spatial localization, artifact removal, and cognitive function mapping. The mean labor time for a neurologist to perform such a talk using Matlab toolkit (30 ± 10 minutes) the large diversity is due to the nature of the visual analysis process and the human factor.

We proposed a novel automated convolution neural network (CNN) model and tool for brain activity labeling using

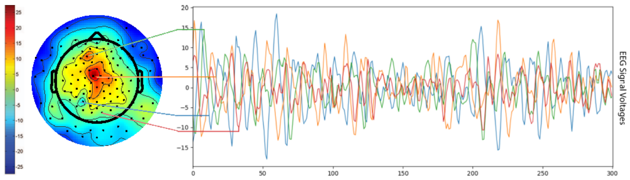

Figure 2: The EGI HydroCel Geodesic Sensor Net 128-Channel Map's layout for the total brain average of EEG biomarkers shows 108 chosen electrodes, with a heatmap showing the EEG nodes.

visual representation output for the most popular and currently applied Matlab tool (such as ICLable) that neurologists and neuron scientists can use to expedite the analyses and save labor time and efforts for medical personnel. The proposed system was trained, tested, and verified using CCHMC Data sets where all EEGs were blinded and coded regarding participant, diagnosis group, and collection date.

EEG Heatmap

Brain activity can be inferred from EEG topographic maps. The utilization of brain mapping allows for the visualization of the brain's interconnection and functionality [Hooi, Nisar, and Voon2015]. The determination of a functionally integrated relationship between geographically dispersed brain regions is aided by brain functional connectivity [Pedapati and Schmitt2023] [Györfi2022] and [Mammone et al.2018]. The detailed components of the topographical representation is shown in Fig. 2

Proposed Architecture Method

The proposed architecture is a novel method of automated rejection of the EEG ICA analysis of the medical personnel, and neurology scientists used to perform manually, and it then takes approximately 30 minutes per patient per recording. The proposed architecture is a system that can be tapped into an established ICA rejection pipeline process without disturbing or altering the clinical setup or the devices involved; the architecture is shown in Fig. 3 The architecture is based on a CNN-based model using the EEG topographic heatmap output report images.

The power spectral density of each segment channel was calculated using the Welsh method, employing a Hamming window. The power within the six frequency bands was calculated as follows: 0.1–4 Hz (delta, δ), 4–8 Hz (theta, θ), 8–14 Hz (alpha, α), 14–30 Hz (beta, β), 30–47 Hz (low gamma, γ_1), and 47–64 Hz (high gamma, γ_2)

The architecture is based on a CNN-based model using the EEG topographic heatmap output report images. The power spectral density of each segment channel was calculated using the Welsh method, employing a Hamming window. The ultimate aim of this study is to reduce the complexity and power consumption of the proposed system for future hardware implementation prospectus. Thus, within the N.N design, we have three activation functions: ReLU, Leaky ReLU, and Binary Step functions.

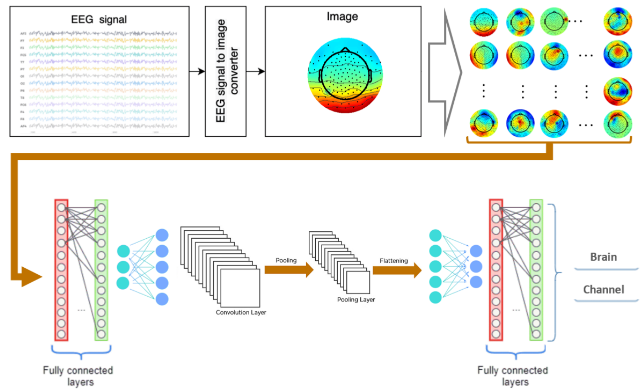

Figure 3: The proposed architecture process diagram

Table 1: Test subjects age statistcal data

Age					
Min	**1st Que**	**Median**	**Mean**	**3rd Que**	**Max**
6.25	11.96	14.58	19.90	25.58	44.58

The clinical trials and data collection was done at Cincinnati Children's Hospital Medical Center (CCHMC); the data was transformed into datasets for training, verifying, and testing the CNN model using a 128-channel HydroCel electrode net (Magstim EGI, Eugene, OR) and an EGI NetAmp 400 at a 1000Hz sampling rate. Resulting in 5000 IC component interface dash images, extracted to heatmap 250×250 images. The clinical data was collected from nine (9) females and fifty (50) males; the age information and the diagnosis of the human subjects are listed in Table 1. The ML model was constructed with four (4) convolution blocks with initial batch normalization ads scaling layers, padded with a flattening and two (2) dense layers at the end. Due to space limitations, we couldn't demonstrate the graphic representation, but it is available for public use on our GitHub page.

Results Discussion

The proposed architecture was implemented and simulated using TensorFlow and Keras libraries on an Intel Core i9 CPU @ 2.40GHz, with NVIDIA GeForce RTX 2080S GPU. The model used 1,066,863 trainable parameters and six non-trainable parameters.

The worst-case scenario for the accuracy of perdition is 82.36%, and the mean accuracy is 89.45%. With an average time of execution, the ICs rejection task saved the neurologist time by $7200\times$.

Conclusion

This research explores the use of ML to classify IC-tagged EEG Images. The proposed method utilizes the spatial sensitivity of CNNs to extract features from intricate neural representations, offering an effective tool for identifying patterns linked to various cognitive states.

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