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Automatic Identification of Brain Independent Components in Electroencephalography Data Collected while Standing in a Virtually Immersive Environment - A Deep Learning-Based Approach

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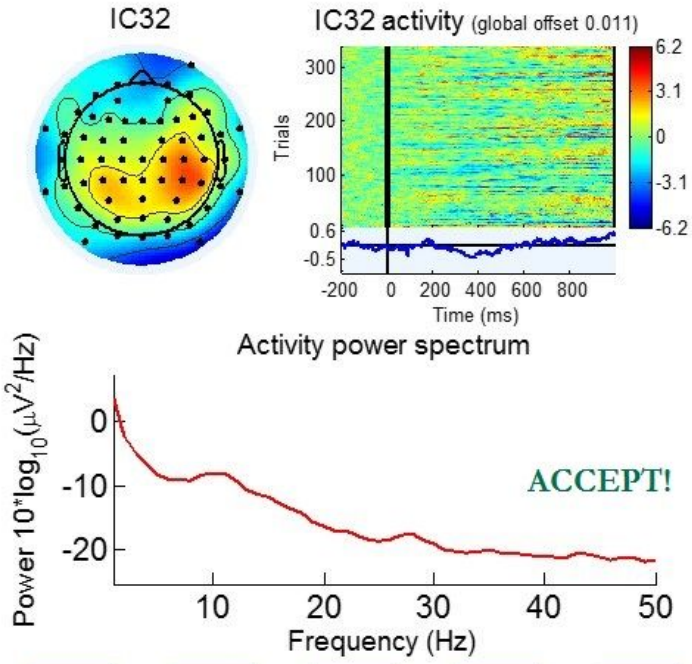
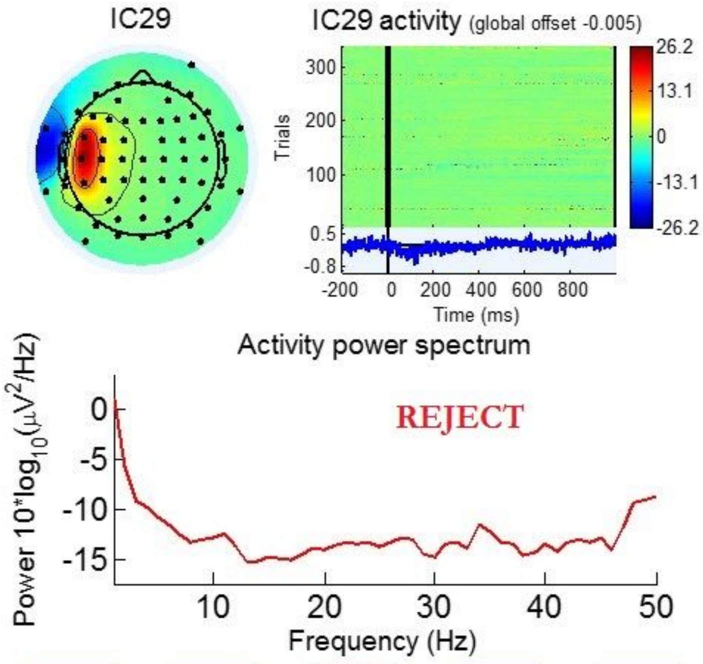
Motivation

- **Real-time brain computer interface (BCI) applications**
  - Electroencephalography (EEG) is used for monitoring brain activity
  - Automating an EEG signal processing pipeline is imperative to the exploration of real-time brain computer interface (BCI) applications
  - EEG analysis demands substantial training and time for removal of distinct unwanted independent components (ICs), generated via independent component analysis, corresponding to artifacts.
- **Procedural way to identify and eliminate signal artifacts**
  - The considerable subject-wise variations across these components motivates defining a procedural way to identify and eliminate these artifacts
  - An automated approach would greatly facilitate IC selection and hence EEG-based research beyond trained individuals

- **Develop human postural control enhancement technologies**
    - An automated independent component (IC) categorization would not only aid speed and consistency but also assist online EEG processing for brain-computer interfaces (BCI) to facilitate neural rehabilitation.
    - Several studies have explored VR and EEG-based setups to provide insights into neural connectivity and adaptation [1]-[4]. VR and EEG-based setups require real-time artifact rejection to develop novel acrophobia therapies and human postural control enhancement technologies.

Artifactual IC rejection





Related works

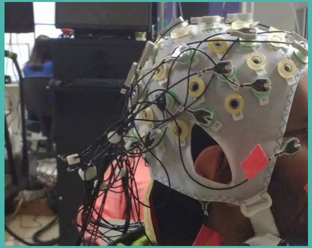
- ICLabel classifier (proposed in [5])
  - It estimates seven IC categories using DL with near-real-time classification of online-decomposed EEG data
- However, there is a need to continue exploring the application of machine learning to automate IC classification of EEG data from noisy, visually stimulating and more real-world scenarios for future BCI applications

DeepIC-virtual

- We propose **DeepIC-virtual**, a CNN **deep** learning classifier to automatically identify brain components in the **IC**s extracted from the subject's EEG data gathered while they are being immersed in a **virtual** environment.
- We examine the feasibility of DL techniques to provide automated IC classification on a noisy upright stance EEG data.
- Ground truth labelling of generated ICs by a trained specialist was done by looking at all the four components of the IC representation diagram whereas a CNN discriminates brain components from artifacts only by learning on one of the components, i.e. the scalp topographical map.

Experimental Setup

- Brainvision 64 Channel ActiCHamp EEG System



- EEG signal recording software

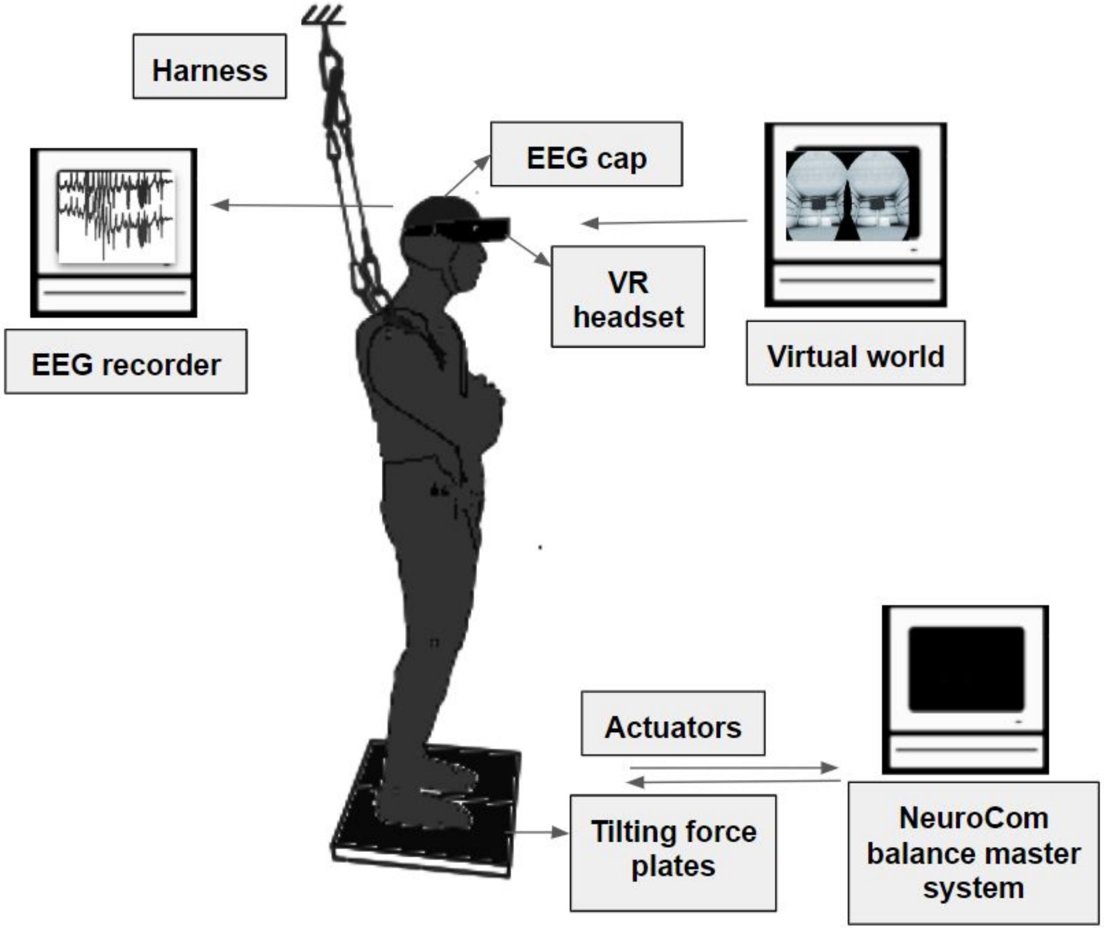
- HTC Vive virtual reality headset
- Force plate
- Python

Experimental Setup

- The protocols for this study were approved under the Institutional Review Board number 17010.
- **Data collection design:** a HTC Vive VR headset, a NeuroCom SMART Equitest Clinical Research System, a Brainvision 64-channel EEG head cap and a safety harness
- **VR assessment system:** Real-time EEG data recording setup [1], while a subject stands quietly to height and depth alterations and induced perturbations.
- Administrated pseudo-randomized virtual surroundings with varying height settings and induced 10-degree toe-down perturbations while recording the subject's EEG signals in a secure setting.

EEG data collection setup:

The training and testing data for this study was accumulated from a designed system with real-time EEG recording setup while a subject stands quietly to pseudo-randomized height and depth alterations and induced perturbations



Study participants

- 5 healthy young adults aged 20.4 $\pm$ 0.80 years (2 females) and 1 male healthy older adult aged 79 years from the local community.
- **Four trials**, individually lasting for **240 seconds** with eight pseudo-randomly ordered height settings (ground level, 2.5, 5, or 7.5 meters in height and in depth) in the virtual world during each trial.
- During two of the trials, **10-degree toe-down perturbations** were induced at all height levels.
- Subjects were instructed to **stand still** on the NeuroCom force plate while wearing the HTC Vive headset during the entire session.

Data Analysis

- IC data generation
- Types of ICs
- IC classification

IC data generation

- Real-time EEG data from scalp electrodes were **recorded at a 1000 Hz sampling rate**.
- The EEG signals, time-synched to the experiment in VR, were epoched into 1 second segments and processed via a **band pass finite impulse response (FIR) filter** to refine any noises.
- The filtered EEG, denoted by X, is a linear mix of source signals from 64 head cap electrodes, hence **ICA** is performed to determine weights matrix W and **statistically independent components** (ICs) I.
- The separating weights matrix W is computed such that the **statistical independence between the components of I = WX is maximized**, over all invertible matrices W.

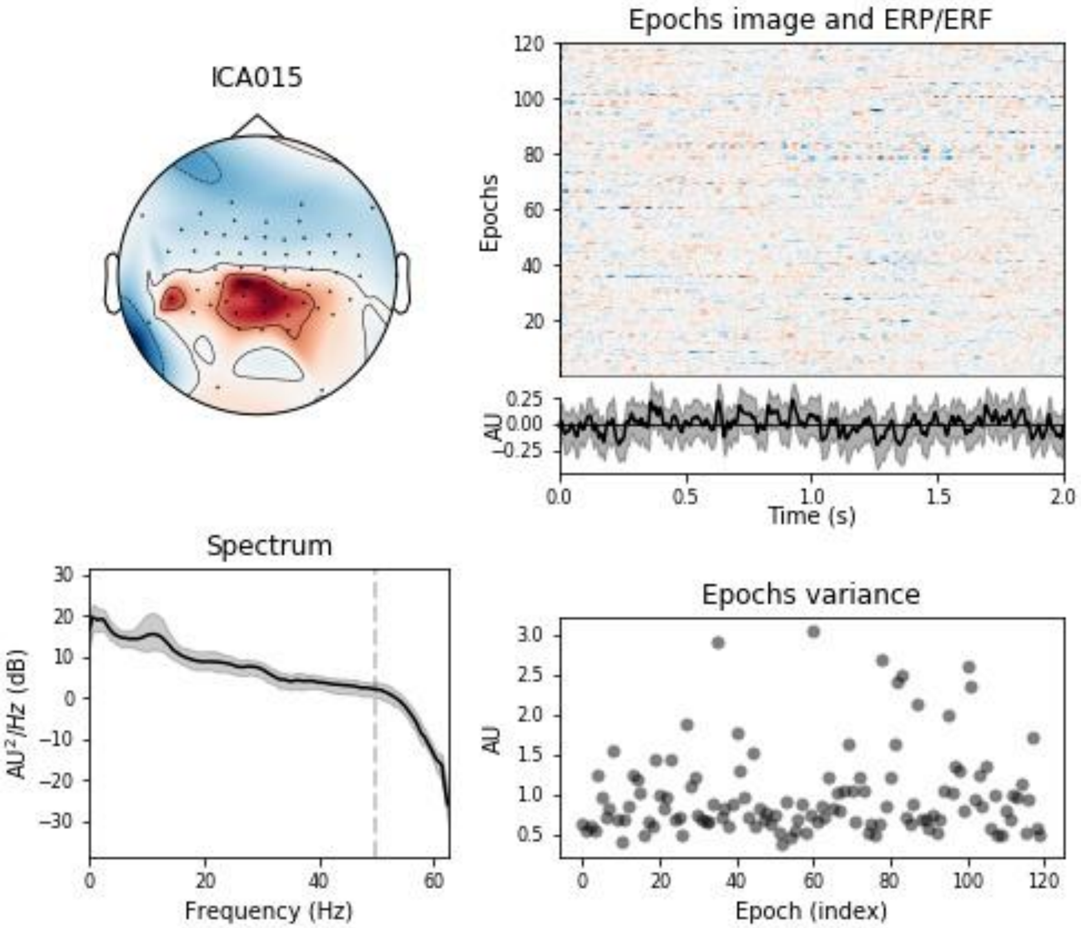
IC representation diagram

- A IC representation diagram comprising of the following was used by the specialists.
  - a **scalp topographical map** depicting positive (red), negative (blue) and null (white) weights of the IC on 64 channels indicated by black dots
  - a **power spectral density (PSD)** diagram representing the power distribution of the IC's activity
  - an **event-related potential** (ERP)
  - a **time series** illustrating a section of the IC's activity
- ICs can be categorized as *good* acceptable ICs sourcing from the brain and *bad* removable ICs (further classified into 6 subtypes) that are vital to eliminate prior to performing further analysis on EEG [5].

Brain ICs

- **Brain components** emerging from the cerebral mantle are identified as spatially coherent signals with broad and connected activation from numerous scalp electrodes.
- Their PSD usually include an increase in the 8-12 Hz frequency range.

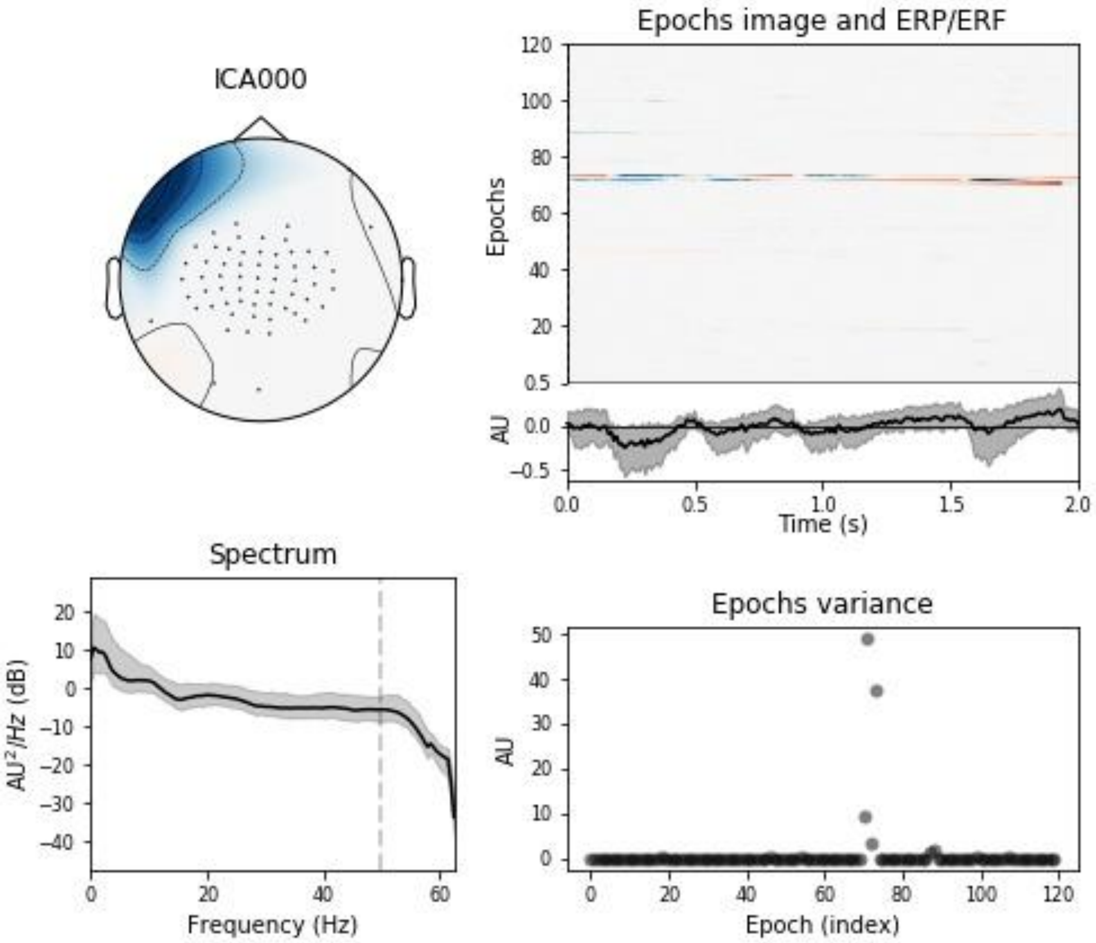
An accepted IC:
The heat map demonstrates coherent signals from multiple channels with red, blue and white colors depicting positive, negative and null weights respectively.



Artifactual ICs

- The artifactual ICs can be subdivided as
  - **muscle components** originated by motion of the muscles with a substantial proportion of activity in a solitary region,
  - **eye components** depicting blinks, vertical or horizontal eye movements,
  - **cardiac components** denoting the activity of the heart,
  - **channel noise** originated via damaged or disconnected scalp electrodes with strong magnitude on only one channel,
  - **line noise** as ambient electric fields generally produced by the external sources,
  - **other artifacts** as unacceptable ICs that do not constrain to the defined subtypes.
  - We define **hard to decide** class for ICs which were intricate and difficult for the specialist to assign to any one of the above mentioned categories.

A rejected muscle artifact IC: Restricted contribution in the scalp heatmap diagram can be observed.



IC distribution in our data

- 1637 labelled ICs with 285 brain, 149 muscle, 83 eye, no cardiac, no channel noise, 146 line noise, 769 other artifacts and 205 hard to decide components
- After eliminating the 205 ambiguous ICs, we retained **285 and 1147 ICs classified as *good* and *bad* components** respectively with an imbalance ratio of 1:4.
- We identified components that are acceptable for EEG analysis (*good* brain ICs) from those which are not (*bad* artifactual ICs).

Deep learning-based approach

- Given the nuances in the ICs, significant training is required for researchers to carry out visual inspection and classification.
- Advanced DL-based investigations may be an appropriate approach for automating the IC classification task.
- IC ground truth labelling by a trained specialist was done by looking at all the four components of the representation diagram whereas a CNN discriminates brain components from artifacts only by learning on the scalp topographical maps without considering the other three components.

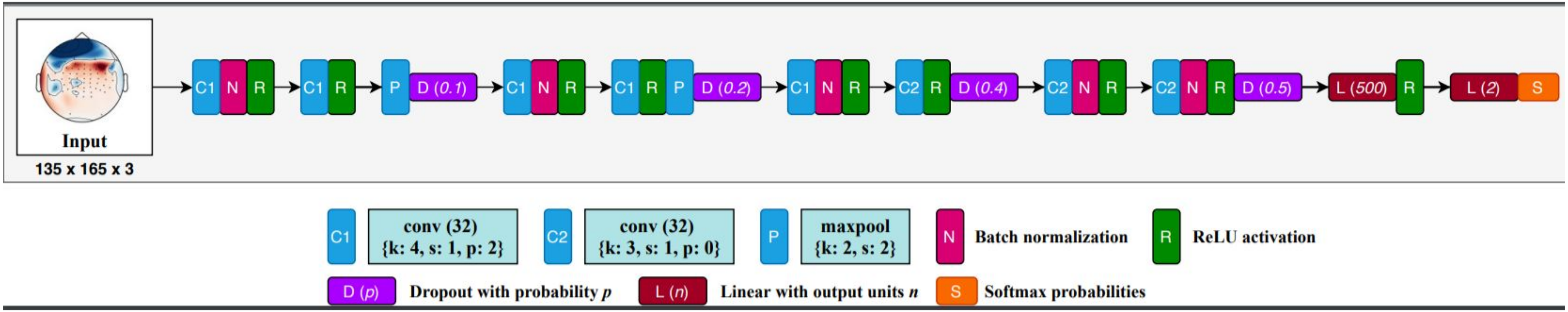
IC classification

- **1432 scalp images** were colored and 135x165 pixels in size
- **Randomly stratified samples** into 80% of data for training and 20% for testing
- 1145 topographical maps in the **training set**, with 228 *good* and 917 *bad* ICs (112 muscle, 70 eye, 118 line noise and 617 other artifacts)
- 287 maps in the **test set**, with 57 *good* and 230 *bad* ICs (37 muscle, 13 eye, 28 line noise and 152 other artifacts)
- A **supervised CNN** architecture was utilized to categorize *good* brain ICs and *bad* artifactual ICs

CNN architecture

- **8 convolutional layers** with ReLU activation, batch normalization, dropout, max polling
- **2 fully connected layers** with ReLU non-linearity.
- Network was trained using the root mean square propagation (**RMSProp**) optimization scheme and the cross entropy loss function.
- **Xavier initialization** assigned initial weights from a Gaussian distribution.
- **Class weights** were assigned to loss function restraining the network from always selecting the majority class to boost accuracy.
- The classifier network was trained for **100 epochs** with a mini batch size of 16 and with an adaptive learning rate initially set to 0.001.
- Prediction efficiency for the classifier was weighed via the test set **confusion matrix, accuracy, F1 score and area under curve (AUC)**.

CNN architecture



Results

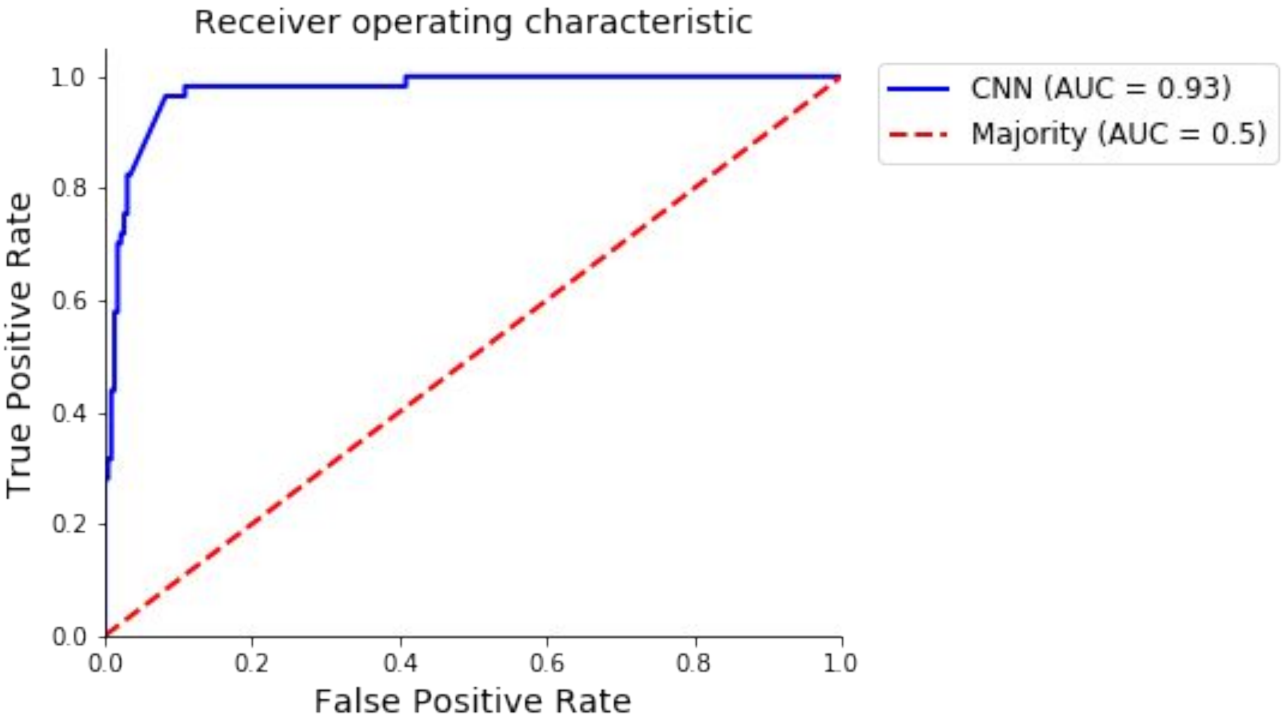
- Test set binary classification accuracy of 89.20%
- F1-score of 0.783
- AUC of 0.926
- Only 1 out of the 57 brain ICs was miss-classified as an artifact.

- Confusion matrix
- ROC of AUC

Confusion matrix

		Actual	
		good	***bad***
Predicted	***good***	True positive = 56	False positive = 30
	bad	False negative = 1	True negative = 200

Receiver operating characteristic



Conclusions

- Attained an accuracy and AUC of 89.20% and 0.93 respectively categorizing *good* versus *bad* IC topographical maps.
- Most of the brain ICs are known to be topologically coherent structures with connected broad cortical activities.
    - Thus, scalp topographical information may provide sufficient data for accurate automatic and objective IC classification.
    - These motivate further exploration on how spatial topology plays a role in such a classification task.
- Given the variability in artifactual ICs, these results will encourage clinicians to automate and study BCI methods to explore neural responses while in a visually immersive task.

- Entire data for this study was manually classified by a researcher depicting the challenge of time and training inherent in such investigations.
- With the creation of DeepIC-virtual, we hope to lower the entry bar in terms of both knowledge and equipment while performing EEG and BCI explorations.

Future works

- Verification of the examined test setups for a larger and more diverse cohort involving subjects with motion-related disorders and over multiple experiments.
- Use supervised transfer learning and multi-class classification methods to explore the efficiency of accurately discriminating the sub groups of bad ICs.
- Examining the role of spatial proximity and connectivity of EEG electrodes in the IC categorization task.
- Investigating the addition of attention or weights to the network architecture.

Acknowledgements

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The William A. Chittenden

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