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Variable Channel Configuration Supporting Model for the Diagnosis of Schizophrenia

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Abstract

When trying to classify schizophrenia using electroencephalography (EEG) data and a machine learning model, online datasets, research labs, and hospitals all use different EEG channel configurations and have different datasets. This strongly limits the interoperability between datasets and different institutions, preventing optimal training and classification. The purpose of this study was to figure out a way to be able to diagnose schizophrenia while maintaining compatibility with data sets with various channel configurations. A random zeroing of channels per epoch was used to make the model adaptable to different channel configurations. This model showed a relatively high level of accuracy from zero percent of the channels being zeroed out up to ninety percent of the channels being zeroed out. Therefore, it can be concluded that there is a high potential in the future for labs and datasets with different EEG configurations to eventually be able to share and use data, as shown by the relatively consistent accuracy, meaning more accurate and better classification.

Keywords: Artificial Intelligence, Schizophrenia, Machine Learning, Diagnosis

1. Introduction

Schizophrenia is a chronic brain disorder that affects around 21 million people worldwide [1]. It causes psychosis and a decline in functioning [2]. It affects around 1% of people worldwide [3].

Patients with schizophrenia have positive symptoms (like delusions or hallucinations), negative symptoms (like social withdrawal), and cognitive symptoms (like difficulty in paying attention or verbal learning) [1]. Higher rates of other medical and mental illnesses, like drug usage disorders, with rates up to 41%, also show up in patients with schizophrenia [1]. The intensity and appearance of psychotic symptoms are modified by stressors like urbanization, social standing, and childhood trauma [3]. Patients with schizophrenia are more likely to have metabolic syndromes because of their disordered lifestyle, unhealthy diets, lack of exercise, and higher rates of smoking [1]. In patients with schizophrenia, increased rates of mortality manifest, usually due to suicide, injury, poisoning, metabolic syndromes, diabetes, and cancer [1]. However, treatment with an antipsychotic drug decreases the risk of mortality [1]. Therefore, diagnosing patients in a timely manner and medically intervening may drastically decrease the mortality rate, highlighting the need for a fast method to diagnose schizophrenia.

The medical diagnosis of schizophrenia requires the presence of two or more symptoms; one of those symptoms must be positive [2]. Positive symptoms (symptoms that indicate exaggerated ideas, viewpoints, or actions) include delusions, disorganized speech, hallucinations, and abnormal movements [2]. Negative symptoms (symptoms that indicate a lack of normal mental functions) include social withdrawal, apathy, lack of emotions, and lack of emotional expression [2]. As per the DSM-5 (Diagnostic

and Statistical Manual of Mental Disorders, 5th Edition), to be able to diagnose schizophrenia for a patient, said patient needs to show symptoms that cause a decline in both social and occupational functioning for at least six months [2].

However, there is still ongoing research on how best to classify schizophrenia and find its etiology, as current methods haven't been found to be fully satisfactory [1]. Some theories propose that schizophrenia may develop from genetic abnormalities or susceptibilities that interact with abnormal neurodevelopment in a fetus; these abnormalities cause the brain to show pre-psychotic features in pre-puberty or pubescent patients [1]. In addition, large-scale genome-wide association studies (GWAS) have advanced, which have brought knowledge to the genetic origins of schizophrenia; the genetic origin of schizophrenia involves the interaction of certain genes and certain environmental factors [3]. However, non-genetic factors can also play a role in the development of schizophrenia, including immigration status, childhood abuse or neglect, or pregnancy complications [1]. In addition, alterations in select brain regions or neuroplasticity could also be included in the classification of schizophrenia [1]. Using neuroimaging, structural and functional changes in brain regions that are related to schizophrenia have been discovered [3]. Although there has already been research into this topic, there is a high need for more accurate characterization, diagnosis, and treatment of patients affected by schizophrenia, that is more personalized [1]. One way in which people have set out to improve the diagnosis of patients is by using artificial intelligence. Some artificial intelligence and machine learning models have been developed to predict schizophrenia onset, its course, and its needed therapy [1]. Artificial intelligence has also shown its benefits in the early diagnosis of high-risk populations, can create personalized treatment plans, can develop prognostic plans, and predict the rate of disease progression [4]. In addition, the World Health Organization states that artificial intelligence can lead to enhanced diagnostics, personalized medicine, disease prevention, improved patient care, drug development, and medical imaging [5]. They can also identify factors that usually tend to be characteristics of schizophrenia, using tools like EEG (electroencephalography) features, and magnetic resonance imaging [1]. Thus, artificial intelligence has the potential to revolutionize the fields of schizophrenia treatment, research, and diagnosis.

EEG procedures vary between labs and different hospitals in terms of the number of EEG channels and their placements, so one model trained in one hospital may not work effectively in a different hospital or lab. There is a wide variation of EEG-based schizophrenia diagnosis models online, but none of them can train off of and diagnose multiple EEG channel configuration variations. Current models include RF (Radio Frequency) Classifiers, SVMs (Support Vector Machines), KNNs (K-Nearest Neighbors), BTs (Bradley-Terry Model), DTs (Decision Tree Model), PNNs (Probabilistic Neural Network), LDAs (Latent Discriminant Analysis), F-LSSVMs (Functional Least Squares Support Vector Machine), ANFISs (Adaptive Neuro-Fussy Inference System), LR (Logistic Regression) classifiers, BH (Bayesian Hierarchical), CNNs (Convolutional Neural Networks), and MLPs (Multi-Layer Perceptron) [6]. SVMs, decision trees, random forests, and statistical methods are traditional machine learning models and use a limited number of features, meaning they could be limited [7]. There have been advancements, like DNNs, deep neural networks, that allow models to work directly on high dimensional raw data and figure out how to extract the best data themselves [7]. However, DNNs struggle when faced with diverse datasets with different channel configurations [7]. These models also use multiple preprocessing methods, including FFT (Fast Fourier Transform), ICA (Independent Component Analysis), wavelet transformation, and bandpass filters [6]. These models aren't optimized to work on variable dimensionality EEG datasets, which means that they cannot train off of multiple datasets, and their usage is limited to hospitals and labs

with the same EEG channel configuration. The current limitation of machine learning models is the ability to apply the models to patients in the hospital, where EEG electrode placement and recording are not standardized. Thus, the purpose of this study was to set out to try to find a method to support variable channel configurations, in this case, using channel zeroing while training.

The prediction of this study was that the accuracy would severely drop when only four channels or less were given. The result was that when the model was given only two channels, it classified the disease relatively accurately; the accuracy stayed relatively steady until only 2 or less channels were given. Therefore, the claims that a small number of common factors (channels) are strictly necessary to classify schizophrenia and that a variable channel machine learning model is possible are supported. This suggests that there is potential for the data of different labs and datasets with different channel configurations to work together.

2. Methods

2.1. Datasets

One of the datasets used to train this model was the RepOD EEG dataset [8]. It contains the EEG data of 28 individuals, 14 healthy and 14 patients with paranoid schizophrenia, each patient's EEG recording stored in a separate file [8]. For healthy controls and patients with paranoid schizophrenia, there is an equal split of seven women and seven men [8]. Each session was 15 minutes, with the patients in a resting state with their eyes closed, at a sampling of 250 Hz using the 10-20 system [8]. There were 19 electrodes, at Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2, and FCz as a comparison electrode [8].

Another dataset used to train this model was the EEG of Healthy Adolescents and Adolescents with Symptoms of Schizophrenia from the Laboratory of Neurophysiology and Neuro-Computer Interfaces at Moscow State University [9]. It contains the EEG data of 39 healthy subjects and 45 subjects with symptoms of schizophrenia [9]. Each session was a minute long, recorded at 128 Hz [9]. There were 16 electrodes at F7, F3, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2 [9]. A custom-made file was used to convert the EEA format files to EDF files compatible with the data processor.

2.2. EEG Preprocessing

The preprocessing was based on the Classification Of Schizophrenia EEG Dataset Using Deep Learning Dataset [10] but was modified. The preprocessing loads the EEG data from the EDF files, classifying them as healthy or schizophrenic based on the file label. Both of the files are resampled to the 128 Hz sampling frequency for consistency in the data. Then, the model uses a bandpass filter to filter out frequencies below 0.5 and above 50 Hz. The channels that are specified within the code are then selected by the preprocessor. After this, the data is split into ten-second chunks of EEG data with labels, with zero meaning healthy and one meaning schizophrenic. The preprocessor then saves the healthy and schizophrenic data in two separate files, Raw_Healthy.pkl and Raw_Schizophrenia.pkl, which are used by the model. Data segments were then randomly shuffled into training and testing datasets, using a 70:30 split, without patient-level separation. When the dropout model runs, it applies z-score normalization per channel; the non-dropout model uses min-max scaling.

2.3. CNN Architecture

The model used is a CNN model, based on the Classification Of Schizophrenia EEG Dataset Using Deep Learning Dataset [10] but modified. To allow the model to adapt to varying EEG channel configurations, the input data is put through a custom ChannelDropout layer that zeroes out a specified percent of

channels; this layer is not present in the non-dropout model. Next, a Convolutional 2D layer with 10 filters with a kernel size of (1, 50) and ReLU activation is given its output. Then, the output of the Convolutional 2D layer is passed through a MaxPooling2D layer with a pool size of (1, 2). Two convolutional layers are then added, one with 16 filters and a kernel size of (1, 30) and another with a kernel size of (2, 1) and 16 filters. Another MaxPooling2D layer is utilized, with a pool size of (1, 4). The output is then flattened into 1D and passed through a dense layer with 20 units and a ReLU activation, and a dropout layer with a rate of 0.5 to prevent overfitting. The output layer is a single dense layer with a sigmoid activation function for binary classification. The resulting model is compiled with the Adam optimizer and trained for 30 epochs. The random state is set to 42.

2.4. Training Methodology

In order to make the dropout model independent of the number of channels and to allow for variable EEG channel input, it was attempted to build a model that trained off of a dataset that randomly zeroed out a varying percentage of channels during training. This model was then tested on data with varying levels of channel zeroing. Models were trained on the same training dataset but with dropouts from 0.0, meaning that per epoch, 0% of the channels would be randomly zeroed out during training, to 1.0, meaning that 100% of the channels per epoch would be randomly zeroed out during training; this was done in intervals of 0.1 or 10%. Then, they were tested on the same testing dataset, but from 0% of the dataset zeroed out to 100% of the dataset zeroed out, in intervals of 10%.

2.5. Hardware Configuration

This model was trained on a computer using Python 3.12.10. The packages used were Numpy 1.26.4, Sklearn 1.6.1, Tensorflow 2.20.0 without CUDA support, and MNE 1.9.0. It was trained on a Dell XPS 15 running Windows 11 Home Version 25H2 Build 26100.7171 with an Intel Core i7-12700H, 16 Gigabytes of DDR5 RAM, a one-terabyte SSD, and a NVIDIA GeForce RTX 3050 Ti Laptop GPU.

3. Results

3.1. Non-Dropout CNN Model

The model was trained and evaluated, without any internal zeroing, on two separate EEG datasets: a Rep OD dataset and a dataset from the Laboratory for Neurophysiology and Neuro-Computer Interfaces from Moscow State University. When it was trained and tested utilizing 5 evenly split k-folds on the RepOD dataset, it had a mean validation accuracy of 76.89% with a standard deviation of 22.00% [Figure 1]. It had a mean loss of 0.3981 with a standard deviation of 0.2686 [Figure 2]. On the Laboratory for Neurophysiology and Neuro-Computer Interfaces dataset, it had a mean validation accuracy of 58.32% with a standard deviation of 7.31% [Figure 1]. The mean loss was 0.7347 with a standard deviation of 0.0715 [Figure 2].

3.2. Dropout CNN Model

The model trained off of the 90% dropout dataset had the best accuracy. Respectively, its accuracies from 0% dropout to 100% dropout in testing data, in increments of 10% were 82%, 82%, 81%, 82%, 81%, 81%, 81%, 81%, 78%, 76%, 76%, and 54% [Figure 3]. At 90% dropout in the test data, meaning 2 channels being shown to the model, it had an accuracy of 76.9%, the highest accuracy out of all the models [Figure 3]. Accuracy remained relatively high when only around two channels remained, suggesting that two channels could be sufficient to classify schizophrenia and not act as a bottleneck. It also had the highest accuracy overall, staying in the 80s for most of the testing datasets, relative to other models [Figure 3]. All of the models trained with a 40% dropout or above, except the 60% dropout and the 100% dropout,

had accuracies above 70% when not all channels were zeroed out, supporting the claim that a variable channel model with consistent performance across channel configurations is possible [Figure 3]. As expected, all models dropped to either 45% or 54% accuracy when there was 100% dropout in the testing data [Figure 3]. In addition, the model trained on 100% dropout stayed relatively consistent at around 54% throughout the entire training set [Figure 3]. Therefore, it is possible to create a model that performs consistently accurately with different channel configurations.

4. Conclusions and Discussions

The non-ChannelDropout model's results were very inconsistent. When it was training, for some of the folds, it would plateau at around 50 percent. With the larger RepOD dataset, it achieved a relatively high accuracy of around 77% with a very high standard deviation of 22%. When trained off a train-test split of 70-30% without k-fold, it achieved an accuracy of around 81.5%. This is likely due to a not large enough dataset being split between five folds.

The dropout model's results support the claim that a model can be created that can have relatively consistent accuracy across channel configurations and different channel numbers, as long as the amount of channels given is above a certain threshold. This is because the accuracy stayed relatively consistent, unless there was a 100% dropout, between different EEG channel dropout configurations.

There were some limitations to this experiment that would limit its generalizability and accuracy. Firstly, no train-test patient split was applied to the training and testing datasets, so some of the same patient's data could have been in both the train and test splits, potentially leading to data leakage and possibly inflated accuracy. In addition, Gaussian noise wasn't applied, meaning that the model created may not be as generalizable or robust as it could be. In addition, only two datasets, with slightly different channel configurations and both from Eastern Europe, were used, even further limiting the generalizability of this model, as the data is only from one geographical region of the world from people of similar ethnicities. Adding on, more rigorous statistical analysis methods for testing the accuracy could have been used for the dropout model.

This finding has the potential to increase coordination between labs, hospitals, and databases for EEG and schizophrenia significantly, because hospitals, labs, and databases with different EEG setups are able to use datasets from other places with different EEG channel configurations for their own purposes.

Some scientific questions left to be posed are which model architectures work best with variable length EEG data and if the accuracy of the model changes as more and more datasets from different regions of the world with potentially different EEG patterns are added. Future studies could address these questions and address the shortfalls listed above, like implementing k-fold and train-test patient separation. In order to make it actually applicable to patients, train-test patient splitting is especially needed.

5. Figures and Tables

Figure 1: Mean Validation Accuracy for the Non-Dropout CNN Models Trained and Tested on Different Datasets Graph

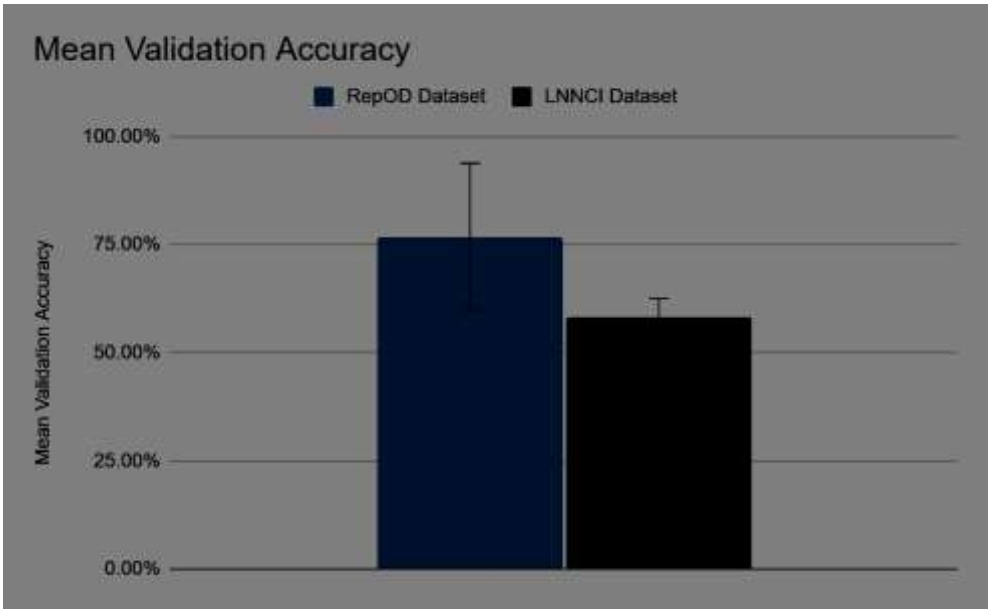


Figure 2: Mean Loss for the Non-Dropout CNN Models Trained and Tested on Different Datasets Graph

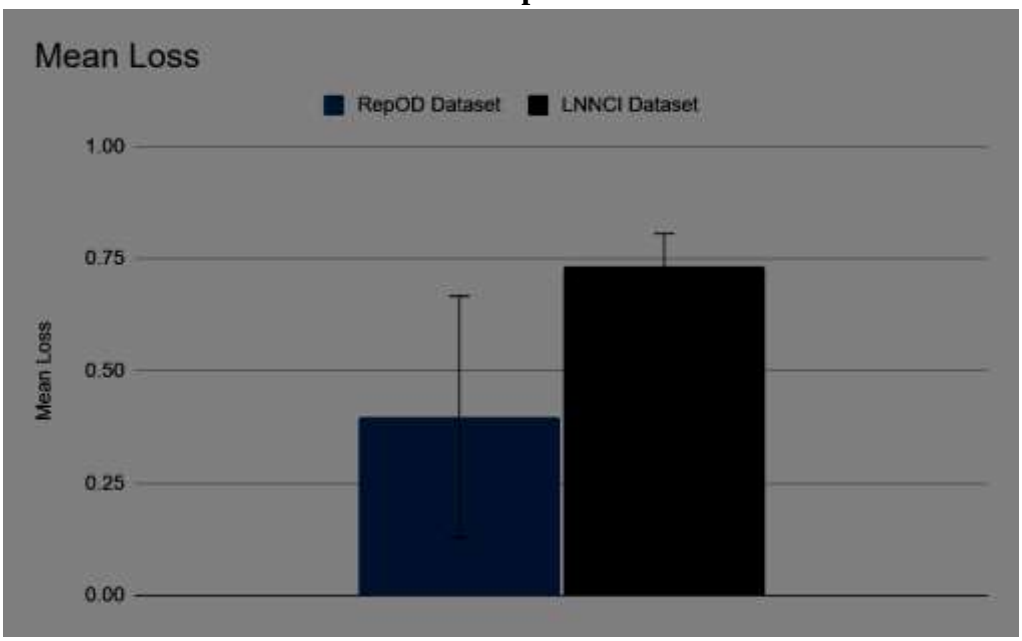
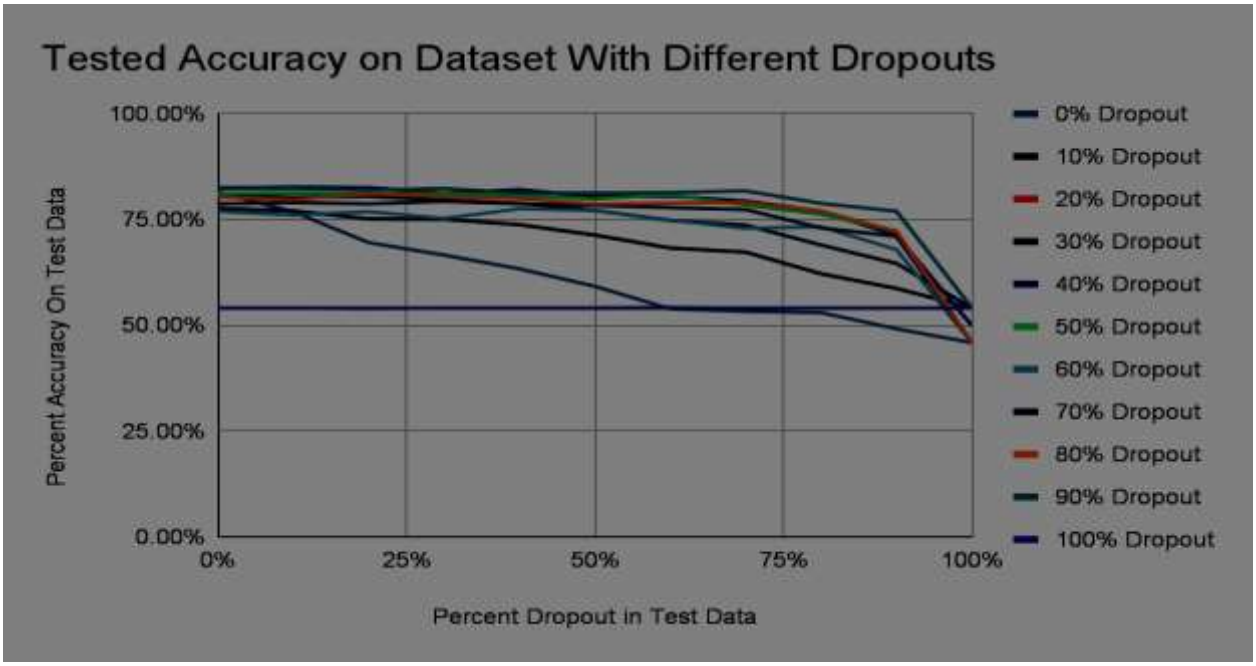


Figure 3: Different Models Trained on Different Dropouts' Accuracy on Different Dropout Test Datasets Table

Percent Dropout in Test Data	0% Dropout Model	10% Dropout Model	20% Dropout Model	30% Dropout Model	40% Dropout Model	50% Dropout Model	60% Dropout Model	70% Dropout Model	80% Dropout Model	90% Dropout Model	100% Dropout Model
0%	81.49%	77.64%	54.09%	80.99%	82.46%	81.08%	76.95%	78.72%	80.3%	82.27%	54.09%
10%	76.85%	77.04%	54.09%	80.20%	82.66%	81.28%	76.06%	79.01%	79.7%	82.36%	54.09%
20%	69.56%	75.17%	54.09%	80.49%	82.56%	80.99%	76.85%	78.72%	81.08%	81.97%	53.99%
30%	66.60%	75.07%	54.09%	79.61%	81.18%	81.18%	75.27%	79.31%	80.49%	82.36%	54.09%
40%	63.35%	73.79%	54.09%	78.82%	82.07%	80.69%	77.54%	78.72%	80%	81.28%	54.09%
50%	59.21%	71.33%	54.09%	77.14%	80.39%	79.90%	77.14%	78.33%	78.62%	81.28%	54.09%
60%	53.89%	68.28%	54.09%	74.78%	80.59%	80.89%	74.88%	77.83%	78.92%	81.38%	54.19%
70%	53.30%	67.29%	54.09%	73.69%	79.31%	78.42%	72.91%	77.34%	79.01%	81.77%	53.99%
80%	53.00%	62.17%	54.09%	68.97%	76.95%	76.26%	73.30%	73%	77.04%	78.82%	54.09%
90%	49.16%	58.72%	54.09%	64.63%	71.23%	72.22%	67.88%	71.03%	72.22%	76.95%	54.09%
100%	45.91%	54.09%	54.09%	54.09%	49.91%	45.91%	45.91%	45.91%	45.91%	54.09%	54.09%

Figure 4: Different Models Trained on Different Dropouts' Accuracy on Different Dropout Test Datasets Graph



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8. References

1. Laura O., Simone P., Umberto V., "Schizophrenia: A Narrative Review of Etiopathogenic, Diagnostic and Treatment Aspects", Multidisciplinary Digital Publishing Institute, August es/2022, 11 (17), 1-22. https://www.mdpi.com/2077-0383/11/17/5040
2. Enkhmaa L., et al., "Neurobiology of Schizophrenia: A Comprehensive Review", Cureus, April 2022, 14 (4), 1-7. https://www.cureus.com/articles/92077-neurobiology-of-schizophrenia-a-comprehensive-review
3. Vaani B., et al., "Unravelling the Complexity of Schizophrenia: A Comprehensive Review", International Journal of Medical Science and Diagnosis Research, April 2025, 9 (2), 11-16. https://www.researchgate.net/publication/390731285_Unravelling_the_Complexity_of_Schizophrenia_A_Comprehensive_Review
4. Shijie J., et al., "Can artificial intelligence be the future solution to the enormous challenges and suffering caused by Schizophrenia?", Nature, February 2025, 32, 1-16. https://www.nature.com/articles/s41537-025-00583-4
5. António M., Joana R., Tiago D., "Artificial Intelligence and Schizophrenia: Crossing the Limits of the Human Brain", IntechOpen, March 2024, 1-18. https://www.intechopen.com/chapters/1185407
6. Jagdeep R., et al., "A systematic review of EEG based automated schizophrenia classification through machine learning and deep learning", Frontiers, February 2024, 18, 1-12. https://www.frontiersin.org/journals/human-neuroscience/articles/10.3389/fnhum.2024.1347082/full
7. Jose C., et al., "Going deep into schizophrenia with artificial intelligence", ScienceDirect, July 2022, 245, 122-140. https://www.sciencedirect.com/science/article/pii/S0920996421001791
8. Elzbieta O., Wojciech J., "Graph-based analysis of brain connectivity in schizophrenia", Public Library of Science, November 2017, 12 (11), 1-28. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0188629
9. Haiteng J., et al., "Assisting schizophrenia diagnosis using clinical electroencephalography and interpretable graph neural networks: a real-world and cross-site study", Neuropsychopharmacology - Nature, July 2023, 48, 1920-1930. https://pmc.ncbi.nlm.nih.gov/articles/PMC10584957/
10. Muhammad A., "Classification of Schizophrenia EEG Dataset Using Deep Learning" [Code], GitHub, May 2024. https://github.com/MuhammadAhmedAbbasi/Classification-Of-schizophrenia-EEG-dataset-Using-Deep-Learning/