Multivariate EEG Analysis for Schizophrenia Detection: Leveraging Entropy Measures and Machine Learning Techniques across Channel Configurations

Tushar Goyal, Utkarsh Mishra, Vasant Kumar Sharma, Sayog Shendre

**Abstract -** Mental health conditions are experiencing a significant global surge, with schizophrenia emerging as one of the most common and rapidly spreading disorders, leading to a considerable increase in affected individuals and highlighting the critical importance of early detection for improved prog- nosis and intervention. Our project investigates the potential of Electroen- cephalogram (EEG) signals, which capture the electrical activity reflecting the behavior of different brain lobes, as a non-invasive tool for the early detec- tion of schizophrenia, specifically aiming to identify which cerebral lobes and their corresponding electrodes are most responsible for discernible patterns and thus prove most helpful in this endeavor. To explore this, we utilized a dataset comprising EEG recordings from 28 subjects, including both in- dividuals diagnosed with schizophrenia and healthy controls, acquired using a 19-electrode system strategically placed across the frontal, parietal, tem- poral, and occipital lobes. Recognizing that electrode distribution reflects lobar activity, we bifurcated the data into three distinct datasets to analyze the contributions of different brain regions: an 11-electrode set focusing on the frontal and temporal lobes, a 16-electrode set incorporating the frontal, temporal, and parietal lobes, and the full 19-electrode set covering all four lobes. By training various machine learning models independently on each of these three datasets and meticulously analyzing the performance results from each configuration, we aim to pinpoint which specific electrode sub- sets, corresponding to particular brain lobes or combinations thereof, yield the most robust and accurate detection of schizophrenia, thereby providing a data-driven approach to identify the most relevant neural indicators and enhance the potential for earlier diagnosis.

*Preprint submitted to Elsevier May 22, 2025*

# Introduction

Brain health challenges are becoming more common around the world, affecting how people think, feel, and act. One really tough condition is schizophrenia. It can deeply mess with how someone’s brain works, making it hard for them to think clearly, feel things as others do, or react in ways that fit the situation.

In our project, Our approach involves the systematic analysis of EEG data acquired from two distinct cohorts: healthy control participants and individuals with a confirmed diagnosis of schizophrenia. EEG signals, re- flecting the electrical activity of the brain captured from various electrode placements on the scalp, provide valuable insights into neural functioning. Majorly there are 4 lobes in human brain which includes frontal, parietal, temporal and Occipital. All these lobes behave differently in different sit- uations and produce EEG signals on 19 different electrode. The study of variation in signals on these electrode in healthy patient and schizophrenia positive patient can help us to achive our goal.

There are various ways to detect schizophrenia using EEG Signals like Buetnner et al[.[1]](#_bookmark6) proposed a study based on Random Forest Classification model.Based on their methodology, Buettner et al. reported an overall clas- sification accuracy of 71.43% for distinguishing between healthy individuals and those diagnosed with schizophrenia. This study exemplifies the applica- tion of signal processing and machine learning techniques to identify potential electrophysiological markers of schizophrenia in EEG data.

In this research, they looked at EEG recordings from 63 individuals with schizophrenia and 70 healthy people. They had a clever three-step process: First, they used a special technique to understand how signals flow and con- nect between different parts of the brain based on the EEG data. Then, they mapped out these brain connections like a sort of network. Finally, they used the unique patterns in these brain networks to see if they could tell the two groups apart.

One of our major aim is to get an idea how different regions of brain affect and behave differently. Melissa et [al.[2]](#_bookmark7) in there research shows Auditory hallucinations across the psychosis spectrum: Evidence of dysconnectivity involving cerebellar and temporal lobe regions.

Gosh et al.[[3]](#_bookmark8) in his research, This research takes on the challenge of using

brain wave recordings (EEG) to help spot schizophrenia, a really tough, life- long mental illness. While scientists know EEG holds clues, getting a precise diagnosis from it has been tricky and is still quite new. The study aimed to build a smart system to do just that, specifically by looking at how complex the brain signals are (using ’entropy’ measurements) and giving more impor- tance to the most relevant spots (electrodes) on the scalp. They used publicly available EEG data and tested different computer models to learn to tell the difference between people with schizophrenia and healthy individuals. Their main new idea was carefully picking out the best brain channels and giving them extra weight before feeding them into the models. The exciting result was that this focused approach, weighting the most informative channels, re- ally boosted accuracy, even achieving a perfect 100% score with one specific model (Na¨ıve Bayes). The researchers believe this method of zeroing in on and emphasizing the key brain signals makes their system a significant step forward compared to current EEG-based ways of diagnosing schizophrenia.

Krishnan et al. [[4]](#_bookmark9) Addressing the challenge of using EEG signals for

precise schizophrenia diagnosis, this research proposed a multivariate analy- sis approach. It involved using Multivariate Empirical Mode Decomposition (MEMD) to break down the complex multichannel EEG signals into sim- pler components called Intrinsic Mode Functions (IMFs). The study then measured the ”randomness” or complexity of these IMF signals using five different entropy measures (Approximate, Sample, Permutation, Spectral, and Singular Value Decomposition entropy). Crucially, these entropy mea- sures showed a statistically significant difference between the brain signals of healthy individuals and those with schizophrenia. These entropy values were then used as features to train various machine learning models to distin- guish between the two groups. Among the tested models, a Support Vector Machine with a Radial Basis Function (SVM-RBF) classifier achieved the highest performance, reaching 93

In the referenced work by R. Sharma et [al[5],Researc](#_bookmark10)hers used EEG data and machine learning methods, including SVM with an RBF kernel, to differen- tiate schizophrenia patients from healthy individuals. The SVM achieved 100% precision, highlighting machine learning’s promise for accurate diagno- sis.

In Kevin Volkan’s pap[er[6],](#_bookmark11) offers an overview of schizophrenia’s impact on life quality and longevity, covering genetic, environmental factors, and the evolution of treatments. While noting the ongoing reliance on antipsychotics despite side effects, he highlights new treatments, including innovative drugs

and immunotherapies. Volkan also emphasizes the growing focus on psy- chotherapies aimed at recovery and prevention to reduce schizophrenia’s im- pact.

Buc[kley[7],](#_bookmark12) Buchanan, Tamminga, and Schulz, the 1999 Congress on Schizo- phrenia Research highlighted advances in early detection, viewing schizophre- nia as a neural connectivity disorder, and the role of cognition. It also focused on new antipsychotics and progress in genetic and environmental research. In their literature review, [Millier[8]](#_bookmark13) The team examined schizophrenia’s eco- nomic, psychological, and social impact, noting that costs vary, particularly in developing countries with limited mental health support. They called for greater public awareness of these challenges.

In their review, Rukhsana Naw[az[9],](#_bookmark14) Saima Gul, Rafat Amin, Tanzeel Huma, and Fadwa Al Mughairbi the study on schizophrenia in Pakistan highlighted rising rates of the disorder amid neglected mental health services. It noted poor responses to antipsychotics, possibly due to genetic differences, empha- sizing the need for personalized treatment strategies.

C. [Jones[10]](#_bookmark15) cognitive behavioral therapy (CBT) doesn’t offer a clear ad- vantage over simpler, more affordable therapies for schizophrenia. Despite considerable research, the overall evidence quality is low, highlighting the need for better studies before firm conclusions can be made.

The results showed that schizophrenia patients had weaker temporal corre- lations, particularly in the alpha and beta bands, with shorter, less stable oscillations in the beta band during the resting state with eyes open. Inter- estingly, during video watching, patients displayed increased stability in the alpha band. These findings shed light on the neural and cognitive dysfunc- tions associated with schizophrenia.

Martha E. Shen[ton[11]](#_bookmark16) reviewed MRI advancements in understanding schizo- phrenia, tracing research from Kraepelin and Bleuler to modern imaging. Analyzing 193 studies, she highlights key brain abnormalities, including ven- tricular enlargement and changes in the amygdala, hippocampus, and cortical regions. Shenton suggests these abnormalities may be neurodevelopmental and evolve over time, calling for future research on specific patient groups and advanced imaging techniques.

E.P. Ho[lmes[12]](#_bookmark17) studied the impact of a semester-long course on severe men- tal illness and its effect on societal attitudes. The study involved 83 partici- pants from both specialized and general psychology courses. Results showed that while the course improved attitudes, the impact varied based on par- ticipants’ prior knowledge and contact with mental illness. Those with more

prior exposure experienced less attitude change, highlighting the influence of pre-existing factors on educational outcomes.

James [Chapman[13]](#_bookmark18) in his paper discusses the challenges of early schizophre- nia diagnosis, noting the lack of consensus on its early symptoms. Both older and recent literature focus more on differentiating schizophrenia from other conditions, often describing early stages vaguely. Diagnosis is typically de- layed until more overt symptoms, like disordered thinking and affect, appear, which may take years.

Yi-hang [Huang[14],](#_bookmark19) study explored how childhood trauma, including emo- tional, physical, and sexual abuse, affects mental health disorders like schizop- hrenia, bipolar disorder, and depression. It found that emotional abuse linked to depression and sexual abuse to positive and disorganized symptoms, high- lighting the need for early recognition and tailored interventions.

J. van de [Leemput[15]](#_bookmark20) and team reviewed the genetic and epigenetic fac- tors in schizophrenia, focusing on neuro development, glutamate regulation, and immune activation. Despite strong genetic evidence, identifying specific causative genes is challenging. The paper also explores epigenetic mech- anisms like DNA methylation and histone modification, influenced by en- vironmental factors, and discusses future research potential in uncovering schizophrenia’s molecular causes. Rehman [[16]](#_bookmark21) in her reserach also shows the schizophrenia detection using entropy by considering different brian sec- tions

Figuring out if someone has schizophrenia accurately is still a really tough job in mental healthcare. The way we mostly do it now is by doctors observ- ing people and listening to what they tell us about how they feel or what’s happening in their minds. But this isn’t a clear-cut test; it relies a lot on personal views and can be easily misinterpreted. Because of this guesswork, people sometimes get the wrong diagnosis or don’t get the right help soon enough, which really hurts their chances of getting better and living well.

Our dataset is informed by research conducted by Elzbieta Olejarczyk [[17],](#_bookmark22) who explored brain connectivity in schizophrenia using EEG data from the same number of patients and controls. This research looked into various connectivity measures, such as Phase-Locking Value (PLV), Phase-Lag In- dex (PLI), and Directed Transfer Function (DTF), analyzing both raw and preprocessed EEG data using techniques like current source density (CSD) and reference electrode standardization.

The main goal of this research is to leverage EEG data to build a de- pendable diagnostic model for detecting early indicators of schizophrenia.

Through detailed analysis of EEG patterns and the identification of specific biological markers associated with the condition, our aim is to establish a strong and objective diagnostic instrument. This would allow for quicker in- tervention and tailored treatment strategies, ultimately enhancing the man- agement of schizophrenia and improving the lives of those affected.

# Related Works

* 1. *Models*

Machine learning models are algorithms or frameworks that use data to learn patterns and make predictions or decisions. Machine learning (ML) models can play a significant role in the detection and diagnosis of schizophre- nia, a complex mental health disorder.

* + 1. *Gradient Boosting*

Gradient Boosting [[18]](#_bookmark23) is a machine learning technique that builds a strong predictive model by sequentially adding weaker models, typically de- cision trees, where each new tree is trained to correct the errors made by the combined predictions of all previous trees. This iterative error correction is guided by the ”gradient” of a loss function, which helps the algorithm determine the best direction to improve the overall model’s performance by focusing on the most significant remaining mistakes, ultimately combining these ”mistake-fixing” models into a powerful ensemble.

* + 1. *Extreme Learning Machine*

An Extreme Learning Machine (ELM) [[19]](#_bookmark24) is a type of feedforward neural network, commonly used for classification, regression, clustering, and other machine learning tasks. What makes ELMs ”extreme” and distinguishes them from traditional feedforward networks (like those trained with back- propagation) is their unique training approach, particularly for networks with a single hidden layer. The output function of ELM for a generalized SLFN can be expressed as:

*L*

Σ

*f* (**x**) = *G*(**w***i, bi,* **x**)*βi* = **h**(**x**) · ***β****.* (1)

*i*=1

where ***β*** represents the output weight vector connecting the hidden layer to the output layer. The activation function *G*(**w***i, bi,* **x**) is parameterized by

**w***i*, the input weight vector, and *bi*, the bias of the *i*-th hidden node. The term **h**(**x**) = [*G*(**w**1*, b*1*,* **x**)*, . . . , G*(**w***L, bL,* **x**)]*T* defines the nonlinear feature mapping from the input **x** to the hidden layer.

ELM aims to minimize both the output weight norm and the training error. This optimization problem is defined as:

*N*

Σ

min |***β*** · **h**(**x***i*) − *ti*| and min ***β *** *.* (2)

*i*=1

where *ti* is the target output corresponding to the *i*-th training sample.

If the training error is reduced to zero, i.e.,

*N*

Σ

|***β*** · **h**(**x***i*) − *ti*| = 0*.* (3)

*i*=1

the solution for ***β*** is computed as:

***β*** = **H**†**T***.* (4)

where, **T** is the target output matrix, and **H**† is the Moore-Penrose general- ized inverse of the hidden layer output matrix **H** = [**h**(**x**1)*, . . . ,* **h**(**x***N* )]*T* .

To address potential overfitting, one can relax the zero training error condition, introducing slack variables *ξi*. The modified optimization problem becomes:

Σ

subject to:

1

min

2

*N*

 ***β *** 2 + *C ξi.* (5)

*i*=1

*ti*(***β*** · **h**(**x***i*)) ≥ 1 − *ξi,*

*ξi* ≥ 0*, i* = 1*,* 2*, . . . , N.*

where, *C >* 0 is a regularization parameter controlling the trade-off between the margin and training error, and *ξi* represents the error for the *i*-th sample.

The decision function for this formulation of ELM is:

Σ

*f* (**x**) = sign

*Ns*

*s*=1

*αstsK*ELM(**x***,* **x***s*)!

*.* (6)

where, *αs* are the Lagrange multipliers, *ts* are the target outputs, and *K*ELM(**x***,* **x***s*) is the kernel function for ELM.

* + 1. *Twin Extreme Learning Machine*

A Twin Extreme Learning Machine (TELM) [[20]](#_bookmark25) is a machine learning model designed specifically for binary classification, building upon the princi- ples of the standard Extreme Learning Machine (ELM) while incorporating concepts from Twin Support Vector Machines. Unlike a traditional ELM which typically learns a single hyperplane to separate two classes in the hid- den layer’s feature space, TELM aims to find two non-parallel hyperplanes, where each hyperplane is optimized to be as close as possible to the data points of one class while simultaneously being maximally distant from the data points of the other class. The Twin Extreme Learning Machine (TELM) model solves the following pair of Quadratic Programming Problems (QPPs):

1



min

**Uw **2 + *c* **e**⊤*ξ*

subject to

**w**1*,ξ*1 2

1 1 2 1

−**Vw**1 + *ξ*1 ≥ **e**2*, ξ*1 ≥ 0*.* (7)

and

1



min

**Vw **2 + *c* **e**⊤*η .*

**w** *,η* 2

2 2 1 2

2 2

subject to

**U***w*2 + ***η*** ≥ **e**1*,* ***η***2 ≥ 0*.* (8)

Here, *c*1 *>* 0 and *c*2 *>* 0 are user-defined parameters.we derive their corre- sponding Wolfe dual problems, which are given by:

subject to

2

max **e**⊤***α*** −

***α*** 2

1 ***α***⊤**V** **U**⊤**U** + *ϵ***I** −1 **V**⊤***α****.* (9)

and

subject to

max **e**⊤***γ*** −

***γ*** 1

0 ≤ ***α*** ≤ *c*1**e***,*

1 ***γ***⊤**U** **V**⊤**V** + *ϵ***I** −1 **U**⊤***γ****.* (10)

2

0 ≤ ***γ*** ≤ *c*2**e***.* (11)

Here, ***α*** and ***γ*** are vectors of Lagrange multipliers. After obtaining the optimal values of ***α*** and ***γ***, the decision variables are calculated as:

and

1

***β*** = − **U**⊤**U** + *ϵ***I** −1 **V**⊤***α****.* (12)

***β*** = − **V**⊤**V** + *ϵ***I** −1 **U**⊤***γ****.* (13)

2

For classifying an unseen test data point **x** ∈ R*n*, we use the decision rule:

*f* (**x**) = arg min *dk*(**x**) = arg min |*h*(**x**)***β****k*| *.* (14)

*k*=1*,*2 *k*=1*,*2

* + 1. *Random Vector Functional Link*

A Random Vector Functional Link (RVFL) [[21]](#_bookmark26) network is a type of artificial neural network characterized by its simple architecture and efficient learning process. It is a single-hidden layer feedforward network, similar in structure to a basic multilayer perceptron, but with a key difference: direct connections between the input layer and the output layer, in addition to the connections from the hidden layer.

Let ***θ*** = (*θ*1*, θ*2*, . . . , θP* )*T* , where *P* = *L* + *n*, represent the weight vector connecting to the output layer. Here, *L* is the number of enhancement nodes (hidden layer nodes).

The weight vector for the enhancement layer is given as ***ϕ****l* = (*ϕl*1*, ϕl*2*, . . . , ϕlm*)*T* , and *b* is the bias introduced in the enhancement nodes. The activation func-

tion *g*(·*,* ·*,* ·) produces the output for the *l*-th enhancement node with respect to the *i*-th training sample as:

*ql*(**x***i*) = *g*(***ϕ****l, bl,* **x***i*)*.* (15) where, *l* = 1*,* 2*, . . . , L* and *i* = 1*,* 2*, . . . , m*.

The Hessian matrix **H**, which represents the transformation from input to enhancement nodes, is defined as:

 

*q*1(**x**1) · · · *qL*(**x**1)

 



**H** = .



. . .

. *.* (16)

*q*1(**x***m*) · · · *qL*(**x***m*)

The regularized optimization problem for RVFL is expressed as:

min **y** − **T*θ *** 2 + *C * ***θ *** 2*.* (17)

where, **T** = [**H X**], and *C >* 0 is the regularization parameter.

By performing partial differentiation with respect to ***θ***, the solution in the primal space is derived as:

***θ*** = (**T***T* **T** + *C***I**)−1**T***T* **y***.* (18)

where, **I** is the identity matrix.

For a new input sample **x**, the RVFL classifier is defined as:

*f* (**x**) = sign([**q**(**x**) **x**]***θ***)*.* (19)

where, **q**(**x**) = [*q*1(**x**) *q*2(**x**) · · · *qL*(**x**)]. The classifier *f* (**x**) separates the classes with a hyperplane in the feature space.

* + 1. *Enhanced Deep Random Vector Functional Link*

Enhanced Deep Random Vector Functional Link (edRV[FL)[22]](#_bookmark27) is an ad- vanced extension of the traditional Random Vector Functional Link network, designed for robust and efficient supervised learning. It leverages random- ization and deep architecture while addressing key limitations in scalability and representation power. In edRVFL, the core idea is to stack multiple RVFL layers such that each layer receives not only the input data but also the concatenated outputs of all preceding layers. This deep stacking enriches the representational capacity of the model without backpropagation.

# Proposed Methodology

* 1. *Data Collection*

This project focuses on the detection of schizophrenia (SCZ) using EEG signals using data related to RepoD [[23].](#_bookmark28) Figure **??** and figure **??** shows the EEG signals for healthy and unhelathy sunjects respectively. This provides a verified set of 28 EEG signals from 14 people with delusional schizophrenia and healthy patients. Data were acquired including F7, F4, T3, O2, C4, F3, P3, T5, T4, PZ, CZ, FP2, C3, T6, F8, P4, FP1, O1, Fz using a typical

10-20 EEG assembly system with 19 electrodes. The signal was recorded at a sampling rate of 250 Hz. This data record aims to identify patterns of EEG signals that distinguish between positive schizophrenia and healthy people by analyzing variations in brain activity on various electrodes. Data were collected under different conditions to provide a deeper understanding of how these signals change with different mental states and how these changes

indicate schizophrenia. Preparing data such as filtering, artifact removal, epoching and other data is suitable for cleaning and machine learning of very important signals. As shown in Figure [1,](#_bookmark0) the EEG signals for a healthy patient exhibit more regular patterns, while the unhealthy patient (Figure [2)](#_bookmark1) shows irregularities across several frontal, temporal, and parietal channels.

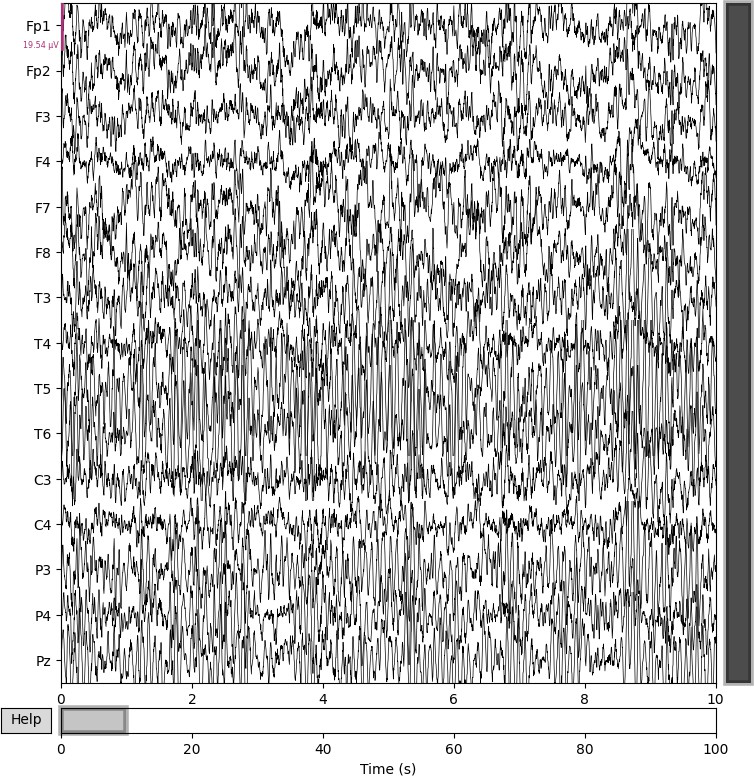


Figure 1: Healthy schizophrenia patient EEG signal on 16 different electrodes

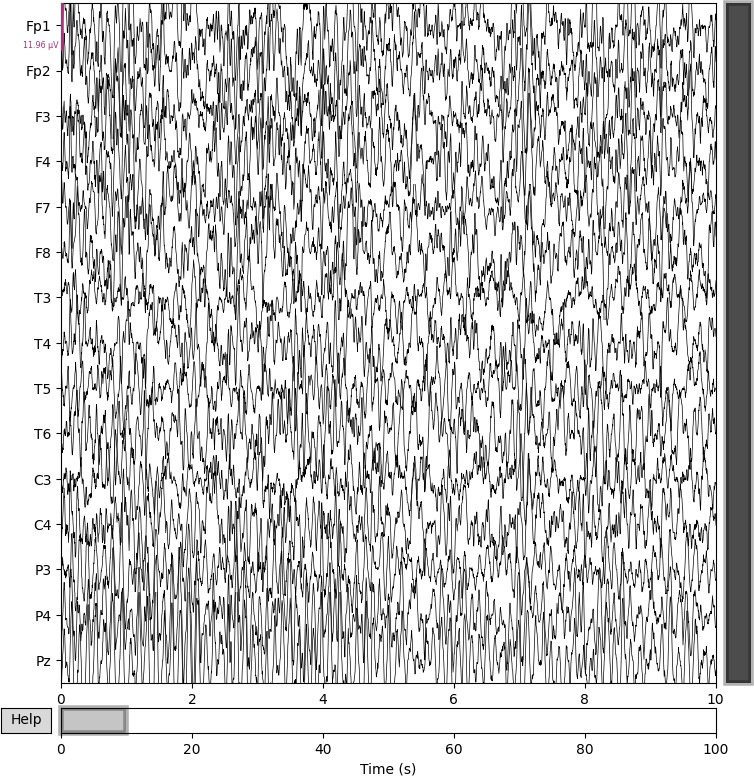


Figure 2: Unhealthy schizophrenia patient EEG signal on 16 different electrodes

* 1. *Data Preprocessing*

Figure [3](#_bookmark2) shows the steps we need to follow. While working on .edf files (European data format), first read the EEG signals using a Python library like mne. From these files, we extract important metadata such as EEG signal length, number of channels (electrodes), and sample rate. Analysis shows that EEG signals differ from record to record. To address this, segment

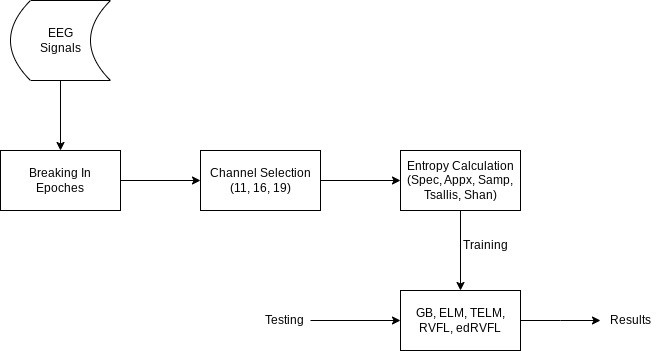


Figure 3: Flowchart of implemented models based on entropy

the data into ERAS. This makes up each epoch for 2 seconds and contains 500 samples (based on a sampling rate of 250 Hz). After segmenting the complete signal with the epoch, select 50 epochs as test samples from each signal and each electrode for further analysis. The EEG electrodes are shown in specific rags as follows:

* **Frontal Lobe**: Fp1, Fp2, F3, F4, F7, F8, Fz
* **Temporal Lobe**: T3 (T7), T4 (T8), T5, T6
* **Parietal Lobe**: P3, P4, P7, P8, Pz
* **Occipital Lobe**: O1, O2, Oz
* **Central (Motor Cortex)**: C3, C4, Cz

We create three datasets based on combinations of these lobes to analyze their respective contributions to schizophrenia classification.

* 1. *Feature Extraction*

After breaking each EEG signal into **50 epochs** of **2 seconds** each, the next step involves the extraction of entropy-based features. For every epoch, we compute five distinct entropy measures for each selected electrode: Shannon Entropy, Sample Entropy, Approximate Entropy, Spectral Entropy,

Tsallis Entropy This entropy characteristic records various aspects of sig- nal complexity and randomness. This is extremely important when proving neurological abnormalities such as schizophrenia.

In our study, special attention is given to the **frontal**, **temporal**, and **parietal lobes**, as these brain regions have shown significant involvement in schizophrenia according to multiple neurophysiological studies.

* The **frontal lobe** is associated with cognitive functions such as decision- making, attention, and executive management that are usually im- paired in people with schizophrenia.
* The **temporal lobe** is essential for auditory processing and language understanding, and is often associated with symptoms such as auditory hallucinations.
* The **parietal lobe** played a role in sensory integration and spatial orientation, with abnormalities in this area associated with unorganized behavior and perception.

Focusing on these lobes helps in identifying the most discriminative brain regions for schizophrenia diagnosis and enhances the interpretability of the EEG-based classification model.

* 1. *Feature Selection*

Before running any model, choosing the right features is one of the most important steps especially when working with EEG signals. These brain signals contain a lot of information, but not all of it is useful for diagnosis. That’s why it’s important to focus on the features that really matter the ones that show noticeable differences between healthy individuals and those affected by schizophrenia. By narrowing it down to the most meaningful data, we can help the model make more accurate and reliable predictions. Below are some of the functions used:

**Spectral Entropy**: This explains the complexity of the frequency con- tent of the signal. We illustrate the energy spreading by calculating the dis- tribution of service over different frequencies using entropy equations. High spectral entropy indicates complex signals with energy over many frequen- cies, and low entropy indicates more simple signals with most of their energy in narrow frequency bands. The spectral entropy *H*spec is given:

*N*

Σ

*H*spec = − *Q*(*fi*) log(*Q*(*fi*)) (20)

*i*=1

where:*Q*(*fi*) is the normalized PSD at the frequency *fi*, The number of frequency bins in the spectrum is represented by *N* .

**Approximate Entropy**: Approximate entropy is a useful measure for identifying the regularity or complexity inherent in a time series of EEG sig- nals. Through the calculation of APEN, the extent to which predictable as opposed to random neural activity can be utilized to detect anomalies like schizophrenia can be measured. Large APEN values indicate more irregu- larities in the brain activity, and this may be a sign of schizophrenia, while smaller values indicate more normal or typical brain activity.

ApEn(*p, s, T* ) =

1

*T* − *p*

*T* −*p*

ln

Σ

*j*=1

*Dj*(*p, s*)

*Dj*(*p* + 1*, s*)

(21)

where *p* is the embedding dimension, *s* is the tolerance, *T* is the length of the time series. *Dj*(*p, s*) counts the number of vector pairs of length *p* within tolerance *s* at the *j*-th position, while *Dj*(*p* + 1*, s*) counts similar vector pairs of length *p* + 1. These quantities are used to calculate the logarithmic ratio that quantifies the system’s complexity.

**Sample Entropy**: Metrics called rehearsal tropics are used to quantify how complex or unpredictable time series such as EEG signals are. It is particularly useful for the analysis of physiological signals such as EEG. This makes the goal often constitutes by assessing irregularities or variations in signals that may indicate specific conditions, such as schizophrenia. Abtsch entropy is closely related to approximate entropy (Apen). It provides a more consistent and reliable estimate, especially for short time series. By calcu- lating the likelihood that an equivalent pattern will be discovered within a particular time frame, SAMP measures the predictability or degree of random numbers in a time series, and thus quantifies its regularity. The definition of a sampling ropy (SE) is as follows:

SE(*k, ϵ, L*) = − ln  *C*(*k, ϵ*) (22)

*C*(*k* + 1*, ϵ*)

where *L* is the number of data points in the time series, *ϵ* is the tolerance, and *k* is the embedding dimension (usually 2 or 3). While *C*(*k* + 1*, ϵ*) counts

comparable vector pairs of length *k* + 1 within the same tolerance, *C*(*k, ϵ*) indicates the number of similar vector pairs of length *k* within tolerance *ϵ*.

**Tsallis Entropy**: Complexity or destruction of a system can be quanti- fied with the use of Tsallis entropy, the Shannon entropy generalization. It was established in 1988 by physicist Constantino Zaris as part of research on unoptimized statistical mechanics that describe systems with fractal ge- ometry, long-range interactions, and long-range memory. Tsallis entropy can be used in numerous fields including information theory, statistical mechan- ics, and neuroscience. Even when nonlinear and unbalanced systems are employed, this is particularly helpful: B. B. EEG signals in brain activity analysis.

The order’s Tsallis entropy *α* for a distribution of probabilities {*rj*} is given by:

!

*Tα* =

1

*α* − 1

*M*

1 − *α*

*r*

Σ

*j*

*j*=1

(23)

The Tsallis entropy of order *α*, denoted as *Tα*, is defined in terms of the probability *rj* of the *j*-th event, where *j* ranges over all possible events or states. The total number of possible events or states is represented by *M* , and the order parameter *α*, which satisfies *α* ≥ 1, has a significant impact on how the entropy is formed.

**Shannon Entropy**: This quantifies uncertainty or randomness of the signal. Compute the value of each symbol in the signal depending on the likelihood each symbol (voltage level, intensity value) can present. More entropy is a more random signal with no greater range of values and no pre- vailing symbols. Less entropy is a less predictable signal with fewer distinct values.

For a discrete random variable *Y* with probability distribution {*q*1*, q*2*, . . . , qM* }, the Shannon entropy *G*(*Y* ) is defined as follows:

*M*

Σ

*G*(*Y* ) = − *qj* log(*qj*) (24)

*j*=1

where *M* is the number of alternative occurrences or states, and *qj* is the probability of the *j*-th event or result.

* 1. *Feature Vector Preparation*

We have already extracted entropy-based features from different EEG signal segments. Before training the classification models, it is essential to

organize these features into a consistent format. Our approach involves train- ing on data from **28 subjects**, with **50 randomly selected epochs** from each EEG signal. For each epoch, entropy features are computed from se- lected electrodes. We prepare **three distinct datasets** based on different combinations of EEG electrodes corresponding to specific brain lobes:

* **Dataset 1 (All 19 Channels)**: Entropy features are extracted from all 19 EEG electrodes. For each epoch, 5 entropy values are computed per electrode, resulting in a feature vector of length 95 (19 × 5). Thus, the final dataset shape becomes:
* **Dataset 2 (Frontal, Temporal, Parietal – 16 Channels)**: Feature extraction is limited to 16 electrodes associated with the frontal, tem- poral, and parietal lobes. Each epoch yields a feature vector of length 80 (16 × 5), producing a dataset of shape:
* **Dataset 3 (Frontal and Temporal – 11 Channels)**: Only 11 elec- trodes from the frontal and temporal lobes are considered. Each epoch yields a feature vector of length 55 (11 × 5), resulting in:

This separation into three datasets allows us to study the discriminative power of different brain regions in schizophrenia detection. Each dataset is used independently to train and evaluate machine learning models, enabling a comparative analysis across brain lobes.

* 1. *Model Training:*

We are training and evaluating five different models: Gradient boosting, ELM, TELM, RVFL, edRVFL. For each model, we will assess its accuracy and overall performance. Additionally, we need to fine-tune each model by adjusting hyperparameters and exploring different scenarios to achieve the best results according to our specific requirements. This process will help identify the model that performs optimally for our dataset and application, ensuring the most effective diagnosis of schizophrenia.

# Result Analysis and Comparison

After obtaining results from different models, the next step is to con- duct a comparative study to determine the best model for the given dataset, specifically for the diagnosis of schizophrenia. This involves analyzing the performance metrics of each model, such as accuracy, precision, recall, F1 score, and any other relevant evaluation criteria.

# Performance metrics

After training the model, the next step is to evaluate its performance by assessing its accuracy in predicting the labels. This involves testing the model on a separate validation or test dataset to determine how well it generalizes to new, unseen data. Accuracy is calculated as the proportion of correctly predicted labels compared to the total number of predictions made. This evaluation helps gauge the model’s effectiveness and provides insights into its ability to accurately classify or predict outcomes based on the input data.

* 1. *Accuracy*

In machine learning, accuracy is a key metric used to evaluate a model’s performance. It measures how effectively the model correctly identifies the class or outcome for given inputs. Accuracy is calculated as the proportion of correctly predicted cases (both true positives and true negatives) out of the total number of examples in the dataset. This metric provides a general sense of the model’s overall performance, but it may not fully capture performance nuances, especially in cases with imbalanced classes or where false positives and false negatives have different costs.

*Accuracy* = ((*tp* + *tn*)*/*(*tp* + *tn* + *fp* + *fn*)) ∗ 100 (25)

* 1. *Precision*

Precision is the proportion of true positive predictions among all positive predictions made by a model. It measures how accurate the model’s positive predictions are, indicating the relevance of the instances identified as posi- tive. A high precision value means that when the model predicts a positive outcome, it is likely to be correct, thus reducing the number of false positives. This metric is especially important in situations where false positives carry significant costs, making accuracy in positive predictions critical.

* 1. *Recall*

Recall, also known as sensitivity or the true positive rate, measures the proportion of actual positive cases that a model correctly identifies. It re- flects the model’s ability to capture all relevant instances in the dataset. A high recall indicates that the model effectively identifies most true positive cases, even if it results in some false positives. This metric is especially cru- cial in scenarios where failing to detect a positive case could lead to serious consequences.

* 1. *F1 Score*

The F1 score provides a balanced evaluation of a model’s performance by considering both precision and recall. Precision measures how accurately the model identifies positive cases, while recall assesses how effectively it cap- tures all positive cases within the dataset. A higher F1 score signifies that the model performs well in both aspects, reflecting its ability to accurately identify positive instances while minimizing missed cases. This comprehen- sive metric offers a nuanced view of the model’s overall effectiveness, making it a valuable indicator for assessing performance in scenarios where both pre- cision and recall are crucial.

# Result Analysis

Table [1](#_bookmark3) summarizes the performance of different machine learning meth- ods applied to schizophrenia detection using data from 11 EEG channels. Five techniques were evaluated: Gradient boosting, ELM, TELM, RVFL, and edRVFL. The results, likely representing accuracy, varied across the methods. The lowest performance was observed with ELM at 87.71%, while the highest results were achieved by edRVFL at 93.82% and Gradient boost- ing at 93.71%. This comparison indicates that both edRVFL and Gradient boosting were the most effective models among those tested for detecting schizophrenia using this specific 11-channel EEG configuration.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Sr. No. | Method | Accuracy | Precision Score | Recall | F1 Score |
| 1. | Gradient boosting | 93.71% | 0.95 | 0.92 | 0.93 |
| 2. | ELM | 87.71% | 0.90 | 0.86 | 0.87 |
| 3. | TELM | 88.86% | 0.92 | 0.86 | 0.88 |
| 4. | RVFL | 88.87% | 0.92 | 0.86 | 0.88 |
| 5. | edRVFL | 93.82% | 0.94 | 0.94 | 0.94 |

Table 1: Comparison of Various Machine Learning Methods and Their Results. with 11 channels

Table [2](#_bookmark4) presents a comparison of the performance results obtained from vari- ous machine learning methods applied to schizophrenia detection, specifically utilizing data from 16 EEG channels. Five methods were evaluated: Gradi- ent boosting, ELM, TELM, RVFL, and edRVFL. The results show accuracies ranging from 90.5% (ELM) to 97.39% (edRVFL). Notably, edRVFL achieved

the highest performance at 97.39%, closely followed by Gradient boosting at 96.79%. TELM and RVFL yielded identical results of 92.79%. The table indicates that edRVFL and Gradient boosting were the most effective mod- els for schizophrenia detection when using the 16-channel EEG configuration among the methods tested.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Sr. No. | Method | Accuracy | Precision Score | Recall | F1 Score |
| 1. | Gradient boosting | 96.79% | 0.97 | 0.96 | 0.97 |
| 2. | ELM | 90.5% | 0.92 | 0.89 | 0.90 |
| 3. | TELM | 92.79% | 0.94 | 0.91 | 0.93 |
| 4. | RVFL | 92.79% | 0.94 | 0.91 | 0.92 |
| 5. | edRVFL | 97.39% | 0.97 | 0.97 | 0.97 |

Table 2: Comparison of Various Machine Learning Methods and Their Results. with 16 channels

Table [3](#_bookmark5) summarizes the performance results of different machine learn- ing methods applied to schizophrenia detection using data from all 19 EEG channels. The evaluated methods include Gradient boosting (97%), ELM (90.79%), TELM (93.64%), RVFL (93.64%), and edRVFL (96.67%). The

results indicate that Gradient boosting achieved the highest performance at 97%, with edRVFL close behind at 96.67%. TELM and RVFL yielded iden- tical results of 93.64%. Overall, for the 19-channel configuration, Gradient boosting and edRVFL demonstrated the strongest performance among the methods presented.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Sr. No. | Method | Accuracy | Precision Score | Recall | F1 Score |
| 1. | Gradient boosting | 97% | 0.98 | 0.96 | 0.97 |
| 2. | ELM | 90.79% | 0.91 | 0.90 | 0.91 |
| 3. | TELM | 93.64% | 0.96 | 0.91 | 0.93 |
| 4. | RVFL | 93.64% | 0.96 | 0.91 | 0.93 |
| 5. | edRVFL | 96.67% | 0.97 | 0.97 | 0.97 |

Table 3: Comparison of Various Machine Learning Methods and Their Results. with 19 channels

# Conclusion

Based on the comparative analysis across the three electrode configura- tions presented in the tables (11, 16, and 19 channels), several key conclu-

sions emerge regarding machine learning-based schizophrenia detection using EEG. Firstly, there is a notable overall improvement in detection accuracy as the number of channels increases from 11 (Frontal and Temporal) to 16 (adding Parietal), highlighting the valuable contribution of parietal lobe ac- tivity. While the performance gain from 16 to 19 channels (adding Occipital) is less dramatic or shifts slightly in ranking, it indicates that the optimal set of discriminative features is either predominantly captured by 16 channels or distributed across all 19. Consistently across all three configurations, Gradi- ent boosting and edRVFL proved to be the most effective methods, regularly achieving accuracies above 93%, and peaking at 97.39% (edRVFL, 16 chan- nels) and 97% (Gradient boosting, 19 channels). Other methods like ELM, TELM, and RVFL showed consistently lower, albeit still reasonable, per- formance. These results underscore the potential of Gradient boosting and edRVFL algorithms and emphasize that electrode selection, particularly the inclusion of parietal channels, is crucial for achieving high accuracy in the early detection of schizophrenia from EEG signals.

# References

1. S. J. J. Jui, R. C. Deo, P. D. Barua, A. Devi, J. Soar, and U. R. Acharya, *“Use of entropy for detection of neurological disorders with EEG (electroencephalogram) signals: A review of the last decade in (2012-2022),”* IEEE Access, vol. 11, no. June, pp. 71905–71924, 2023, doi: 10.1109/ACCESS.2023.3294473.
2. Melissa Hwang, Youkyung S. Roh, Jessica Talero, Bruce M. Co-

hen, Justin T. Baker, Roscoe O. Brady, Dost

O¨ ngu¨r, Ann K.

Shinn, *Auditory hallucinations across the psychosis spectrum: Ev- idence of dysconnectivity involving cerebellar and temporal lobe re- gions*NeuroImage: Clinical, Volume 32, 2021, 102893, ISSN 2213-1582, https://doi.org/10.1016/j.nicl.2021.102893.

1. Goshvarpour, A., Goshvarpour, A. *Schizophrenia Diagnosis by Weight- ing the Entropy Measures of the Selected EEG Channel. J. Med. Biol.*

Eng. 42, 898–908 (2022). https://doi.org/10.1007/s40846-022-00762-z

1. Palani Thanaraj Krishnan and Alex Noel Joseph Raj and Par- vathavarthini Balasubramanian and Yuanzhu Chen *“Schizophrenia de- tection using MultivariateEmpirical Mode Decomposition and entropy*

*measures from multichannel EEG signal”* Biocybernetics and Biomed- ical Engineering,Volume 40, Issue 3,2020, Pages 1124-1139,ISSN 0208-

5216

1. R. Sharma, S. Tripathi and K. K. Sekhon, ”Detection of Schizophrenia using Machine Learning,” 2023 3rd International Conference on Advance Computing and Innovative Technolo- gies in Engineering (ICACITE), Greater Noida, India, 2023, pp. 505-512, doi: 10.1109/ICACITE57410.2023.10183069. keywords:

Support vector machines;Machine learning algorithms;Mental disorders;Predictive models;Brain modeling;Prediction algo- rithms;Electroencephalography;SVM;LSTM;CNN;Deep Learn- ing;EEG;Machine Learning;Schizophrenia.

1. Volkan, Kevin. (2020). Schizophrenia: Epidemiology, Causes, Neurobi- ology, Pathophysiology, and Treatment. Journal of Health and Medical Sciences. 3. 487-521. 10.31014/aior.1994.03.04.143.
2. Buckley PF, Buchanan RW, Tamminga CA, Schulz SC. Schizophrenia research: a progress report, summarizing proceedings of the 1999 International Congress on Schizophrenia Research. Schizophr Bull. 2000;26(2):411-9. doi: 10.1093/oxfordjournals.schbul.a033462. PMID: 10885640.
3. Millier A, Schmidt U, Angermeyer MC, Chauhan D, Murthy V, Toumi M, Cadi-Soussi N. Humanistic burden in schizophre- nia: a literature review. J Psychiatr Res. 2014 Jul;54:85-93. doi: 10.1016/j.jpsychires.2014.03.021. Epub 2014 Apr 4. PMID: 24795289.
4. Rukhsana Nawaz, Saima Gul, Rafat Amin, Tanzeel Huma, and Fadwa Al Mughairbi, “Overview of schizophrenia re- search and treatment in Pakistan,” *Heliyon*, vol. 6, no. 11,

pp. e05545, 2020. https://doi.org/10.1016/j.heliyon.2020.e05545. h[ttps://www.sciencedirect.com/science/article/pii/S2405844020323884.](http://www.sciencedirect.com/science/article/pii/S2405844020323884)

1. Jones C, Hacker D, Meaden A, Cormac I, Irving CB, Xia J, Zhao S, Shi C, Chen J. Cognitive behavioural therapy plus standard care versus standard care plus other psychosocial treatments for people with schizophrenia. Cochrane Database Syst Rev. 2018 Nov 15;11(11):CD008712. doi: 10.1002/14651858.CD008712.pub3. PMID:

30480760; PMCID: PMC6516879.

1. Martha E. Shenton, Chandlee C. Dickey, Melissa Frumin, Robert

W. McCarley, A review of MRI findings in schizophrenia, Schizophrenia Research, Volume 49, Issues 1–2, 2001, Pages 1-

52, ISSN 0920-9964, https://doi.org/10.1016/S0920-9964(01)00163-3.

(h[ttps://www.sciencedirect.com/science/article/pii/S0920996401001633)](http://www.sciencedirect.com/science/article/pii/S0920996401001633))

1. E. Paul Holmes, Patrick W. Corrigan, Princess Williams, Jeffrey Canar, Mary Ann Kubiak, Changing Attitudes About Schizophrenia, Schizophrenia Bulletin, Volume 25, Issue 3, 1999, Pages 447–456, https://doi.org/10.1093/oxfordjournals.schbul.a033392
2. Chapman J. The Early Symptoms of Schizophrenia. British Journal of Psychiatry. 1966;112(484):225-251. doi:10.1192/bjp.112.484.225
3. Yi-hang Huang, Chao Liu, Jian-biao Zhang, Shuai-biao Li, Ling- ling Wang, Hui-xin Hu, Yuan Cai, Zhenhua Zhu, Min-yi Chu, Yi Wang, Qin-yu Lv, Simon S Y Lui, Zheng-hui Yi, Li Hui, Ray- mond C K Chan, A Transdiagnostic Network Analysis of Childhood Trauma and Psychopathology, Schizophrenia Bulletin, 2024;, sbae137, https://doi.org/10.1093/schbul/sbae137
4. van de Leemput J, Hess JL, Glatt SJ, Tsuang MT. Genetics of Schizophrenia: Historical Insights and Prevailing Evidence. Adv Genet. 2016;96:99-141. doi: 10.1016/bs.adgen.2016.08.001. Epub 2016 Sep 27.

PMID: 27968732.

1. M, Rehman B, Rizvi A, et al., *“Schizophrenia,”* [Up- dated 2024 Feb 23]. In: StatPearls [Internet]. Treasure Is- land (FL): StatPearls Publishing; 2024 Jan-. Available: h[ttps://www.ncbi.nlm.nih.gov/books/NBK539864/.](http://www.ncbi.nlm.nih.gov/books/NBK539864/)
2. Olejarczyk E, Jernajczyk W (2017) Graph-based analysis of brain connectivity in schizophrenia. PLoS ONE 12(11): e0188629. https://doi.org/10.1371/journal.pone.0188629
3. A. B. Desai, D. R. Gangodkar, K. Pant and B. Pant, ”Harnessing the Potential of Light Gradient Boosting Machine for Accurate Diagnosis of Schizophrenia from EEG Signals,” 2024 14th International Conference on Cloud Computing, Data Science Engineering (Confluence), Noida, India, 2024, pp. 568-574, doi: 10.1109/Confluence60223.2024.10463450.
4. Guang-Bin Huang, Qin-Yu Zhu, Chee-Kheong Siew, Extreme learn- ing machine: Theory and applications, Neurocomputing, Vol- ume 70, Issues 1–3, 2006, Pages 489-501, ISSN 0925-2312,

https://doi.org/10.1016/j.neucom.2005.12.126

1. Yihe Wan, Shiji Song, Gao Huang, Shuang Li, Twin ex- treme learning machines for pattern classification, Neurocom- puting, Volume 260, 2017, Pages 235-244, ISSN 0925-2312, https://doi.org/10.1016/j.neucom.2017.04.036.
2. S.A. Varaprasad, Tripti Goel, M. Tanveer, R. Murugan, An effective diagnosis of schizophrenia using kernel ridge regression-based optimized RVFL classifier, Applied Soft Computing, Volume 157, 2024, 111457,

ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2024.111457.

1. M. Hu, J. Herng Chion, P. N. Suganthan and R. K. Katuwal, ”Ensemble Deep Random Vector Functional Link Neural Network for Regression,” in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 53, no. 5, pp. 2604-2615, May 2023, doi: 10.1109/TSMC.2022.3213628.
2. Olejarczyk, Elzbieta; Jernajczyk, Wojciech, 2017, ”EEG in schizophre- nia”, https://doi.org/10.18150/repod.0107441, RepOD, V1