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DETERMINING THE FUNCTIONAL BRAIN CONNECTIVITY IN DYSLEXIC CHILDREN USING FUZZY C MEANS CLUSTERING ALGORITHM

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Abstract: The study involves using fuzzy implication relations between the collected signal properties acquired from chosen channels of the lobes to analyse the functional brain connectivity between the pairs of brain lobes for a specific learning problem. The fuzzy implication relation of the Dienes-Rescher type was selected because it most closely resemblespropositional implication in terms of logical semantics. In a learning assignment involving fruits and animals, the Dienes- Rescher type implication has been successfully used to examine similarities in functional brain connectivity for healthy(normal) youngsters (below 2 years old). Children with dyslexia condition are known to have altered brain connection patterns from healthy subjects.

***Index Terms* -** dyslexia, brain-lobes, children, fuzzy.

I. INTRODUCTION

The brain of a person with dyslexia has a different distribution of metabolic activation than the brain of a person without reading problems when accomplishing the same language task. There is a failure of the left hemisphere rear brain systems to function properly during reading[6]-[7]

Children with the dyslexia condition are known to have altered brain connection patterns from healthy subjects. This very discovery offers up a new field of study to distinguish dyslexics from their non-dyslexic peers. In addition, groups of dyslexic children are created using the Fuzzy C Means clustering algorithm based on similarities in their potential functional brain connectivity. Such similarities among dyslexics point to a commonality in the incorrect termination of brain circuits, a well-known symptom of the disorder. The objective of this paper is to measure the interaction between pairs of brain-lobes during the execution of a cognitive task undertaken by Dyslexia children using functional brain- connectivity analysis by using Fuzzy C Means approach. According to studies, reading-related brain regions are not fully activated during reading activities in individuals with dyslexia.

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In recent times, researchers in cognitive science and psychology have utilized various brain imaging technologies, including electroencephalography (EEG) [1], functional Near-Infrared Spectroscopy (fNIRS) [2], functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET scan), among others, to investigate the interactions between different brain regions. Among these modalities, fNIRS has emerged as a promising alternative to the widely

used EEG. While fMRI offers superior imaging capabilities compared to fNIRS, this study opts for fNIRS due to its portability, satisfactory spatial resolution performance[4], and relatively lower cost.

Determining functional brain connectivity using fNIRS data presents a significant challenge due to the wide variability observed within and across experimental sessions. To address this challenge, fuzzy sets and logic have demonstrated effectiveness in handling such diverse data. In this study, we employ fuzzy sets and logic to examine the interconnectivity between pairs of brain modules[5]. The investigation of potential causal connectivity from brain lobe A to B involves two key steps. Firstly, the fNIRS brain images obtained are converted into appropriate features, which are then represented using three fuzzy membership functions: High, Medium, and Low. Secondly, the causality between the fuzzy-encoded features extracted from brain lobe A to B is evaluated. This is achieved by calculating the fuzzy implication relations between the fuzzified features obtained from the respective lobes and determining whether the strength of these implication relations exceeds a predefined threshold level (in this case, 0.5) across all experimental instances of similar child learning sessions.

Three basic experiments are presented in this work. In the first experiment, healthy toddlers under the age of two are asked to learn about animals and fruits from their photos to determine their (fuzzy implication relational) brain- connectivity.

The brain-connectivity results are consulted to assess the ranges of connection weights (strength of fuzzy relations) between channels of active pairs of lobes following the determination of the functional brain-connectivity of a

sizable group of healthy children. Finally, for comparable learning activities, the brain-connectivity strength of children with dyslexia in the same age range is assessed. It is true that children with dyslexia typically have brain connectivity strengths that are outside the range of relational strengths with the same connection weight for healthy subjects. The above results demonstrates that the active brain-connectivity of dyslexia children differs a lot from those of healthy children. The second experiment investigates fuzzy c means clustering[3] of brain-connectivity weights for children with dyslexia that are taken in a set order. It is observed that the resulting clusters show variation in the way that neural pathways terminate for the same cognitive task, learning, and this has a significant influence on the way that student groups are divided according to how comparable their brain-connectivity is for training[2].

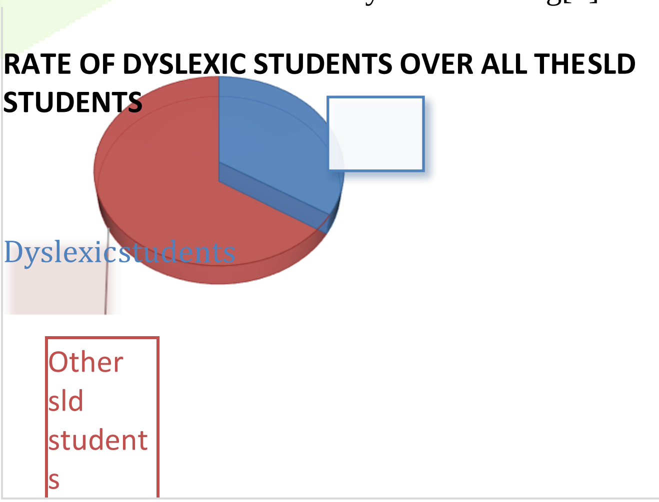


fig 1- pie chart showing the rate of dyslexic students according to WHO

The paper is divided into 5 sections. In Section II, the principle of fuzzy implication relations in brain-connectivity analysis is introduced. Section III provides a framework for the experimental protocol design. Details of experiments with a f-NIRS device are presented along with results and interpretations. Performance analysis is undertaken in Section

IV. Result and discussion are listed in Section V followed by tables and figures in Section VI.

Acknowledgement and References are listed in sections VII and VIII respectively.

II. BRAIN CONNECTIVITY ANALYSISPRINCIPLES PROPOSED USING FUZZY IMPLICATIONRELATIONS

2.1. Principle of the proposed fuzzy relational approach

Taking into consideration two lobes A and Bfrom an experimental human brain, let us take $a_{u,i}$ as the ith feature of channel u, extracted from brain lobe A and $b_{v,j}$ as the j- th feature of channel v, extracted from lobeB of the brain.

Taking $\mu_L(a_{u,i})$, $\mu_M(a_{u,i})$, $\mu_H(a_{u,i})$ as 3 membership functions indicating $a_{u,I}$ is Low, $a_{u,I}$ is Medium and $a_{u,I}$ is High respectively. Now, again taking $\mu_L(b_{v,j})$, $\mu_M(b_{v,j})$, $\mu_H(b_{v,j})$ as the membership functions of $b_{v,j}$ is Low, $b_{v,j}$ is Medium and $b_{v,j}$ is High respectively. The functional forms have been used toconstruct $\mu L(a_{u,I})$, $\mu M(a_{u,I})$, $\mu H(a_{u,I})$

as,

$\mu L(a_{u,i})=e^{(-ka u,i)2}$

here k is a real constant$\mu M(a_{v,i})=e^{(-k\ a_{u,I})^{-2}}$

here -a stores the central value in the spaceof $a_{u,i}$ $\mu H(a_{u,i})=e^{(ka u,i)}$,

here k stands for the same as above The definitions of $\mu H(b v,j)$ are same asabove.

The implication relation between $a_{u,I}$ isL/M/H and bv,j L/M/H can be given as: $RX,Y(a_{v,I},b_{v,j})=f(\mu X(a_{v,i}), \mu Y(b_{v,j})$Where $X,Y \in \{L,M,H\}$ and f('‚') is an implication function.

So, for $X \in\{L,M,H\}$ and $Y \in\{L,M,H\}$ we get 3x3=9 implication relations for rules if $a_{u,i}$ is X or $b_{v,j}$ is Y. If $a_{u,i}$ is X then $b_{v,j}$ is Y is confirmed if $RX,Y(a_{u,i},b_{v,j})>th$ will be the predefined threshold.

As per the current situation, a threshold th=0.5 is chosen as it is the middle value on the range[0,1], and provides equal chanceof persistence or non-persistance ofconnectivity between $a_{u,I}$ is X and $b_{v,j}$ is

For keeping the results free from experimental errors , experimental instances for all trains which are within or across sessions are repeated for computations of $RX,Y(a_{u,I},b_{v,j})$ for a fixed setof X, Y, i, j. If the results similar for all test cases, we can conclude that the relation representing the fuzzy concepts-au,i is X to $b_{v,j}$ is Y does exist. So,, now the above steps are repeated for all possible valuation space, that is, X,Y,I,j and the graph is constructed which represents the mapping between pairs of concepts $a_{u,I}$ is X to $b_{v,j}$ is Y which have relational strength greater than predefined threshold. Notably, the relational strength $RX,Y(a_{v,I},b_{v,j})>th$ denotes one-way connectivity between these fuzzy concepts, affirming the directional flow of signals from A to B in brain lobes. To ascertain the presence of reverse connectivity from Y to X (or from lobe B to A), we examine whether the relation$(RY,X(b_{v,j},a_{u,i})$exceeds the threshold. This technique offers a significant advantage in verifying directed brain connectivity. Figure 2 presents a diagrammatic representation of the process of deriving five features: average (m), variability (var), asymmetry (sk), peakedness (ku), and randomness (entropy), along with their fuzzy representation (fuzzification) at three levels: LOW (L), MEDIUM (M), and HIGH (H).Details regarding the extraction of these features (m, var, sk, ku, and E) are provided in Section III.

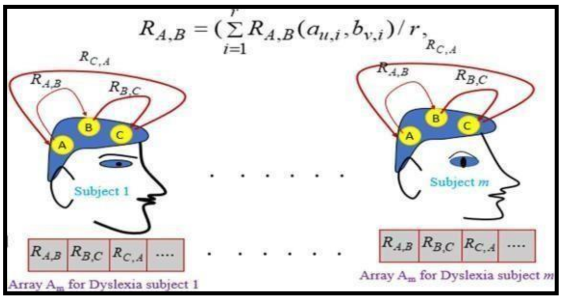


fig 2- computing average relational strength between pairs of lobes in Dyslexia patients and placing them in an array in fixed order of their occurrence.

2.2. Fuzzy Connectivity Maps for Children with Dyslexia

In Section II-A, while examining the connectivity between brain lobes A and B, we first consider all the most probable causal connections between feature $a_{u,i}$ taken from channel X and feature $b_{v,j}$ taken from channel Y for all feasible combinations of i and j. However, in practically, it is more probable that the connectivity between the same feature extracted from two channels will be stronger (if a connection exists at all)compared to the connectivity between two different features from two channels. Therefore, starting from this section onward, we will be focussing on analyzing the connectivity at the feature level between two channels.

Assuming there are r pairs of concepts, such as ($a_{u,1}$ is X and $b_{v,1}$ is Y), ($a_{u,2}$ is X and $b_{v,2}$ is Y)…. ($a_{u,r}$ is X and $b_{v,r}$ is Y) connected by implication relations of the form: "if $a_{u,i}$ is X then $b_{v,j}$ is Y."[2] For each pair of concepts, representing brain regions, we establishconnectivity (edges) from the node $a_{u,i}$ is X and $b_{v,i}$ is Y, and repeat this process for all r pairs of concepts for features i = 1 to r. This process effectively constructs a graph representing brain connectivity for r concepts. Additionally, we maintain an incidence matrix of fuzzy weights to track the relational connectivity between pairs of concepts.

If we replicate the procedures of constructing graphs for r features across N healthy experimental subjects, we can generate N× r incidence matrices, each corresponding to one feature per individual. These matrices contain fuzzy relational strengths as their data. To define the relational strength $R_{X,Y}(a_{u,i}, b_{v,j})$ in the s-th incidence matrix, we introduce an additional dimension s to $R_{X,Y}(a_{u,i}, b_{v,j})$, which resulted in in $R_{X,Y}(a_{u,i}, b_{v,j},s)$. To determine the range of relational strength from $a_{u,i}$ is X to $b_{v,i}$ is Y, we calculate both the maximum and minimum values by considering the union and intersection, respectively, of $R_{X,Y}(a_{u,i}, b_{v,j},s)$ for s = 1 to N. These values are then stored as the minimum and maximum in $\bar{R}_{X,Y}(a_{u,i}, b_{v,i})$, where the minimum value is denoted by α and the maximum value by β:

$\bar{R}_{X,Y}(a_{u,i}, b_{v,i})=[\alpha_i, \beta_i]$, ….(3.5)

$\alpha_i=\mathrm{Min}^{N}_{S=1} R_{X,Y}(a_{u,i}, b_{v,j},s)$, ….(3.6)

$\beta_i=\mathrm{Max}^{N}_{S=} R_{X,Y}(a_{u,i}, b_{v,j},s)$ ….(3.7)

The incidence matrix $\bar{R}_{X,Y}$, monitors the variation $R_{X,Y}(a_{u,i}, b_{v,j})$ across N healthy subjects for feature i. Now, let $\bar{R}_{X,Y}(a_{u,i}, b_{v,i})$represent the measurement of $R_{X,Y}(a_{u,i}, b_{v,j})$ for the unknown child, which falls outside the range [α,β] for feature i. If this occurs fora large portion of connection weights, such as more than 70% for many features (e.g., 90% of r), the unknown child is classified as having Dyslexia. The selection of 70% and 90% thresholds in this study is arbitrary and is subject to further experimentation, which was limited due to the pandemic's constraints on laboratory availability. It is crucial to note that we operate under a closed- world assumption, considering thatthe child is either healthy or has Dyslexia, without considering other diseases.

2.3. The average connection betweentwo brain pair lobes

By calculating the average strength of relational connection between pairs of lobesfor signal transfer in one direction, considering all potential features, channels, and fuzzy sets X, Y, one may determine the degree of directed average brain connectivity between pairs of lobes. Let X and Y be fuzzy sets, and let $R_{A,B}$ be the average relational connection betweenpairs of lobes A and B over all features, independent of the number of channels.

2.4. Clustering using fuzzy c means algorithm

Cluster analysis encompasses a wide range of techniques that aim to partition a given data set X into c subsets (clusters) that replicate X through union, are all nonempty, and are pairwise disjoint. It is thus said that the clusters represent a hard (i.e., nonfuzzy)c-partition of X. The excellent work by Duda and Hart (1973)[3]discusses several techniques, each with its own mathematical clustering criterion for finding "optimal" groups. The flaw in the underlying axiomatic model, which states that every point in X is categorically categorised with other members of "its" cluster and hence has no apparent resemblance to other members of X, is a key aspect of this kind of algorithm. Zadeh (1965) proposed one such method to describe how similar a particular point is to all the clusters.[3] The secret to Zadeh's theory[3] is to use a function, known as the membership function, whose values, or memberships, range from zero to one to express how similar a point is to eachcluster. Every sample will belong to at least one cluster; memberships around unity indicate that the sample and the cluster are highly similar, while memberships near zero indicate that the sample and the cluster are not particularly similar.

III RESEARCH METHODOLOGY

3.1. Experimental set-up

The experiment was carried out at Jadavpur University's Artificial IntelligenceLaboratory in Kolkata, India. Utilising an entire brain f-NIRS (NIRScout^{TM} imager) system, the brain's hemodynamic response is recorded. With 8 infrared sources and 8 infrared detectors, the f-NIRS device utilisedin this experiment—manufactured by NIRx Medical Technologies LLC—allows for 8 × 8
= 64 potential source-detector linkages, which are referred to as channels. Twenty of the 64 potential channels are chosen if the distance between the source anddetector pair is under a predetermined 3 mm threshold that is established in the system [8]. Inthe suggested brain- connectivity network, the centre point of each channel is referred to as a node, and the link between two nodes (channels) isrepresented as an edge.

3.2. Participants

Twenty kids under the age of two took part in the experiment. Twelve out of the twenty kids have dyslexia illness. Before permittingany kid to take part in the trials, their parents had to give their written agreement.To conduct the experiment, all safety precautions and ethical considerations are upheld in accordance with the 1970 Helsinki Declaration, which was updated in 2004 [9]. To prevent the potential for muscular artefacts to be picked up, children were urged to lie down in comfortable postures.

3.3. Pre-processing

We have worked with fNIRs dataset for brain imaginary signals. On considering the first 16 columns of each of the file anddividing each into segments: having 18seconds data considering 8 samples per second. To divide the data into smaller segments with 18 seconds of data per segment at 8 samples per segment at 8 samples per second,the following steps are followed:

Step 1: We have calculated the total numberof samples in 18 seconds of data at 8 samples per second:

18 seconds * 8 samples/second = 144samples
….(3.8)

Step 2: We have then determined the number of segments in the data by dividing the total number of samples by thenumber of samples per segment by the following formula:

Number of segments = Total number ofsamples / Number of samples per segment
= Total number of samples / 144

[//144 is used to return integer value inplace of float value.]

Step 3: We have then used the pandas groupby() method to group the data by segment number and then used the pd.DataFrame() constructor to create a new dataframe for each segment.

- Total segments after dividing thefiles into segments is 21.

For each segment we have plotted the data from column '15' against the index. We use the segment data frame's index as the x-axis and the column containing the data as the y-axis.

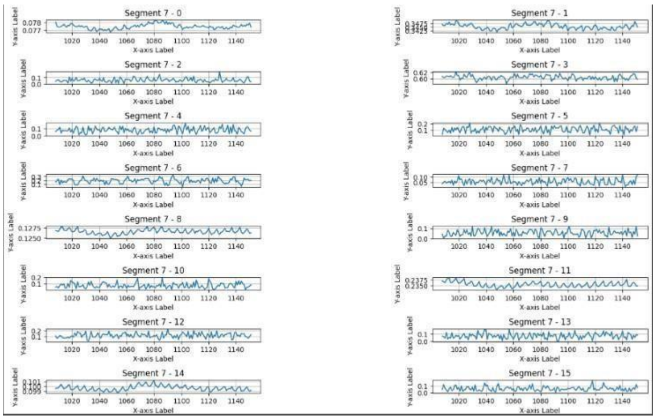


fig 3- segment 7 raw data plotting for 16columns among all the 21 segment raw data

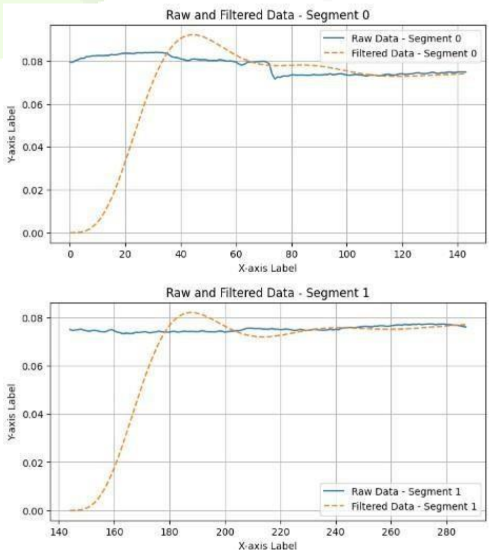
The fig 3 represents the raw data plotting for segment 7 among the rest 21 segments for each 16 columns (ranging from 0-15).

The plotting for the rest segment is the same.

3.4. Filtering

In the fields of digital and analogue signal processing as well as telecommunication systems, filters are crucial. Theapproximation issue and the synthesis problem are the two main components of a typical analogue filter design. Due to the limited word length in the past, digital filters also had accuracy issues. However, with the advent of 32-bit word lengths and floating-point capabilities, digital filters are now frequently employed. A filter's main purposes are to restrict a signal to a specific frequency range or channel or to simulate the input-output relationship of a system,such a phone line echo or a mobile communication channel [14]. The Butterworth filter has a roll-off ofminus 20 dB per pole and a maximally flat response, meaning that there is no passband ripple. Since the first 2N - 1 derivatives of the transfer function are equal to zero when $j\omega = 0$, it is a "flat maximally magnitude"filter at that frequency [15]. As N increases, the Butterworth filter's phase response getsincreasingly nonlinear. The cut off frequency and the number of poles are the two factors that theoretically describe this filter.

A particular kind of signal processing filter called the Butterworth filter aims to have a frequency response that is as flat as feasible throughout the passband. Additionally, it is called a maximally flat magnitude filter. British engineer and scientist Stephen Butterworth originally mentioned it in a 1930 article titled "On the Theory of Filter Amplifiers"[10].



By adding equal ripple to the passband, the Chebyshev Type I filter reduces the absolutegap between the ideal and real frequency response throughout the whole passband. Response of the stopband is maximum flat. The speed at which the passband and stopband change is faster than with the Butterworth filter [16]. Cauer filters are another name for an elliptical filter. There are two types of elliptic filters: passband and stopband. Theyuse the lowest order of any available filter type to satisfy filter requirements. Ellipticfilters reduce the stopband and passband ripple's transition width for a given filter order. Butterworth, Elliptical,

and Chebyshev filters are applied to each column of each segment separately and then the filtered data for each segment is plotted.
fig 4- butterworth filter plot for segment 0 and segment 1
Figure 4 shows the plotting between raw data and filtered data where Butterworth filter isused to filter the data.
After analysing the plotting of all the three filters, we selected Butterworth filtered data to work further with our further analysis. We have selected Butterworth filter as it has less ripples compared to Elliptical and Chebyshev filter.

3.5. Wavelet Decomposition and Feature Extraction

The wavelet transform is a mathematical technique used to analyze the frequency content of a signal at different scales. Wavelet transforms decompose a signal into components that represent different frequency bands, allowing us to analyze both high and low-frequency components separately. It demonstrates how to perform wavelet decomposition on a series of data segments and extract statistical features (such as mean, standard deviation, skewness, and kurtosis) from the resulting wavelet coefficient[13].

To find the wavelet decomposition of filtered data, we use Python libraries like PyWavelets. PyWavelets allows us to perform various types of wavelet decomposition, including continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The type of wavelet ('db4') is used and the level of decomposition is (level=1). More levels provide a finer resolution of frequency components but may also introduce more noise. The pywt .wavedec function performs the wavelet decomposition on the data from each segment, producing a list of wavelet coefficients at different levels.

From the artifact-free independent components gathered from the filtered data of the f-NIRS device, the crucial set of characteristics must be retrieved. A significant collection of features—referred to as static features—is taken out of each channel for the current situation. The mean (m), standard deviation (sd), skewness (sk),Kurtosis (ku) are the static properties of the filtered data are as follows:

Mean (m): 0.067913737539274466
Skewness (sk): -1.795001834187044
Standard deviation(sd):0.025813186757287113Kurtosis (ku): 1.6215987800637208

3.6. Clustering and analysing the output

Cluster analysis encompasses a wide range of techniques that aim to partition a given data set X into c subsets (clusters)that replicate X through union, are all non empty,and are pairwise disjoint.

In 1965, Zadeh presented one such method to describe how similar a single point is to all the clusters (1965). The secret to Zadeh's theory is to use a function, known as the membership function, whose values, or memberships, range from zero to one to express how similar a point is to each cluster. [3] Every sample will belong to at least one cluster; memberships around unity indicate that the sample and the cluster are highly similar, while memberships near zero indicate that the sample and the cluster are not particularly similar.

Popular clustering algorithm fuzzy C-Means (FCM) clustering assigns a degree of membership to each data point for each cluster, meaning that each data point belongs to multiple clusters with varying degrees of membership. This allows for more nuanced classification and better handling of data points near cluster boundaries. Unlike traditional hard clustering methods like K-means, FCM assigns a degree of membership to each data point for each cluster.

A fuzzy partition's quality may be gauged using the partition coefficient. The fuzzy partition P will perform better the closer C(P) is near 1. The partition coefficient maybe used to compare the results of a fuzzy clustering technique for a range of n values. The number of clusters (C) is taken as '3' into which the data is divided.
The Fuzzy Partition Coefficient (FPC):0.9999723039880029.

The data (data_features) is assumed to be a 2D array with each column representing a feature and each row representing a datapoint. Since the code transposes data features, the data is passed to the c means function as a transposedarray, which is commonly used for clustering.

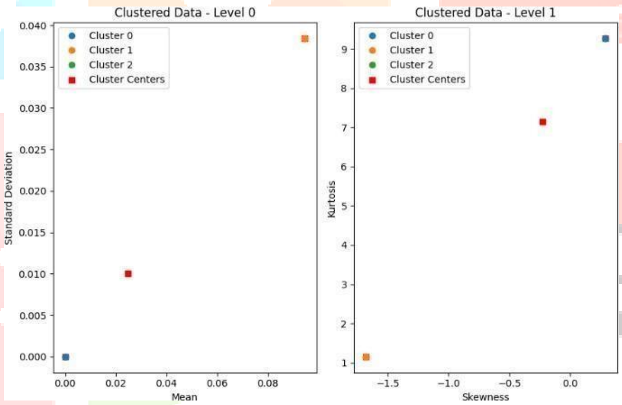
Fuzzy c-means clustering: The function c means from the skfuzzy library is used to perform fuzzy c-means clustering on the data.The number of clusters are then found. The fuzziness parameter (m); value of2 represents a common choice and allows for a moderate degree of fuzziness. error=0.005: The stopping criterion for the iterative optimization process. The algorithm stops when the change in cluster centers is less than this value. maxiter=1000: The maximum number of iterations the algorithm will perform to converge. The c means function returns multiple outputs. In this thesis, the important ones are:

- cntr: A 2D array where each row represents a cluster centres
- The membership matrix, where each column represents a data point and each row represents a cluster. Each value in thematrix indicates the degree of membership of a data point to a specific cluster.
- The centroids are extracted from the cntr array and transposed to match the data layout (each column now represents afeature).

Fuzzy c-means clustering is used to group data into clusters and print the centroids of each cluster. In fuzzy c-means, data points can belong to multiple clusters with varying degrees of membership, allowing for soft clustering.

Membership Matrix:
[[1.87109844e-16 1.00000000e+00 1.87109844e-16 1.00000000e+00] [1.00000000e+00 4.86413429e-16 1.00000000e+00 4.86413429e-16] [3.43537546e-16 7.08647472e-15 3.43537546e-16 7.08647472e-15]]

Cluster Centers:
[[8.08285332e-09 4.14071436e-072.88569660e-01 9.26704051e+00
-3.46865897e-10]



[9.44232297e-02 3.83923035e-02 -1.68045438e+00 1.15540263e+001.20279523e-03]
[2.47381140e-02 1.00587727e-02 -2.27298412e-01 7.14185823e+003.15122181e-04]]

fig 5- cluster data plotting in 2D graph

One measure that helps evaluate the effectiveness of clustering is the Silhouette Score. Determining the efficacy and dependability of clustering algorithms requires evaluating the quality of clustering. As clustering is an unsupervised learning problem, the groups cannot be validated by explicit labels. As a result, internal validation criteria such as the Silhouette Score must be used to assess the clustering findings. After the clustering and getting the FPC (Fuzzy Partition Coefficient) value as 0.9999723039880029 we then finally find the silhouette score. The silhouette score compares a data point's cohesiveness (similarity to its own cluster) to its separation (difference from other clusters).

It falls between -1 and 1:

- A value of 1 denotes a complete separation of the clusters, with the data points being far from otherclusters and extremely near to their own cluster.
- Data points are equally spaced between clusters when the value of0 denotes overlapping clusters.
- Incorrect clustering is indicated by a

-1 (data points are closer to other clusters than to their own).

On the final execution we get a perfect silhouette score of 1.0. A high silhouette score on average suggests that theclusters
are clearly defined and different from each other.

IV. PERFORMANCE ANALYSIS

This section discusses the relative effectiveness of the suggested method in comparison to current brain-connectivity algorithms, as well as the selection of the optimal fuzzy implication function for brain-connectivity mapping. The outputs of the suggested fuzzy implication relation- based technique are fed into a classifier as features to comprehend the brain- connectivity algorithm's performance. Thefuzzy relational matrix RB,A is first reshaped to form a segmented data, which is then treated as a feature to train and later test a fuzzy c means clustering classifier with silhouette score. This is done to classify the two classes: dyslexic and healthy subjects based on the fNIRs responses of the subjects.
As the FPC (Fuzzy Partition Coefficient) is nearer to 1 we get to analyse that the fuzzy partition P is better and significant and the clustering will be performed in a clear manner. After the clustering is performed, silhouette score is found to analyse how much compact the clusters are. As mentioned above, the silhouette score is perfect 1.0 so we can say that the clustering performance is high and dyslexic and non- dyslexic clusters are well-separated.
Based on the results of the analysis, it can be said that the Fuzzy Inference System and Random Forest (WEKA) are the best classifiers overall for both dyslexic and normal subjects. This is because both algorithms have a 100% accuracy, sensitivity, specificity, and precision rate, which indicates that they can distinguish between dyslexic and normal subjects. Furthermore, only the Fuzzy Inference System and Random Forest (n=200) classifiers show the most potential for usage as the classification model fordyslexia screening, passing all statistical analyses. This makes them the best choice for detecting dyslexic people. Notably, categorization can change based on the kinds of tasks that need to be completed [11].
Although Naïve Bayes and Decision Tables could not attain 100% accuracy, the outcomes had an accuracy rate higher than 90%[12].

V. RESULT AND DISCUSSION

The study presents a unique fuzzy implication relational method for brain-connectivity analysis. The methodology is beneficial because it has the innate ability to identify directional causation in brain connection, something that the conventional Granger causality-based approach is unable to accomplish.

The suggested method has proven effective in assessing the brain connection of healthy individuals and identifying the potential range of connectivity weights among different brain modules. According to conducted experiments, children with dyslexia have brain connection that is stronger than that of healthy people for the same weight. Therefore, it is simple to distinguish between dyslexics and their healthy counterparts using the suggestedstrategy.

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Our consider is to recognize designs within the information that recognize between dyslexic and healthy children utilizing fuzzy c-means clustering. The clustering comes about yielded an silhouette score of 1.0, showing a idealize partition between the two clusters. This result proposes that the clustering calculation was able to successfully categorize the children into two unmistakable bunches based on their information highlights. The culminate silhouette score illustrates a tall level of cohesion inside each cluster and solid partition between the clusters. This clear qualification is an empowering finding, because it suggests that there are quantifiable differences within the information that can be utilized to distinguish between dyslexic and sound children. Such contrasts may be due to cognitive, phonetic, or neurodevelopmental characteristics that are showed within the information highlights. The remarkable clustering execution underpins the viability of the highlights utilized within the examination. The chosen information highlights show up to capture important and significant angles of dyslexia and wellbeing in children. Typically, a vital step toward the advancement of vigorous, data-driven demonstrative instruments that may encourage early distinguishing proof and intercession for dyslexic people.

Be that as it may, whereas the outline score is a great degree of clustering quality, it is vital to consider additional strategies of approval and confirmation. Future inquire about might incorporate visualization of the clusters, cross-validation with other clustering calculations, or comparison with known clinical analyse to affirm the precision of the clustering comes about.

The commonsense suggestions of our discoveries are critical. The clear division between dyslexic and sound children highlights the potential for creating focused on screening instruments based on the distinguished information designs. Such devices seem help within the early location of dyslexia, opportune intervention, and bolster for influenced people.

In conclusion, the tall outline score gives strong evidence that the clustering approach is fruitful in recognizing between dyslexic and sound children. Assist investigate is required to approve these findings and investigate their down to earth applications in clinical and instructive settings.

After all the analyzation, we worked with fuzzy c means clustering algorithm as the partition coefficient and silhouette value gives an accurate performance view for the clustered and un-clustered data differentiating between dyslexic and non-dyslexic children.

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