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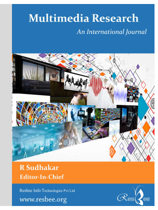

Classification of ADHD with the Functional Connectivity by Usage of Different Atlases in Lahore, Pakistan

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Abstract: Attention Deficit-Hyperactivity Disorder (ADHD) is a psychiatric condition that affects children's abilities. Nowadays computational diagnosis strategies of neuropsychiatric disorders are gaining more attention. Diagnosing this disorder based on fMRI is critical to determine the brain's Functional Connectivity (FC). Millions of children have the symptoms of this disease.The brain is notoriously unreliable for diagnosing neurological conditions. This condition is referred to as a chronic disease.A great number of youngsters exhibit signs of this disease. As a result, the study endeavored to come up with a model and design that is both reliable and accurate for diagnosing ADHD.A variety of techniques used in this present study, such as the local binary encoding method (LBEM) is utilized for future extraction, and the hierarchical extreme learning machine (HELM)is used to extract information on the connectivity functionalities of the brain.To validate our approach, the data of One hundred fifty-three children serve as a sample for the diagnosis, from which one hundred children are ultimately determined to have ADHD.These affected ADHD children are used for our experimental purpose. According to the findings of the research, the results are based on comparing various Atlases given as AAL, CC200, and CC400. Our model gainssuperior performance with CC400 when comparedwith other Atlases.

Keywords: Connectivity functional; fMRI; sparse-auto encoder; Hierarchical extreme learning machine system.

Nomenclature

Acronym	Expansion
ADHD	Attention deficit hyperactivity disorder
FIP	Interaction function pattern
fMRI	Functional magnetic resonance imaging
ML	Machine Learning
MRI	Magnetic Resonance Imaging
LBEM	Local Binary Encoding Method
HELM	Hierarchical Extreme Learning Machine
ERP	Event-Related Potential
FC	Functional Connectivity
ELM	Extreme Learning from Machine
ROI	Regions Of Interest

1. Introduction

Each organ in our body has a certain function. The primary role is to provide instructions to the rest of the body.The brain is an extremely vital and significant organ in our bodies. The brain is responsible for a wide variety of tasks, including thinking, feeling, and performing other functions. Computer diagnostic technology is used for a variety of organ systems to identify a variety of disorders to get effective outcomes. In this regard, researchers have placed a lot of emphasis on various organs and brains to identify the various disorders using the most recent technological advancements. In addition, researchers are aware that the field of neuroscience is making progress toward politeness. Only a very small number of researchers have used the most recent technology to study this organ (the brain). According to [1], neuropsychiatric disorders seem to be rather widespread among children, and a significant number of

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children around the globe appear to be afflicted with these disorders. The medical term for this condition of the brain is called ADHD. According to [2][3], sixty percent of adults experienced this negative effect. The author [4] claims that this condition appears to affect six percent of children and four percent of adults.It seems that a lot of contemporary researchers are paying attention to this problem. They have attempted to construct the framework necessary to overcome this issue using the attention deficit hyperactivity disorder paradigm of a computational system. Previous research by these researchers recommended using automated diagnostic approaches using characteristics derived from functional magnetic resource images.The author [5] has presented the regional homogeneity function, In yet another piece of research, [6] proposes a solution to this problem in the form of a system called low-frequency amplitude fluctuations. In the paper [7],[8] characterized these concerns with the use of the term "ADHD". These issues are associated with irregular activities. Researchers are also making use of data from fMRI scans to classify Parkinson's illness in 2014 [8]. In their research, the researchers at Spatial are also using this approach for fMRI images [9]. It was suggested that a discriminative functional model may be used to identify patients with ADHD [5].

In the past, a great number of researchers have used many different approaches to provide solutions for ADHD [11], [13]. Another researcher 2014 came up with the idea of using spatial analysis for brain functioning systems in conjunction with linear analysis [11]. June [13] used a variety of analyses and models in connection with ADHD and FC in 2015 to develop a correlation and model of the brain to extract nodes and exploit vector graphs. Regarding the classification of ADHD, they provided an explanation based on data from an MRI of the brain. [14] designed data related to fMRI and non-fMRI to classify ADHD. In addition, the research focuses on space-sparse representations with separation. They present a framework for the dual model, which is dependent upon sparse categorization [15]. The universal background model of ADHD was based on the multi-channel feature model [16]. Additionally, according to [15], it has helped improve the diagnosis of ADHD in youngsters. ADHD and the control normal range are classifications that are not simple to establish [15]. According to [19] Todd's classification, the area may be broken down into the parietal, temporal, occipital, and frontal lobes. The method that was just mentioned helps to distinguish Normal and ADHA from one another since it does so by identifying their differences. The clearest indication of ADHA was provided through the structural changes in brain volume that were seen [7].

Within the scope of this study, the researchers made use of the CC400, CC200, and AAL methods as a model for an ADHA-affected patient's brain. In the present investigation, methods for processing, analyzing, and extracting data from ROI and FCs are derived from the field of brain imaging. After that, CC400 was created by using this extraction of two hundred FC as a starting point. WhereHELM is used for data extraction. The findings presented in this research add to FC and compare with a variety of atlases derived from the raw material. The main objective of the proposed method is to accurately predict the Normal, Mixed, attentive, and hyperactive patients.

The organization of this paper is in this order: Section 2 presents the literature review, and Section 3 explains the methodology. The proposed algorithm is explained in section 4. Section 5 covers the result and discussion, Section 8 explains the advantages and disadvantages, and Section 7 concludes the paper.

2. Literature Review

In 2020, Salman *et al.* [29] have used FC of the brain based on fMRI. Initially, raw data on ADHD was collected and the noise was removed. Then the artifacts were pre-processed. Extract FC of the brain was used such as CC400, CC200, and AAL. Using the LBEM algorithm,features of the FC data were extracted and HELM was used to classify the extracted features. Finally, the performance was compared with various atlases. This method achieved the highest performance with the CC400 atlas as compared to other atlases.

In 2022, Catherine Joy*et al.* [30] have worked on a technique for detecting ADHD from EEG signals using tunable Q- wavelet transform which includes data acquisition, tunable Q-wavelet transform, nonlinear feature extraction, and artificial neural. An ANN classifier with a tenfold cross-validation methodology was used to discriminate between ADHD and normal subjects. Performance was evaluated using accuracy, sensitivity, and specificityto classify the ADHD and normal subjects with maximum accuracy.

In 2021, R. Catherine Joy *et al.* [31] have used a computer-aided technology solution forthe detection of ADHD from the EEG signals. It is based on the various entropy and ANN classifier. These techniques effectively detect and classify ADHD subjects, which showedsuperior classification accuracy, specificity, and sensitivity.

In 2022, Sartaj Ahmed Salman *et al.* [32] haveimplemented a kernel hierarchical extreme learning machine to classify the feature vector into ADHD or NC. The fMRI data werepreprocessed to remove noise and artifacts.The detected dynamic changes were used to extract global features from the fMRI data. The work achievedthe highest classification rates compared to other models.

In 2020, Huayu Zhang *et al.* [33] have performed ICAtechniques for statistical analysis of fMRI data,and a group of ICA analyses was conducted to decompose the data into ICs using the GIFT toolbox for all subjects. The principal component analysis was used to define the number of ICs. The resulting components were clustered to estimate the reliability of the decomposition.Finally, the time courses and spatial maps were reconstructed using the group ICA back method. DMN and DAN were suggested to decrease FC.

In 2022, Wonjum Lee *et al.* [34] have suggested a deep learning-based ADHD classification method using children's skeleton data acquired through an ADHD screening game. Acquired datawere divided into standby and game data using RNN, GRU,and LSTM algorithms. Risk and normal children were separated.This technique was used for screening and diagnosis of children's ADHD.

In 2023, Yichun Li*et al.* [35]have diagnosed ADHD using a skeleton-based method that utilized a real multi-modal dataset and detection algorithms.It was a standard measurement and the area under the curve. This method outperforms the conventional methods in accuracy and AUE which makes it more accessible for a high range of initial ADHD diagnoses. It may be widely used for mass screening.

In 2023,Hámori, *et al.* [36] haveimplemented ERP to identify the reinforcement sensitivity as ADHD. Initially, EEG data were recorded and processed to obtain ERP. After examining the ERP amplitude and latency variable, the result was separated into at-risk, not at-risk, inattentive, inattentive, and hyperactive respectively. Furthermore, linear support vector and regression analyses to evaluate the accuracy of ADHD.

2.1 Review

Table 1 portrays the methodology, advantages, and disadvantages of the existing method. We considered eight papers that used a different methodology for the detection of ADHD. Each method has certain benefits and shortcomings, that were explained in detail.

Table 1: *Review Based on Existing Methods*

Author	Methodology	Advantage	Disadvantage
Salman *et al.* [29]	FC	• Accurate diagnosis • Provided evidence for accuracy.	• Expensive and time-consuming. • Required expertise in data analysis and machine learning.
Catherine Joy *et al.* [30]	TQWT and nonlinear feature extraction methods	• Rapid identification and treatment of ADHD. • Automatic detection. • Maximum accuracy.	• EEG signals were not easily accessible in some settings. • May require specialized equipment and expertise to implement. • Limitation in usage.
R. Catherine Joy *et al.* [31]	Computer Aided Technology	• Effectively detect and classify ADHD subjects. • Highest classification accuracy, sensitivity, and specificity.	• Used only a less sample. • Time-consuming process. •
Sartaj Ahmed Salman *et al.* [32]	kernel hierarchical extreme learning machine	• The work achieved superior classification rates compared to the state-of-the-art models.	• Further study was needed to improve the average accuracy of fMRI classification.
Huayu Zhang *et al.* [33]	ICA	• It contributed to the management and treatment of ADHD for adolescents.	• The accuracy of the result is affected sometimes.
Wonjum Lee *et al.* [34]	ADHD screening game	• Used for screening and diagnosis of children with ADHD.	• It's a high-cost process. • Tested to fewer samples.
Yichun Li *et al.* [35]	Skeleton-based method	• Widely applicable for mass screening. • Cost-effective process • It indicates clear differentiation between ADHD subjects and controls in diagnosis outcomes. • Improved diagnosis accuracy.	• It provides only text information.
Hámori, et al. [36]	ERP	• Provided rich sources of data for analysis. • Accurate Result	• The sample exhibited a relatively broad range with regard to substance use heaviness, most adolescents were not heavy (clinical) users.

2.2 Challenges

The challenges experienced during the detection of ADHD are given as follows,

- The new technology helped to detect ADHD accurately [29][30][34][35]. However, the tested samples are too small. The accuracy may vary based on the data and the type of people.

- In Skeleton-based method [31][32][34], used various innovative methods to ease the process of detection of ADHD. Nevertheless, their methods were suitable for only a particular age group and not suitable for types of people.
- When compared to current methods, it produces good results in [30][32]. However, this method cannot be adopted easily. These methods are high-cost, need special equipment, are labor intensive, and do not apply to many clinical settings.

Even though numerous studies have improved the detection of ADHD, it is still difficult for examiners to completely adopt this technology because of its cost, accuracy, machinery, and other factors. Most of the process was tested only in the laboratory and not manually tested. A reliable, easy, and adaptable method is needed for the detection of ADHD.

3. Methodology

The general hospital serves as the source of the data. The ADHA-200 is associated with this data type (ADHA 2011). Three hundred members of the population serve as representatives in the sample. One hundred fifty-six of these individuals are considered normal controls. Sixty-six of these individuals are considered to be mixed ADHA. Sixty-six of these individuals are considered to be in attentive ADHA, and just one individual is considered to be in hyperactive ADHA [22].

Initially, the data from the fMRI is collected from the source and pre-processed. From the pre-processed data, Bold extraction was carried out in each ROIin different layers. Then, FC measures the statical dependence between deoxygenated blood level in some specific area and the time series of electrophysiological activity. The flow process of detection of ROI is explained in Fig 1.

Fig.1. *Atlas visualization*

Here time atlases CC400, CC200, and AAL are used. These atlases are designed through a seed-based correlation matrix. Fig 2 represents the visualization of the atlas and Fig 3 explains the atlas connectomes.

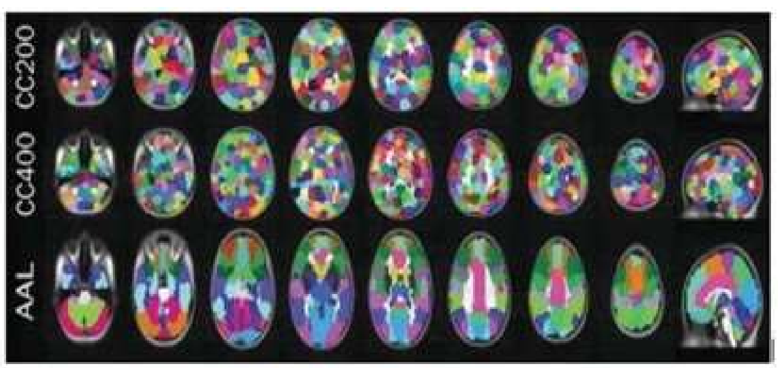

Fig.2. *Atlases Connectomes [32]*

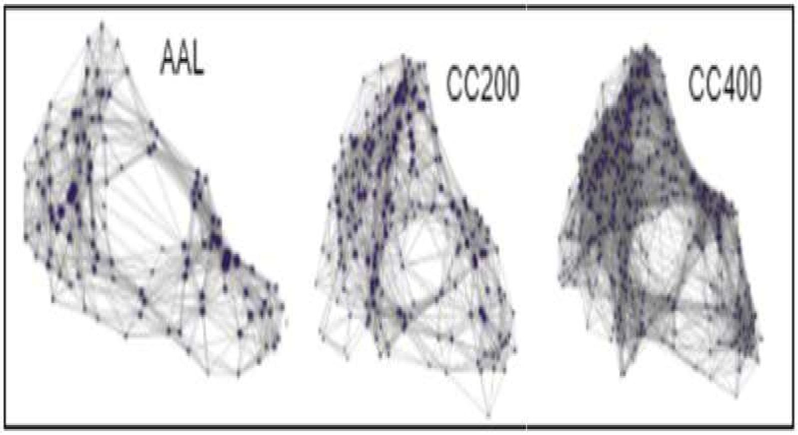

Fig. 3.*Seed-based correlation analysis and ROI-FC maps*

4. Proposed Algorithms

4.1 Binary Local Encoding Technique

In previous studies, LBEM is used to extract the data through the brain's FIP and analyze it through the fMRI dataset [32].

In the current study, LBEM is used and adapted for the extraction and analysis of algorithms. The matrix form of the fully processed-data system is represented in the equation $X = (X_1, X_2, X_3, \ldots X_H)$ belongs to $E^{L\times M}$. Here, Mrepresents the number of times. L is the region number for extraction of FC. The $E^{L\times M}$ value seems to vary in every atlas. $E^{392\times M}$ for CC400, $E^{200\times M}$ for CC200, and $E^{116\times M}$ for AAL.For each vector, $X_H = (X_1, X_2, X_3, \ldots, X_H), 1 \le H \le N$, H represent the FC numbers. So, X_H is the vector column with the X data matrix. Then compare X_H with $Y_H = (K_1, K_2, \ldots, K_t)$, $1 \le H \le N$ In this equation, t is a variable in every template, Where778 is for CC400, 389 is for CC200 and 241 is for AAL.The Y_H is represented as [32]

$$K_{2(j-1)-1} = \begin{Bmatrix} 1, & q_j \le q_{j-1} \\ 0, & q_j > q_{j-1} \end{Bmatrix}, 2 \le j \le L \tag{1}$$

$$K_{2(j-1)} = \begin{Bmatrix} 1, & q_j \le q_{j+1} \\ 0, & q_j > q_{j+1} \end{Bmatrix}, 2 \le j < L-1 \tag{2}$$

$$K_y = \begin{Bmatrix} 1, & q_L \le q_j \\ 0, & q_L > q_j \end{Bmatrix} \tag{3}$$

By the above equation, binary numbers 1 and 0 are used in the elements $Y_H = (Y_1, Y_2, Y_3, \ldots, Y_y)$ that belong to E^{yXM}. The binary number is encoded with a decimal in Figure 6. In the figure, the vector $U = (x_1, x_2, x_3, x_4, \ldots, x_H)$ is encoded into a binary vector $V = (y_1, y_2, y_3, \ldots, y_h)$. The binary vector V is further converted into a decimal form $W = (z_1, z_2, z_3, \ldots, z_H)$.

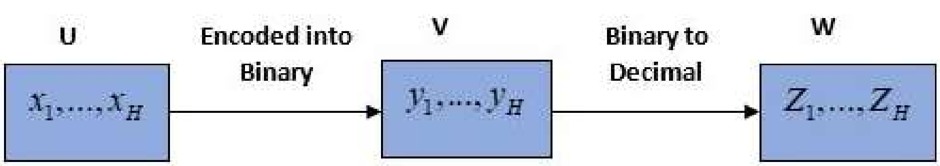

Fig.4. *Encoding of Binary to Decimal*

4.2 ELM

ELM is a single feed-forward neural model [38]. It consists of a single layer with hidden nodes. The nodes and hidden layers are randomly assigned. The hidden layer matrix is represented as [32].

$$T = \begin{bmatrix} k(y_1) \\ \vdots \\ k(y_M) \end{bmatrix} \begin{bmatrix} k(g_1 i_1 + y_1) & \cdots & k(g_N i_1 + y_N) \\ & \ddots & \\ k(g_v i_m + y_1) & \ldots & k(g_n i_M + y_N) \end{bmatrix} \tag{4}$$

Here, k(.)represents the non-linear function for the activation processes the input biases g_1 and biased with g_1. The output weight vector B is generated randomly here the equation is calculatedin Equation 5.

$$B = T\dagger W \tag{5}$$

Where $T\dagger$ is known as Moore- Penrose generalized inverse matrix. W represents the training label matrix.

$$W = \begin{bmatrix} W_1^I \\ \vdots \\ W_M^I \end{bmatrix} \begin{bmatrix} W_{11} & \cdots & W_{1F} \\ \vdots & \ddots & \vdots \\ W_{M1} & \cdots & W_{MF} \end{bmatrix} \tag{6}$$

The result of ELM is obtained from the following equation.

$$h(i_c) = k(i_c)B \tag{7}$$

4.3 Hierarchical Learning from Extreme Machine

This method is very advanced and complex [24]. It's dependent on two main parts: firstly, the supervised classification from extreme machine learning, and secondly, the unsupervised classification system [25]. From here, zero is used as the input layer. The beginning layer is hidden, as shown in Figure 4, and other hidden layers are also extracted from it by the auto-encoding method. With the Given Equation:

$$T_j = r\left(T_{j-1}.B^I\right), 1 \le j \le n \tag{8}$$

Here T_j is the output of the j^{th} layer, and T_{j-1} is the output of $(j\text{-}1)^{th}$ in form layers and for initiation r(.) for use as a hidden layer [26]. After that, Fine-tuning is operated in layers one after another [27]. The $N_j$norm method of regulation is used for auto-encoders and extreme machine learning. For this, an optimization model is given below.

$$PB = \arg\min B\left\{\| UB - Y \|^2 + \| B \|_{N1}\right\} \tag{9}$$

The algorithm is then calculated, where the Kis represented as $\| UB - Y \|^2$

When calculatingB, with this final equation, we obtained

$$m_{j+1} = B_j + \left(\frac{y_{j-1}}{y_{j+1}}\right)\left(B_j - B_{j-1}\right) \tag{10}$$

5. Results and Discussion

The technique of mastery and precision in categorization and analysis is included in this part of the research. To do this, repeated experiments have been carried out using an r-fMRI dataset, including the brain scans of one hundred fifty-three children, of whom one hundred have been diagnosed with ADHD. For these many brains, namely the AAL, CC200, and CC400, selections were made. After the data have been collected, they are preprocessed using a variety of time series according to the various atlases. The r-fMRI is used for the conduct of experiments. The approach of fivefold cross-validation is used. The experiment was carried out thirty times to get an accurate representation of its results. The first ELM to be used with templates produced superior results. That is represented in Table 2, When compared to CC200 and AAL, the accuracy of ELM is achieved. The use of CC400 is superior. In addition to this, the findings of the HELM comparison in the previous section demonstrate varying degrees of accuracy in the various layers.The variation of degree in various layers is explained in Tables 3,4 and 5. The findings are very consistent with the data that was obtained, and it also demonstrates that if data were collected on a large scale using similar experiment techniques, its classification accuracy would increase.

Table 2: *Average accuracy by using elm with dissimilar atlases*

Class	ELM with CC400			ELM with C200		ELM with AAL	
	N.C	ADHD		N.C	ADHD	N.C	ADHD
Fold First	0.989	0.971	❖	0.981	0.961	0.931	0.881
Second	0.981	0.961	❖	0.961	0.951	0.921	0.941
Third	0.991	0.992	❖	0.912	0.891	0.941	0.842
Fourth	0.982	0.961	❖	0.971	0.871	0.981	0.861
Fifth	0.992	0.910	❖	0.941	0.981	0.881	0.883
Average	**98 %**	**96 %**	❖	**95%**	**93%**	**92%**	**88%**

Table 3:*Average accuracy by using HELM with CC400 and multiple layers*

Class Using CC400	Hidden one layer with HELM		Hidden two layers with HELM		Hidden three layers with HELM	
	N.C	**ADHD**	**N.C**	**ADHD**	**N.C**	**ADHD**
Fold First	0.988	0.989	❖ 0.972	0.991	0.982	0.985
Second	0.989	0.961	❖ 0.961	0.989	0.972	0.991
Third	0.995	0.981	❖ 0.991	0.984	0.952	0.946
Fourth	0.989	0.972	❖ 0.992	0.962	0.961	0.871
Fifth	0.986	0.971	❖ 0.989	0.942	0.984	0.951
Average	**99%**	**97 %**	**98%**	**96%**	**97%**	**94%**

Table 4:*Average accuracy using HELM with CC200 and multiple layers*

Class Using CC200	HELM with one hidden layer		HELM with two hidden layers		HELM with three hidden layers	
	N.C	**ADHD**	**N.C**	**ADHD**	**N.C**	**ADHD**
First	0.975	0.989	❖ 0.971	0.981	0.985	0.931
Second	0.963	0.962	❖ 0.961	0.961	0.991	0.921
Third	0.992	0.983	❖ 0.992	0.912	0.946	0.941
Fourth	0.992	0.972	❖ 0.961	0.971	0.871	0.981
Fifth	0.988	0.977	❖ 0.910	0.941	0.951	0.881
Average	97.08%	97%	96%	95%	94%	92%

Table 5:*Average accuracy by using helm and all with multiple layers*

Classes of AAL	One Hidden Layer of HELM		Two Hidden Layers of HELM		Three Hidden Layers of HELM	
	N.C	**ADHD**	**N.C**	**ADHD**	**N.C**	**ADHD**
First Fold	0.989	0.998	➢ 0.889	0.831	0.852	0.848
Second	0.988	0.987	➢ 0.889	0.890	0.881	0.892
Third	0.951	0.889	➢ 0.971	0.982	0.912	0.910
Fourth	0.921	0.891	➢ 0.951	0.941	0.931	0.900
Five	0.910	0.920	➢ 0.951	0.923	0.910	0.915
Average	**95%**	**94%**	**93%**	**91%**	**89%**	**88%**

6. Advantages and Disadvantages

Advantages

- This system is very accurate and efficient as well.
- The method utilized functional connectivity to extract the differences in brain function interactions such as normal, mixed, attentive, and hyperactive.
- The data can also be helpful for detection of neuropsychiatric diseases in the brain.

Disadvantage

- The experiment was carried out with many iterations to getan accurate representation of its results.
- The study does not compare the proposed method with other deep learning models, which could provide a more comprehensive evaluation of the method's performance.

7. Conclusion

To exemplify and design efficient algorithms, the experimentally explored dataset system is being used in our present work. A categorized data system for the brain is now being developed to discriminate between normal people and individuals who have ADHD. In Lahore, Pakistan, our study incorporated several additional hierarchical ELM elements, and the results showed that these features were effective in differentiating normal people from those who had ADHD. The conclusive findings have been categorized as being precisely the same as Ahmad's earlier investigations [28]. In addition to this, it demonstrates a high level of accuracy by making use of the most recent technological advancements. However, the end product has now become quite steady and satisfying. In the future, there will be a lot of experimentation to enhance fMRI classification, which will raise the accuracy of more efficient findings that can be deduced to separate normal people from ADHD sufferers.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensuredthat they have not conducted any studies with human participants or animals.

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