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CLASSIFICATION AND MONITORING OF AUTISM USING SVM AND VMCM

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ABSTRACT

Autism is a lifelong developmental deficit that affects how people perceive the world and interact with each others. An estimated one in more than 100 people has autism. Autism affects almost four times as many boys than girls.
The commonly used tools for analyzing the dataset of autism are FMRI, EEG, and more recently "eye tracking". A preliminary study on eye tracking trajectories of patients studied, showed a rudimentary statistical analysis (principal component analysis) provides interesting results on the statistical parameters that are studied such as the time spent in a region of interest. Another study, involving tools from Euclidean geometry and non-Euclidean, the trajectory of eye patients also showed interesting results.
In this research, need confirm the results of the preliminary study but also going forward in understanding the processes involved in these experiments. Two tracks are followed, first will concern with the development of classifiers based on statistical data already provided by the system "eye tracking", second will be more focused on finding new descriptors from the eye trajectories.
In this paper, study used K-mean with Vector Measure Constructor Method (VMCM). In addition, briefly reflect used other method support vector machine (SVM) technique. **The methods are playing important role to classify the people with and without autism specter disorder**. The research paper is comparative study between these two methods.
Keywords: *(Autism, Eye tracking, Classification, VMCM, SVM).*

1. INTRODUCTION

Autistic people suffer from deficit of visual perception and / or aural and emotional expressions. Autism is not an illness or disease and cannot be healed. Often people feel being autistic is a fundamental aspect of their identity. [1]

To better understand the processes involved in autism, neurophysiologists analyzed responses to stimuli of autistic audio and video. The commonly used tools for analyzing the dataset of autism are FMRI, EEG, and more recently "eye tracking". This device is simple to implement and use, has begun to yield interesting results on the processes possibly involved in the perception of lack of photographs or films involving human presence. Figure 1 can shows a screen of human face (or a movie involving social interactions), and move pupil eye diameter at the same time the position of the patient on the screen. [2]

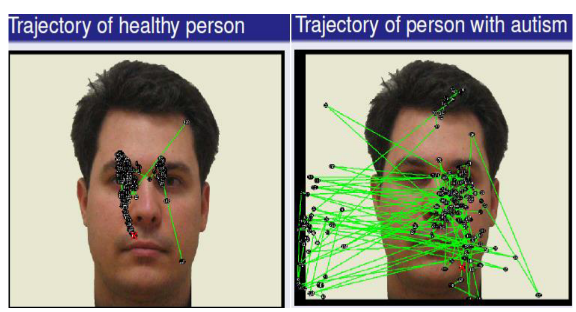

Figure 1: The different between with and without autism spector disorder.

Classification method divided into two steps. Firstly, concerns the informative parameters that allowed this classification. The temporal follow-up and the connection of these parameters with neurophysiologic information can certainly help in understanding the mechanisms put into action in people with autism. However, the test population is composed of more or less rehabilitated with autism, several groups will be proposed. Secondly, generate

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new parameters from the analysis of the trajectory of eye tracking system. Given the complex dynamics underlying the time series, this assumption is realistic if consider that the trajectory corresponds to the output of a nonlinear dynamic system (the brain) excited by an input: the visual stimulus.

The dataset has been obtained from hospital of Tours in the France contains six fields (x, y, distance, left diam, right diam, and time), where x and y which has been obtained from trajectory eyes tracking system. The distance field represents the length of distance between the point (x , y) and central point on screen (384 , 512). Left diam and right diam represent left eye and right eye respectively. And the time field represents the start and end of the experiment on one person. The next step, VMCM has been used to input the dataset and extracting the synthetic centralize distance measure in order to obtaining four classes. Eventually, final results have been calculated using standard deviation equation for each class, and the people with and without autism Spector disorder has been classified. In addition, support vector machine SVM technique was applied on the same datasets of adults and children and then compared these results with the previous results to obtain the best solution.

2- MATERIAL

The recordings were carried out using a look-up system comprising a computer equipped with two analogue cameras as illustrated in figure 2.

Following a projection of images representing neutral faces or deviated eyes, this system makes it possible to capture the directions, movements and positions of the eyes during the projection and to superimpose them in order to calculate in real time the temporal and statistical measurements thanks to the facelab computer tool.

Figure 2: Monitoring system

3- STIMULI

The images projected and taken into account in our research included five neutral faces, a cheerful image and a sad picture of anonymous people between 18 and 35 years of age for adult and 2 to 4 years age for children.

4- TOPICS

Patients and controls who participated in the test were separated into two groups. Ten autistic patients aged 18 to 30 years and ten children also with autism aged 2 to 4 years. 28 adult controls of the same age group and 55 healthy children aged 2 to 4 years.

5- MEASURES RECOVERED BY FACELAB

Among the statistics provided by the FaceLab software, we have:

Fixing time of the image;

The number of fixations of an area of the image;

Non-image fix time; The pupillary diameter,

6- METHODOLOGY

The research working to compare between two methods (VMCM with SVM), these methods is applying on the same group of people with and without autistic disorder, and controls who participated in the test were separated into four groups. Ten autistic adults aged above 15 years, ten normal adults aged above 15 years, ten autistic children aged less than 4 years, and ten normal children aged less than 4 years. See table 1 of the simplify data set which has obtaining from trajectory system (eye tracking system).

Table 1. Data Set Obtaining From Eye Tracking System.

No.	X	Y	Left Diam	Right Diam	Time
1	620	430	3.1	4.9	0.071
2	206	547	3.4	4.4	0.222
3	202	562	3.4	4.1	0.238
4	211	580	3.3	3.7	0.255
5	218	593	3.3	3.4	0.272
6	224	571	3.3	3	0.288
7	127	567	3.5	2.3	0.322
8	142	729	3.5	2	0.339
9	128	568	3.5	1.7	0.355
10	266	668	3.2	0.7	0.422
11	236	693	3.2	0.5	0.439
12	218	685	3.2	0.4	0.456
13	114	683	3.5	0.3	0.473
14	114	681	3.5	0.3	0.489
15	114	683	3.5	0.2	0.506
16	90	766	3.4	0.2	0.523
17	244	617	4.7	0.4	1.058
18	145	614	5.1	0.3	1.075
19	309	672	0	0	3.228
20	620	430	3.1	4.9	0.071

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Each dataset contains five factors (x, y, left diam, right diam, and time series), Euclidean distance has been calculated according to centralize distance measure of image size. Equation (1) shows the calculating of Euclidian distance.

$$E.D. = \sqrt{(x - x2)^2 + (y - y2)^2} \qquad (1)$$

Where the x2,y2 is represent the centralize image distance (384,512). [3]

The input data in VMCM four factors (centralize Euclidian distance, left diam , right diam , and time series). In the beginning, classification need (its different types, its structures) brief reflection establish the mathematical foundations of the (VMCM) in addition their fields of application.

To classify a set of objects is to assign to each one a class or category among several classes defined in advance (supervised class) or not known in advance (unsupervised class). This task is called "classification" or "discrimination". [4] There are two categories: those with supervised learning (automatic learning technique where one automatically seeks to produce rules from a learning database containing examples of cases already treated) and those with unsupervised learning (This method is distinguished from learning supervised by the fact that there is no output value defined a priori). [5]

6.1 Vector Measure Constructor Method

The steps of this algorithm are explained in figure 3. Each step of this algorithm demonstrates in the next sections. [6]

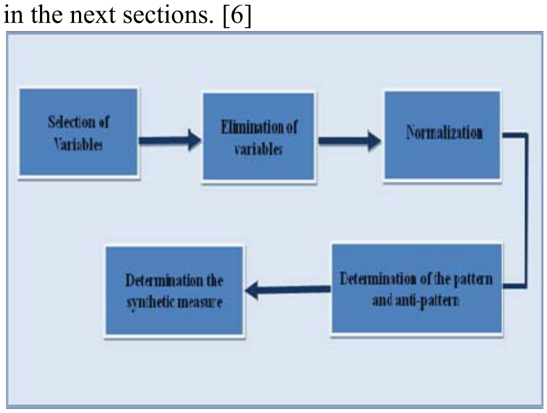

Figure 3: Procedures of Vector Measuring Construction Method-VMCM

6.1.1 Selection of variables

In terms of choice - selection of variables it is possible to apply statistical and formal methods of selection and/ or the analyst can select the variables according to the existing economic theory or knowledge, where his experience plays an important role. Regardless of the preferred approach, the choice-selection of variables is done in such a manner so as to reproduce, describe and measure the investigated phenomenon most accurately. The variables (key factors) are put in the observation matrix.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2k} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{ik} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{w1} & x_{w2} & \cdots & x_{wk} & \cdots & x_{wn} \end{bmatrix}$$

$$X_z = \begin{bmatrix} x_{z1} & x_{z2} & \ldots & x_{zk} & \ldots & x_{zn} \end{bmatrix}$$

Where:
n - number of objects,
M- number of variables,
X(ij) – value of the i - th variable for the j - object.

6.1.2 Elimination of Variables

In the literary sources the elimination of variables is usually performed by using a significance coefficient characteristics

$$V_{Xi} = \frac{\sigma_i}{\bar{X}_i} \qquad (2)$$

Where:
Xi– the i -th variable,
σ_i – Standard deviation of the i – th variable,
$\bar{X}_i$ – mean value of the j- th variable,
Given:

$$\bar{X}_i = \frac{\sum_{j=1}^{N} x_i}{N} \qquad (3)$$

Table 2 shows the STD and mean results of the above dataset.

Table 2: STD and Mean Results for the Dataset

STD	62.821	1.185	1.347	1.560
Mean	209.149	2.882	1.396	2.434

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6.1.3 Standardization

The next step is to be performed in the construction of the measure of development, is to *standardize the variables*. This process not only leads to the elimination of units of measurement but also to the equalization of variable values. Standardization is one of the most commonly used methods of normalization.

$$x'_{ij} = \frac{A_i}{\sigma_i} \qquad (4)$$

Where the A_i meter can be defined arbitrarily, for example:

$$A_i = x_{ij} - \bar{X}_i \qquad (5)$$

Given that x'_{ij} is the normalized value of the -th variable for the -th object.

Table 3 demonstrates a sample of the standardization for the dataset.

Table 3: Sample of Standardization for the Dataset

0.648	0.184	2.601	-1.514
-0.442	0.437	2.230	-1.418
-0.325	0.437	2.007	-1.407
-0.370	0.353	1.710	-1.396
-0.389	0.353	1.488	-1.386
-0.615	0.353	1.191	-1.375
0.854	0.522	0.671	-1.353
1.845	0.522	0.448	-1.343
0.842	0.522	0.226	-1.332
-0.216	0.269	-0.517	-1.289

6.1.4 Determination of the pattern and anti-pattern

After normalizing the variables, the next step is the design pattern of development. Collected variables are divided into stimulants and destimulants . Variables which have a positive, stimulating effect on the level of units are called stimulants, as opposed to inhibitory variables, called destimulants. The coordinates of the pattern measure are defined as the maximum value of stimulants and minimum value of destimulants. The nominants are usually transformed into stimulants or destimulants. In vector measures it is not the position of the pattern that is important but rather the direction (vector) indicating positions of the best objects. The direction is determined on the basis of the pattern that is characterized by high values of both stimulants and destimulants. Anti pattern and pattern can be taken as real objects. On the basis of first and third quartile

$$x'_{iw} = \begin{cases} x'_{iK_{III}} & \text{for stimulants} \\ x'_{iK_{I}} & \text{for destimulants} \end{cases}$$

Where

x'_{iw} is the value of the i-th normalized variable for the anti-pattern.

x'_{iK_I} is the value of the ith normalized variable for the first quartile, and

$x'_{iK_{III}}$ is the value of the i-th normalized variable for the third quartile.

In case of anti-pattern the procedure is reversed. To be more exact, the values of the stimulants from the first quartile and the values of destimulants from the third quartile constitute the coordinates of the pattern:

$$x'_{iaw} = \begin{cases} x'_{iK_{I}} & \text{for stimulants} \\ x'_{iK_{III}} & \text{for destimulants} \end{cases}$$

Where x'_{iaw} is the value of the i-th normalized variable for the anti-pattern.

The first and third quartile constitutes values of 25th and 75th percentile. In a set of numbers, a percentile is the value below which a certain percentage of the numbers in this set can be found. The location of the percentile is determined by the following formula:

$$P_p(X) = N\frac{p}{100} \qquad (6)$$

for complete $N\frac{p}{100}$

for incomplete $N\frac{p}{100}$

Where is N the size of set (in this case the number of objects).

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The coordinates of the pattern is the third quartile for stimulants and first quartile for destimulants. The coordinates anti pattern is first quartile for stimulants and the third quartile for destimulants. Table 4 shows that.

Table 4 : Pattern and Anti Pattern of the Dataset

pattern	0.794	0.522	-0.888	-1.257
anti pattern	-0.618	-0.238	0.671	0.797
Difference	1.413	0.759	-1.559	-2.054

6.1.5 Determining the Synthetic Measure

The values of the variables in the examined objects are interpreted as coordinates of the vectors, The difference in pattern and anti-pattern is also a vector designating the direction in space. [7]
The value of synthetic measure is calculated for each object. This very difference could be seen as one-dimensional coordinate system. Given so, the process of determining the measure becomes the process of determining the coordinate in the coordinates system, which can be illustrated by the following formula:

$$c = \frac{\left(\vec{A},\vec{B}\right)}{\left(\vec{B},\vec{B}\right)} \quad (7)$$

$$c_j = \frac{\sum_{i=1}^{M} x'_{ij}\, x'_{iw}}{\sum_{i=1}^{M} {x'_{iw}}^{2}} \quad (8)$$

$$x'_{iw} = \begin{cases} x'_{ik_{\mathrm{III}}} - x'_{ik_{\mathrm{I}}} & \text{for stimulants} \\ x'_{ik_{\mathrm{I}}} - x'_{ik_{\mathrm{III}}} & \text{for destimulants} \end{cases}$$

Vector measure is normalized as the sum of the weights was calculated on the basis of standard.

$$c_j = \sum_{i=1}^{M} x'_{ij}\, w_i \quad (9)$$

$$w_i = \frac{x'_{iw}}{\sum_{i=1}^{M} {x'_{iw}}^{2}} \quad (10)$$

x'_{ij} Value (i) of the normal variable for the object (j),
M number of variables,
c_j Synthetic measure of value for (j) this object.
x'_{iw} The value of (i) the normal variable to the pattern
w_i Taken as the weight

For the measurement constructed in such a way, all objects which are better than the anti-pattern and worse than the pattern will be characterized by the value of measurement ranging from zero to one. Thus, one can easily determine the object's position in the ranking in reference to the pattern and the anti-pattern [8]. The number adult persons have 20 datasets, 10 for normal persons and 10 for autistic persons.
The data which is input in VMCM algorithm applied on four fields (Centralize Euclidian distance, left diam , right diam ,and time series) in order to obtained the ***synthetic measure*** in the first step. Sample of the synthetic measure is shown in the table 5.

Table 5: Sample of the synthetic measure for the dataset

synthetic measure
0.012
-0.093
-0.040
-0.006
0.027
0.040
0.362
0.549
0.431
0.364

The synthetic measure used in K-mean classification in order to classification [9], four classes has been generated according to k-mean. Eventually, ***standard deviation*** has been calculated, and by using ***class No. 2 for adult and class No.3 for children*** obtained the best results of classify according equation. The figures 4, 5 Show the result for adult and children. And the tables 6, 7, 8, 9 show the classes choses to classification using STD for adult and children.

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Table 6: Classes of STD for Autism Adults

Class1	Class2	Class3	Class4
0.199704081	0.03330892	0.044638864	0.042130929
0.029823877	0.027811778	0.065340502	0.032582528
0.050106381	0.036212558	0.041183419	0.15446793
0.016119911	0.010280423	0.015331107	0.094137746
0.052857078	0.033038588	0.042803148	0.045556556
0.055187124	0.033277615	0.123603811	0.046492943
0.032838549	0.030957272	0.027374588	0.20295703
0.039729302	0.020047039	0.030456183	0.02706767
0.077318356	0.027311557	0.028969583	0.045525634
0.015296112	0.033583991	0.087638724	0.046313822

Table 7: Classes of STD for Normal Adults

Class1	Class2	Class3	Class4
0.04607709	0.059462283	0.059441169	0.046858412
0.046320228	0.052737745	0.027890928	0.112068416
0.045254338	0.023088791	0.045244951	0.025549908
0.050135052	0.025827108	0.048496468	0.029913492
0.106595382	0.046515275	0.013349146	0.070978294
0.029337784	0.05229324	0.040134423	0.096584604
0.047409725	0.043071889	0.065416922	0.062996077
0.044612864	0.047952103	0.041778478	0.0895435
0.041073716	0.066095799	0.040767905	0.031463565
0.035673744	0.072515738	0.024567333	0.015537804

Table 8: Classes of STD for Autism Children

Class1	Class2	Class3	Class4
0.028969583	0.077318356	0.030957272	0.045525634
0.015296112	0.020047039	0.087638724	0.046313822
0.025247651	0.060180891	0.055248113	0.013628233
0.12562667	0.054667638	0.034622233	0.060053671
0.057320435	0.052037988	0.020789709	0.062927365
0.136147763	0.032897769	0.036461567	0.017727404
0.038746454	0.028174971	0.037323476	0.029892681
0.033345018	0.028998917	0.031527535	0.041232353
0.034215929	0.033229577	0.020222176	0.02713851
0.037933426	0.040127695	0.028765855	0.027690862

Table 9: Classes of STD for Normal Children

Class1	Class2	Class3	Class4
0.042082012	0.055088431	0.059250527	0.244752468
0.033356226	0.038732425	0.065563353	0.025334179
0.035722062	0.043177689	0.029306359	0.035969382
0.035401928	0.032212506	0.053703692	0.024600236
0.160365031	0.060128837	0.040089048	0.071780189
0.038764382	0.044742659	0.063615956	0.174438513
0.095064765	0.073434013	0.052647166	0.149434988
0.02054869	0.0197365	0.047619043	0.026176658
0.033059914	0.032323486	0.047480917	0.07714882
0.030567977	0.016728683	0.043430534	0.038463096

The classes which choose in adult and children obtained and represent in figures 4, 5.

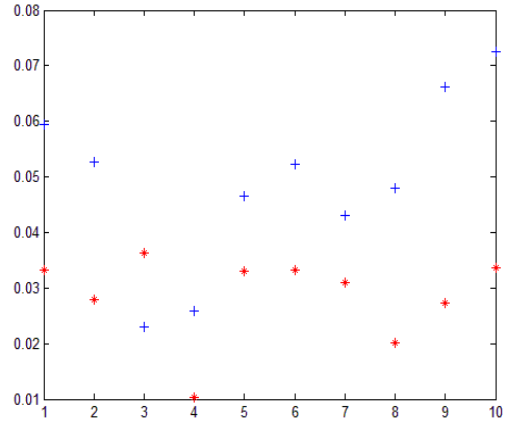

Figure 4: STD result for adults

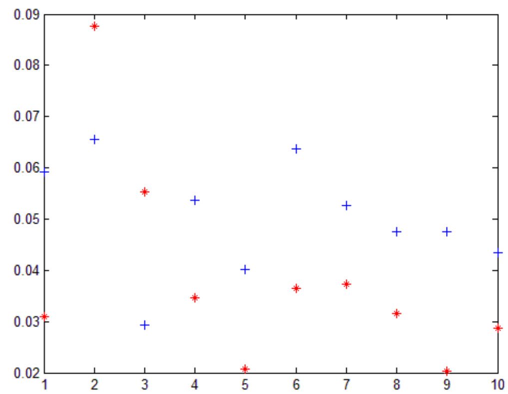

Figure 5: STD for Children

Where the + **(red plus)** present the autism and + **(blue plus)** present the normal

- **Result of classification in adults:**

Figure 4 shows the threshold value which can be used to classify the normal adult person is up to (0.04). Otherwise, the autistic adult person is less than 0.04. The percent of correctness methodology was 80%.

Finally, the test performed to classify people with autism gives: a sensitivity of 78% and a specificity of 80%. The sensitivity is defined: Se = VP / (VP + FN) where VP indicates the true positive and FN the false negative and the specificity is defined by: Sp = VN / (FP + VN) where VN indicates the true Negative and FP false positives.

- **Result of classification in children:**

Figure 5 shows the threshold value which can be used to classify the normal children is up to (0.038). Otherwise, the autistic children are less

than 0.038. The percent of correctness methodology was 90%. Finally, the test performed to classify people with autism gives: a sensitivity of 87% and a specificity is 95%. The sensitivity is defined: Se = VP / (VP + FN) where VP indicates the true positive and FN the false negative and the specificity is defined by: Sp = VN / (FP + VN) where VN indicates the true Negative and FP false positives.

6.2 Support Vector Machine (SVM):

The support vector machine (SVM) is a popular classification technique. However, beginners who are not familiar with SVM often get unsatisfactory results since they miss some easy but significant steps [10], [11].

Support Vector Machines classification method is a supervised classification technique, the main disadvantage of which is the choice of the kernel function. In this Research, briefly reflect apply the three functions which are: linear kernel, polynomial kernel and radial core in order to clearly understand which is the most suitable for the data of the adults as well as those of the children. [12]

6.2.1 Result of classification in adults

In this method, automatic learning is taken as half of the autistic people and half of the normal, that means: 14 autistics out of 28 and 77 out of 145. The nucleus chosen at the beginning is linear then polynomial finally a nucleus Radial base

- **The linear kernel**

The result is as follows:

• A group of 14 contains 10 true autistic and 4 false autistic

• A second group of 77 contains 72 real normal and 5 false normal. **This result obtained 71.43% sensitivity and 93.50% specificity.** Figure 6 shows classification in adults using SVM with liner.

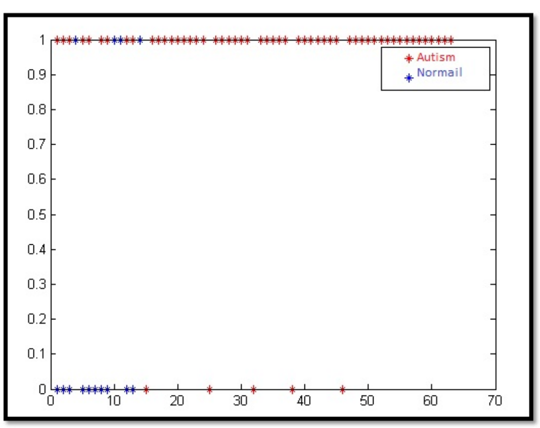

Figure 6: Classification in adults using SVM with linear

- **A polynomial core**

The result is as follows:

• A group of 14 contains 7 true autistic and 7 false autistic.

• A second group 77 contains 72 true normal and 5 false normal.

This gives us 50% sensitivity and 93.50% specificity. Figure 7 shows the classification in adult using SVM with polynomial core.

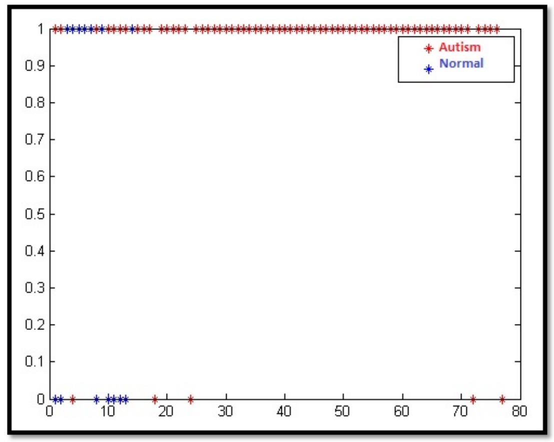

Figure 7: Classification in adults using SVM with polynomial core

- **A core with a radial base**

The result is as follows:

• A group of 14 contains 9 true autistic and 5 false autistic.

• A second group 77 contains 76 real normal and 1 false witnesses.

This result obtained 64.28% sensitivity and 98.70% specificity. Figure 8 shows classification in adults using SVM with radial core.

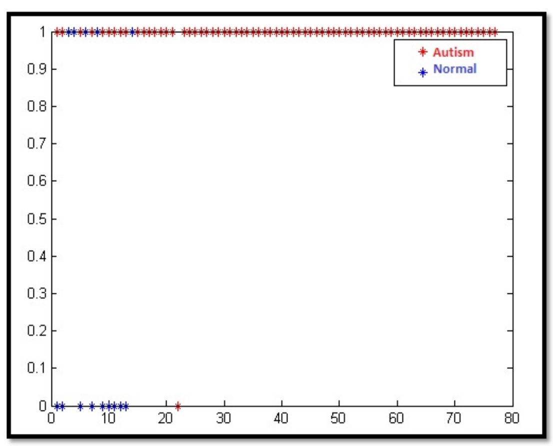

Figure 8: Classification in adults using SVM with radial

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Table 10 shows the final result of performance the sensitivity and specificity with distinguish between liner, poly, and radial core for adult.

Table 10: The performance with core of adults

Performance / core	Liner	Poly	Radi
Sensitivity (%)	**71.4**	50.0	64.3
Specificity (%)	**93.5**	93.5	98.7

6.2.2 Result of classification in children

For this method learning is taken as half of people with autism and half of the normal, that means: 20 autistics and 197 normal. The nucleus is chosen at the beginning linear, then polynomial and finally radial basis.

• The results in linear kernel:

• A group of 20 contains 14 true autistic and 6 false autistic

• A second group of 196 contains 188 true normal and 8 false normal

This result obtained 70% sensitivity and 95.91% specificity. Figure 9 shows classification in children using SVM with liner kernel.

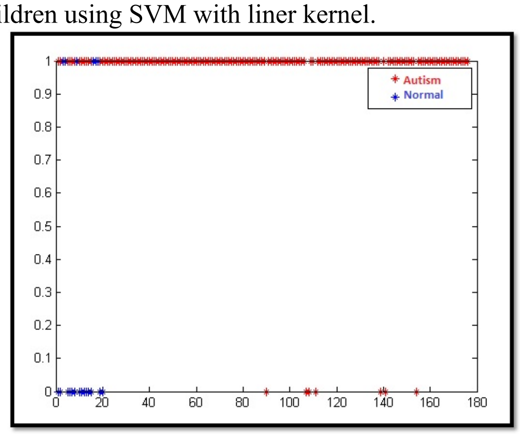

Figure 9: Classification in children using SVM with linear kernel

- **The results in polynomial kernel**

• A group of 20 contains 18 true autistic and 2 false autistic

• A second group of 196 contains 188 true witnesses and 8 false witnesses

This gives us 90% sensitivity and 95.91% specificity. Figure 10 shows classification in children using SVM with polynomial nucleus.

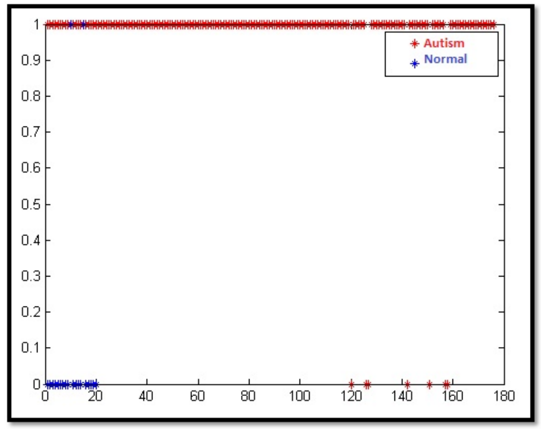

Figure 10: Classification in children using SVM with polynomial nucleus

- **The result in radial core:**

• A group of 20 contains 16 true autistic and 4 false autistic

• A second group of 196 contains 188 true witnesses and 8 witnesses

This result obtained 80% sensitivity and 95.91% specificity. Figure 11 shows classification in children using SVM with radial core.

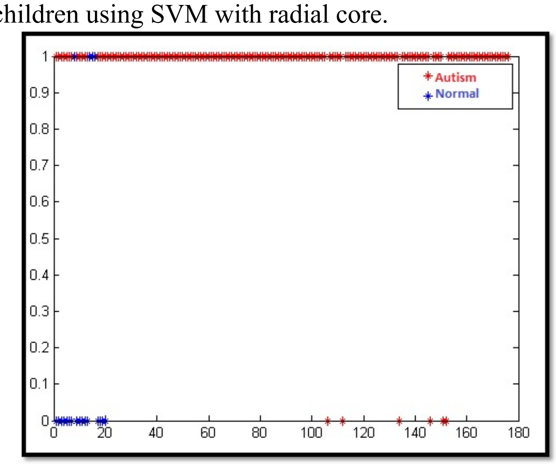

Figure 11: Classification in children using SVM with radial core

Table 11 shows the final result of performance the sensitivity and specificity with distinguish between liner, poly, and radial core for children.

Table 11: The final result of performance and core classification in children using SVM

Performance / core	Liner	Poly	Radi
Sensitivity (%)	70.00	**90.00**	80.00
Specificity (%)	95.91	**95.91**	95.91

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From these results, **it appears that for adults the classification is better using the radial core seen as 64.28% sensitivity and 98.70% specificity, whereas for children, the classification is Better with a polynomial nucleus seen that 90% sensitivity and 95.91% specificity were obtained**. Table 12 shows the final result comparison between two methods VMCM and SVM.

Table 12: The final result of comparison between SVM with VMCM method

Performance/ type	SVM			VMCM
	Liner	Poly	Radi	
Adults	71.4	50.0	64.3	80.0
Children	70.0	90.0	80.0	90.0

Source own elaboration

The comparison results between two methods (SVM, VMCM) it is appears that for adults the classification is better using the radial core seen as 64.28% sensitivity and 98.70% specificity, whereas for children, the classification is Better with a polynomial nucleus seen that 90% sensitivity and 95.91% specificity were obtained in *SVM*. And the classification and recognition rate in *VMCM* method is about 80% in adult and 90% in children.

7- PRIOR WORKS

In table 13 shows the comparison between SVM and VMCM methods and other methods according to parameters or technique used, where (+) represent used parameter in a method and (-) represent didn't used parameter in a method.

Table 13: The comparison of SVM & VMCM with other work study.

Methods / Parameter Subject to analysis	SVM & VMCM Method	A pattern classification	ICD-10 criteria	Fuzzy Cognitive Map	EEG Classification	MRI Classification	Neuroimaging Technique
VMCM technique	+	-	-	-	-	-	-
SVM technique	+	+	-	-	-	-	-
Neural Network	-	-	+	+	-	-	+
PCA	-	-	-	-	-	-	-
Time series	+	-	-	-	-	-	-
EEG	-	-	-	-	+	-	-
MRI	-	+	-	-	-	+	-
Euclidian distance	+	-	-	-	-	-	-
k-mean clustering	+	-	+	-	-	-	+
Data classification	+	+	+	+	+	+	+
Elbow method	-	-	-	-	-	-	-
Signal processing	+	+	-	-	-	-	-
Eye tracking system	+	-	-	-	-	-	-
Pattern recognition technique	+	+	-	-	-	-	-
Fuzzy cognitive map	-	-	-	+	-	-	-
Firebase Cloud Messaging	-	-	-	+	-	-	-
Knowledge Discovery from Data	+	+	-	+	+	-	-

A pattern classification approach [13][14][15]. And method of ICD-10 criteria [16]. The other study was used Fuzzy Cognitive Map [17]. Also the study has been comparison with EEG classification method [18]. MRI Classification study [19] was in comparison with our study. The comparison has been done with Neuroimaging Technique [20].

Conclusion

The eye-tracking technique has been used to study eye movements in typical people. However, it has only been in the last decade that this technique has been developed for use with autistic people. This technique allows us to obtain the dataset and measure several parameters which can be facilitating the discrimination of people with and without autism.

In this research, the comparative study between two methods (VMCM with SVM) can give us best classification accurate.

In VMCM algorithm shows in adults the threshold value which can be used to classify the normal adult person is up to (0.04). Otherwise, the autistic adult person is less than 0.04. The percent of correctness methodology was 80%.

The test performed to classify people with autism gives: a sensitivity of 78% and a specificity of 80%, while in children, VMCM algorithm shows the threshold value which can be used to classify the normal children is up to (0.038). Otherwise, the autistic children are less than 0.038. The percent of correctness methodology was 90%. The test performed to classify people with autism gives: a sensitivity of 87% and specificity is 95%.

The method of support vector machine (SVM) approach gave the best performance in terms of sensitivity / specificity.

In adults, the results in linear kernel obtained 71.43% sensitivity and 93.50% specificity, while in polynomial was obtained 50% sensitivity and 93.50% specificity, and in radial core, the result was 64.28% sensitivity and 98.70% specificity, while in children, the results in linear kernel obtained 70% sensitivity and 95.91% specificity, while in polynomial was obtained 90% sensitivity and 95.91% specificity, and in radial core, the result was 80% sensitivity and 95.91% specificity.

These methods are applying on the same group of people with and without autistic disorder, and controls who participated in the test were separated into groups. Vector measure constructor method (VMCM) with K-mean algorithm was adopted to classify the data of normal and autistic persons. The experiment proved that these algorithms are very efficient to discriminate between people suffer from autism and normal.

Automatic classification tools that can allow a cohort time tracking to evaluate, for example, the degree of rehabilitation or the therapy put in place. In the beginning, used 73 parameters and then reduced this number. The performances of the best detectors and classifiers are the best with sensitivities to neighborhoods of 80% and VMCM was 90% for children and 80% for adult. We recommend using it according the results obtained from these two methods (SVM and VMCM) as a supervised automated classifier.

The goal of this study is to classify people with and without autism specter disorder (ASD) and compare classification results based on two important algorithms in order to obtain the best classification.

In the future work, the studies will be use the neuron signs technologies to classify the signals which obtained by the EEG device.

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