Early Detection Support Mechanism in ASD using ML Classifier

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Abstract: In general the medical examinations will be thoroughly done by the expert while considering the ASD symptoms and will be considered as standard while determining the level of existence of ASD. Based on the past literatures on diagnostic criteria written for statistical measures of ASD, over few cores symptoms are identified that causes shortfalls in body language, verbal and communication further leads to societal issues. Few common and most noticeable ASD symptoms include inadequacy in reproducing regular pattern of behavior due to withering of various sensory organs. India has witnessed a paradigm shift in dealing with persons with disabilities over last two decades. Even though, there is raise in cognizance on symptoms and characteristics of ASD among the parents and professions yet the major gap is still continuing in identifying ASD at the early stage and for providing correct treatment accordingly. The existing early detection screening tools are time consuming, tedious, exclusive, and cumbersome. Also results in incomplete diagnostic process due to lack of complete evidence on the child behavior. To address these problems, an attempt is made in this work using K-Means clustering classifier, one of the ML algorithms in addition with support vector machine. ASD features that are usually found in child below three years are taken as inputs to the model and corresponding responses were identified with accuracy of 96% and 80% respectively in the diagnostic process while categorizing the manifestation of cause and effect on each individual capability. The supervised classification SVM is further converted to the unsupervised clustering problem and observed the accuracy level of 95%. The proposed method is mere perfect with good accuracy level while detecting the autism in children in real time environment.

Keywords: early detection screening tools, ASD, Machine learning classifier, near or perfect autism, accuracy.

1. Introduction

The early child's brain is more prone to rapid development with internal body commands and external environmental inputs. Diagnosis of autism symptoms at the early age of infant is an advantage to the child as the child's brain can easily adopt to the remedial techniques. However, the studies on early autism are very few and found typically hard to diagnose earlier than ages of 4 in the United States, with approximately 27% of cases, remaining are kept undetected till the age grown up to 8 [1]. The existing barrier in early detection results the children to grow differently and make them dependent forever. One of the reasons of difficulty in early detection is deficiency of constructive tools in exposing the root cause and also unavailability of expert persons in the so called field. Hence, it is very much essential to use efficient and accurate measuring mechanism while predicting the level of ASD in children.

Existing literature and studies are reveal that most of the autism screening is happening using various questionnaires focused with the questions about child behavior. These questionnaires usually will be answered by parents and will be monitored by medical practitioner. Finally, the result of autism level will be produced based on predetermined threshold values. Few of the notable questionnaires are Checklist for autism in toddlers (CHAT), Early screening of autistic traits (ESAT), Modified checklist for autism in infants [2], Child Behavior catalog (CBCL) [3], checklist for infants, perceptible checklist like q chat, and other screening tools like 'stat'[4]. All these are applicable for the infant age group of below three years and holds good to the parents or guardians who closely monitor the child. These are efficient but needs multiple sittings with the parent and child along with continuous monitoring by the expert person. But this will not happen in the case of autism carry orphan child who may not have a close monitoring system or an observation facility in the care centers.

Very few literature papers are available with ML based early detection [5, 7, & 8], but are again confined to the questionnaire based process that needs parental help in filling the gaps. The above said problems are addressed in this project using machine learning algorithms for improving the accuracy in early detection methods and mechanisms. The existing behaviors of autism effected child behaviors are collected as database and predicted the behavior whether it is autism prone or not. This will be applicable to the system where child alone can be kept under various sensors observations and the sensor outputs will be given as inputs to the model, such that the model can predict further the level of autism in the child.

Section II discuss about existing methods of ML based early detection, and section III discuss about proposed method of detection. Section IV discuss about results and comparisons, and Section V conclusions.

2.Review On Existing Early Detection Methods

2.1.Based on multiple screening tools

A sequence of primary and secondary level screening tools was used in characterizing the level of autism in the children ages between infant and 3 years [2]. However these screenings required multiple sittings with child that leads to time consuming process. It is essential to detect or diagnose the level of autism in the children at the early stage itself to prevent further delay that leads to a major impact on their normal growth. The other determinant is still the strong social stigma associated with a 'mental disability', which delays the seeking of diagnosis among families across the social spectrum. Poor awareness of the condition among parents and primary care pediatrician often has led to delay in diagnosis [12].

2.2.Ml based Mobile device using ASD Detection app

The team of interdisciplinary researchers from Duke University has developed an app for early ASD detection by combining the ubiquity of mobile devices with the power of machine learning and computer vision [6]. But most of the times the limitations with mobile apps is the accuracy, also adaptability with the latest amendments in autism prone behaviors. In addition, it is not a mere valid measurement to justify by an expert person who evaluates using mobile screeners.

2.3.Combined questionnaire, video captures using ML classifiers

Majority of the work carried using machine learning methods are focused on detection of ASD in the ages above 3 years [1, 7, & 8]. The approach was based on generic ML classifiers that used with short, structured parent-reported questionnaires along with short, semi-structured home videos of children. This approach may be resulting with good accuracy only when the video captures are near perfect, for that continuous monitoring of the child is essential. It is observed from the literature [8] that the use of Support Vector Machine (SVM) and Adaboost algorithms results in better ability using a dataset that includes infant behavior identification parameters. But the complexity with these algorithms lays in their implementation. In order to check the relation among the chosen parameters that are used in the data set and further to classify them the algorithms like support vector machine can be used.

Besides all the factors that are causing autism in children, the early diagnosis is essential that helps them get into early intervention in the name of behavioral therapies. Few observations in infants are like not responding to their names, avoiding direct eye to eye contact, prefer to be alone even while play, less body movements, avoiding physical contacts with others, very few facial expressions or inappropriate expressions at times, and many. Sometimes autism affected infants may have difficulty in understanding other people's feelings. In some cases it is essential to judge through other parameters rather than the actual parameters, like the effect more can be noticed through mouth region first rather than the eye region, weak judgmental ability, adolescents in emotion recognition etc. [9].

2.4.Proposed method of ML based early ASD Detection

Our approach is to use the existing past medical instrument records as data sets that are collected under various diagnosing methods. These data sets are primarily used to train the model as they are more reliable since they will be framed with the collection of outside clinical data. The limitations with the conventional machine learning methods are exhibiting poor performance under less controlled setting environment. The environmental setup plays an important role in producing accurate results.

The work in this paper outlines the use of machine learning classifiers and algorithms in assessing the ASD characteristics of infants who does not have their parents or guardians to be monitored continuously. This overcomes the challenge of repetitive sittings with the parent and child for observatory purpose. Few of the main traits observed under autistic child's behavior are inappropriate eye-contact, not responding to the name when calling, slow movements in waving, partially indexing to any object, loose closing of wrist, lightly body shaking, not supportable for toe walking, seat crawling, not standing properly, mouth open for long time, continuous drooling, not responding to the variation in tones, rolling round, and gestures differences while eating, sleeping or sitting. These parameters are closely monitored and from the past clinical observations to adapt into our datasets for training the model. Also these parameters are more close to the queries that are composed in various questionnaires. From the chosen database, few are identified as are highly impact parameters that cause more deviation in the children behavior from normal to aggressive and are shown in Table 1.

Table 1. Parameters Chosen In The Anlaysis Of Early Asd Detection

Rolling	Drooling	Emotion recognition	Emotion expression	Firm hold	Eye contact	tone identification	abnormal gestures
7	150	66	42	23	35	78	42
1	73	50	10	25	23	48	21
7	187	68	39	15	38	54	41
0	100	88	60	17	47	96	31
0	146	82	0	18	41	71	44
0	105	64	41	14	42	17	22
2	84	0	0	22	0	45	21
8	133	72	0	23	33	72	39
5	44	62	0	25	25	87	36
2	141	58	34	15	25	69	24
7	114	66	0	17	33	58	42
5	99	74	27	18	29	25	32
0	109	88	30	14	33	85	38
2	109	92	0	25	43	84	54
1	95	66	13	15	20	45	25
4	146	85	27	25	29	89	27
2	100	66	20	17	33	67	28
5	139	64	35	18	29	41	26
13	126	90	0	14	43	58	42
4	129	86	20	18	35	25	23
1	79	75	30	23	32	96	22
1	0	48	20	25	25	14	22
7	62	78	0	15	33	91	41
5	95	72	33	17	38	7	27
0	131	0	0	18	43	72	26
2	112	66	22	14	25	57	24
3	113	44	13	22	22	45	22
2	74	0	0	23	0	25	22
7	83	78	26	25	29	67	36

Rolling is common feature among children and is a mile stone appear at the infant age of 6th month. For the age group of 2 months to 36 months, the rolling character is collected from autistic behaviors and given a threshold value in the range of 0 to 20. If the child is able to take a roll at the right age, is given a highest value and the least is given to contrast. Drooling is commonly seen in almost all autistic behaviors, and is taken on time base for how long the child is keeping their mouth open. Emotional recognition is played on the children with various tones to identify the child behavior, and is taken in the range of 0 to hundred. Least values tell us the child is immortal to the emotion, whereas highest indicate the response is not normal but aggressive. Emotion expression is the feature to be extracted from children by applying high degree methods like pinching, hugging etc. and is taken in the range of 0 to 100. Other feature observed is whether the child muscle strength is upright as per the age or not. For this the child is given with toys and observed how firmly that can be handled. The most important feature is eye contact, is taken in the range of 0 to 50. In the similar way, tone identification and abnormal gestures are calibrated.

The overall dataset for training purpose with the chosen threshold values are shown in Table II. These parameters are closely linked to the questionnaires that are operated on the autistic children with the age group of below 3 years. The parental monitoring helps in filling out the questionnaire but the proposed system takes various sensors input that can be placed in the near vicinity of the child for continuous capturing the child behavior.

Most of the past work observed with various ML algorithms in implementing early detection mechanism, in which SVM model identifies with good accuracy results as SVM looks at the interactions between each parameter to a certain degree, though it is complex while implementing.

2.5.Clustering Model

Among the existing models the simplest unsupervised algorithms is k-means clustering, in which well-known clustering problem will be solved using selection of appropriate k-value. The given dataset are going to be classified into clusters by classifying every cluster with associate acceptable k values. Using appropriate k value randomly that many number of centroids will be created, then the distance of each data point will be measured from the centroids and then the new centroids will get swapped with data points every time once the distance found is less. It is repeatedly done till the final centroids will form, by that time data points will get grouped into clusters based on their nearest centroids. Number of clusters can be formed by selecting appropriate value using 'random state' function using 'sklern' platform. If we use random initialization then we need to start with same k random data points as centroid and that helps to initialize all the centroids. The analysis was an outcome of model using the database parameters as mentioned in Table II. These parameters are considered with various threshold levels over 100 children with ages between 1 to 3 years.

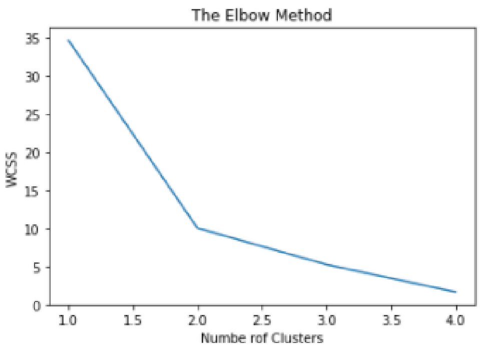
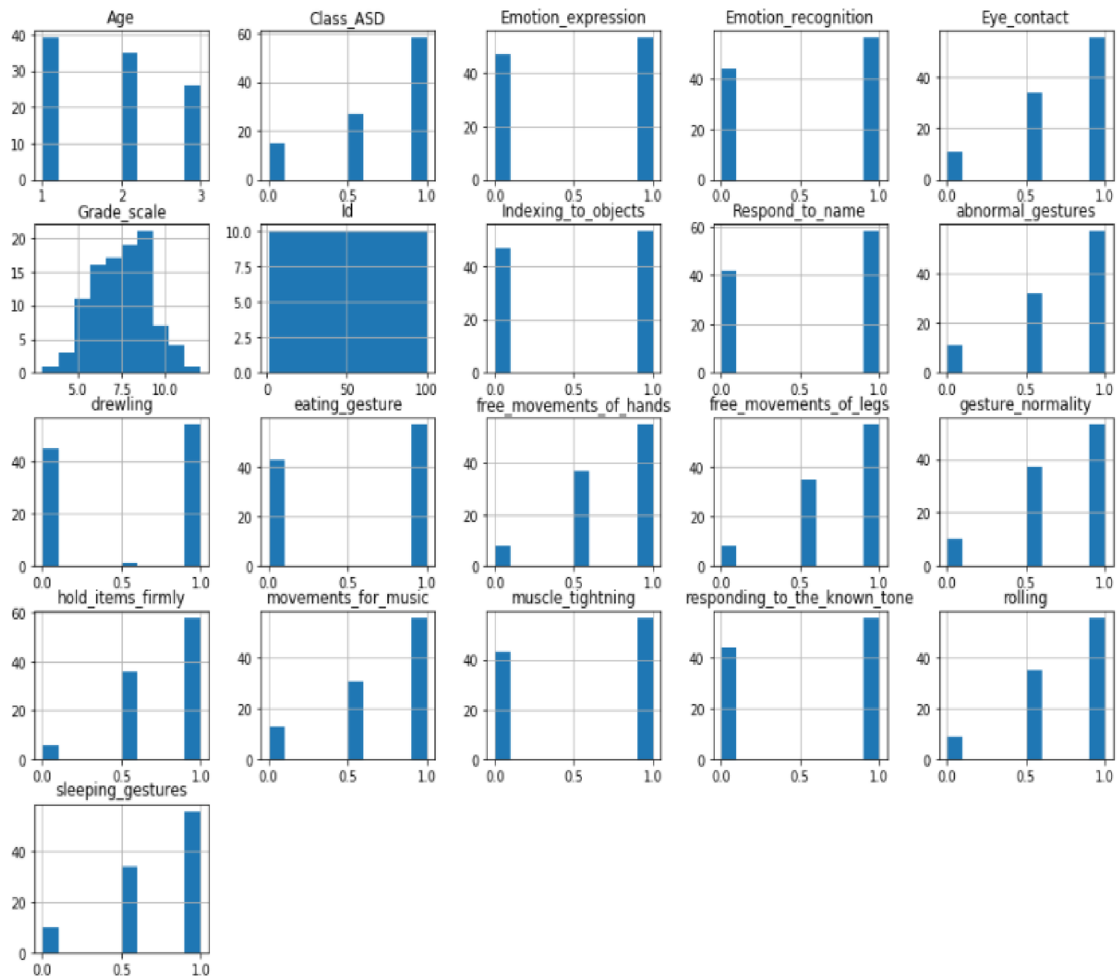


Fig. 1. Optimizing k value

In order to get optimal number of clusters and k, one should observe the graph between assumed number of clusters and Within-Cluster-Sum-of-Squares (WCSS). Where WCSS is obtained as a measure of squared average distance calculated from every point within a cluster to the cluster centroid. This was possible by Elbow method and is shown in Fig.1. K-means results in local minima rather than global. Therefore, the determination of the starting point value of the clustering center will greatly determine the results obtained using it. (Kamson Sirait et.al. 2017).

Fig. 2. Parametric variation observed using k-means



From the curve, the optimal value of k is chosen as 5 with minimal WCSS value. To calculate WCSS, Euclidean distance to be found initially, by drawing a line between a given point and the centroid to which it is assigned. Then repeats the same procedure for all the points within the cluster, take the sum and finally divide with number data points. The two clusters within the data frame are correlated using Euclidean distance, calculated as follows:

$d_{euclidean\,(x,\,y)}=\sqrt{\sum_{i=1}^{n}(x_i - y_j)^2}$...........(1)

where $d_{(x,y)}$ = distance between data and cluster points

x_i =i^{th} data in x data.

Y_j =j^{th} data in y data.

Finally, average across all clusters is calculated. This will give the average WCSS. The chosen k value was applied with the dataset values. The resulting clusters and the toddler groups within the clusters along with the ASD class obtained is shown in Fig. 3.

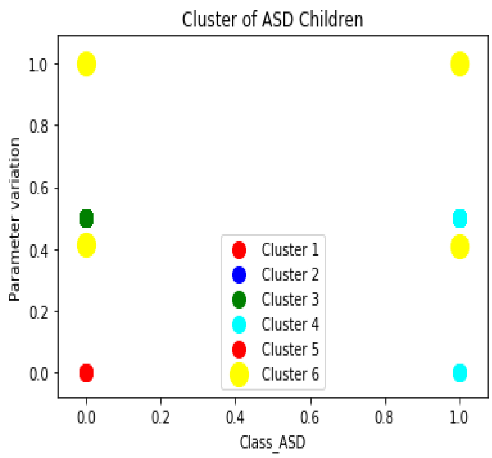


Fig. 3. Cluster class model to assess the level of autism

The cluster class model shown in Fig.3 indicates the group of toddlers belongs to cluster 5 falls under "no ASD observed" class with minimal parametric variation, whereas toddlers belongs to cluster 4 fall under "ASD observed" class. The overall process relies only on respective threshold values of corresponding questionnaire and CHATs that will be filled during the observation period. The accuracy in prediction using this model is observed as 96%.

2.6.Model using SVM (supervised)

Clustering model alone is not feasible while characterizing the level of ASD and hence used support vector machine also. Supervised machine learning involves algorithms that use input variables to predict a target classification (i.e., the dependent variable), which may be categorical or continuous. Unlike unsupervised learning (clustering), supervised learning involves datasets where the target prediction (e.g., diagnosis) will be known at the time of training time itself.

Any supervised learning model is said to be successful if the model can (a) accurately predict the target result for a training dataset to a certain degree of accuracy and (b) be generalized to new datasets beyond those used to train the model. To improve a model's ability to make predictions on future data, a method called cross-validation is often employed. This method allows a subset of the data to be removed before training, so that the model can then be tested using "new" dataset. The cross validity in k-fold is to make the available data into K-subsets and trains the model on all but one of the subsets and tests on the remainder. The process is repeated until the model has been trained on all the available data, and finally the average of the scores must be taken in to consideration.

Inherently the SVM is supervised learning and each class attributes have interrelation with the other class attributes. In the SVM algorithm, each data item or class attribute will be considered as a point in multi-dimensional space choosing known number of features within the dataset. Each feature will represent a particular coordinate in the plot. Further the algorithm uses classification by performing hyper-plane finding that is used to differentiate any two classes. Train data selected with 80% and test data is chosen with 20%, further the accuracy is observed with this prediction model is 80%.

2.7. Model using SVM (Unsupervised)

In this case, the model is converted to unsupervised clustered problem by altering the dataset into unlabeled dataset. This can be done by removing headers from the dataset in the preprocessing stage as shown in Fig. 4.

For predicting the model performance few parameters data have been changed. From Table II, parameters “hold_items_firmly”, “gesture_normality” are modified with new data and applied the model for testing the accuracy, and is observed as 95%.

3.Results and Comparisons

The intention of this work is to bring out a model for assessing autistic behavior in the children of age less than 3 years, without having the intervention of parent or guardian. This model can be used in the cases where child monitoring is purely avoided by human. Instead, this model takes the support of sensor devices or other units for continuous monitoring purpose. The major advantage of this model is the recurrence time of interactions for the sake of behavior collection can be reduced. Though much research has been happened on ASD yet significant improvement is in slow manner as the required datasets are not available completely. In our study, we have collected various ages (up to 3 years) of early detection ASD datasets from the existing clinical data and the results are analyzed by choosing optimal threshold values. Further using K-means classifier the probable groups are predicted based on the significance of each feature. Through that the predictions on ASD range is done easily and are resulted with 96%, accuracy. Further the model extended with SVM supervised and unsupervised manner and reaches 85% and 95% accuracies respectively.

4. Conclusions

It is not that easy to justify the person weather affected with autism or not just by using collected clinical data. However, before presenting the person’s clinical data in front of the expert person, if the data is monitored thoroughly for pre-prediction to say the level of ASD, that helps the expert person and ASD effected person as well by saving much time in diagnosis. That helps in identifying fast for further intervention treatments if required. In this work, we have considered the existing clinical data through which few effective features have been considered that are highly influenced in prediction of ASD.

The selection of features is done using feature selection and ranking methods of available datasets. Further the datasets are exposed with supervised and unsupervised algorithms, and compared the results accuracy. It is observed that the supervised learning algorithm is little behind in accuracy compared to unsupervised clustering algorithm. This is because the supplied features are not adequate to SVM algorithm. If more the dataset then more the prediction accuracy. This kind of pre-prediction work helps in improving the ability of physicians to detect ASD at an early stage rather than spending much time on repeated sittings. As a future scope, the work can be extended with inclusion of few more features for making the data more close to mere perfect prediction also to address neurodevelopmental disorders in connection with ASD.

1	0.5	1	0	0	0	1
1	0.5	1	0	0.5	0	0
0	0.5	0.5	0	1	0	0
1	1	1	0	1	0	0
1	1	0.5	0	1	0	0
0	0.5	0.5	0	1	0	0
1	1	0.5	1	1	1	1
1	1	1	0	1	0	1
1	0	1	1	0	1	1
0	0	1	0	0	0	1
0	0	1	1	0	1	1
0	1	1	0	0	0	1
0	1	0	1	0	1	1
0	0.5	0	1	0	1	0
1	1	0	1	1	1	0
1	0.5	1	1	0	1	0
1	0.5	1	0	1	0	0
1	1	0.5	1	0	1	0
1	1	1	0	1	0	0
1	0.5	1	1	0	1	1
1	1	0.5	0	1	0	0
0	0.5	1	1	1	1	1
0	0.5	0.5	0	1	0	0

Fig. 4. Unlabled dataset used for SVM model

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Table 2 Parameters Chosen In The Anlaysis Of Early ASD Detection

Id	Age	Eye_contact	Respond_to_name	free_movements_of_hands	free_movements_of_legs	muscle_tightning	drewling	hold_items_firmly	Indexing_to_objects	responding_to_the_known_tone	Emotion_recognition	Emotion_expression	gesture_normality	abnormal_gestures	eating_gesture	sleeping_gestures	movements_for_music	rolling	Grade_scale	Class_ASD	FG
1	3	1	1	0.5	1	0	0	0	1	1	0	1	1	1	0	1	1	1	6	0.5	Y
2	2	0.5	1	0.5	1	0	0.5	1	0	0	0	0	0.5	0.5	1	0	1	1	11	1	Y
3	1	1	0	0.5	0.5	0	1	1	0	1	0	1	0.5	0.5	0	0	0	0.5	12	1	Y
4	3	1	1	1	1	0	1	0.5	0	0	0	0	0.5	1	1	0	0	1	9	0.5	Y
5	3	0.5	1	1	0.5	0	1	1	0	1	0	1	1	0.5	0	1	0	0.5	9	1	Y
6	3	0	0	0.5	0.5	0	1	0.5	0	1	0	0	1	0.5	1	1	1	0.5	11	1	Y
7	2	1	1	1	0.5	1	1	0.5	1	1	1	1	1	0.5	1	0.5	1	1	4	0.5	Y
8	2	1	1	1	1	0	1	1	1	1	0	0	1	1	1	1	0.5	1	4	0.5	Y
9	1	0.5	1	0	1	1	0	1	1	0	1	0	1	1	1	0.5	1	0.5	7	0.5	Y
10	1	1	0	0	1	0	0	0.5	1	1	0	1	0	1	0	0.5	1	1	9	1	Y
11	1	0.5	0	0	1	1	0	1	1	0	1	1	0	1	1	1	0.5	0.5	8	1	Y
12	2	0.5	0	1	1	0	0	0.5	1	1	0	1	0	0.5	1	1	1	0.5	9	1	Y
13	3	0.5	0	1	0	1	0	0.5	1	0	1	1	1	1	0	0.5	0.5	0.5	10	1	Y
14	1	1	0	0.5	0	1	0	0.5	0	1	1	1	1	0.5	1	1	0.5	1	8	1	Y
15	2	1	1	1	0	1	1	1	0	0	1	1	0.5	1	1	0.5	0.5	1	6	0	N
16	3	1	1	0.5	1	1	0	1	0	0	1	1	1	1	0	0.5	1	0	7	0	N
17	3	1	1	0.5	1	0	1	1	0	1	0	0	1	1	1	0.5	1	1	6	0.5	Y
18	2	1	1	1	0.5	1	0	1	0	1	1	0	0.5	0.5	1	1	1	1	6	0.5	Y
19	2	0	1	1	1	0	1	0.5	0	1	1	0	1	1	1	1	1	0.5	6	1	Y
20	1	0	1	0.5	1	1	0	1	1	1	0	0	0.5	1	0	1	0.5	1	8	1	Y
21	1	0	1	1	0.5	0	1	0.5	0	1	1	0	0.5	0.5	0	1	1	1	9	1	Y
22	1	1	0	0.5	1	1	1	1	1	1	1	0	0.5	0	1	0.5	0.5	0.5	8	1	Y