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Detection of Attention Deficit Hyperactivity Disorder Using Local and Global Features

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***Abstract*— Attention deficit hyperactivity disorder (ADHD) is a psychiatric condition that affects millions of children and many times last into adulthood. There is no single test that can show whether a person has ADHD. The symptoms vary from person to person. Therefore, it is hard to diagnose ADHD contrary to many physical illnesses. Our aim is to create methods to minimize human effort and increase accuracy of diagnosis of ADHD. We collected structural Magnetic Resonance Images (MRI) from 26 subjects: 11 controls and 15 children diagnosed with ADHD. The data was provided from NPIstanbul NeuroPsychiatric Hospital. We developed automatic, effective, rapid, and accurate framework for diagnosing ADHD. The models were built on the k-nearest neighbors algorithm (KNN) and naive Bayes using Matlab machine learning toolbox. Shape and texture feature extraction technique was used. Area, Perimeter, Eccentricity, EquivDiameter, Major Axis Length, Minor Axis Length, Orientation are characteristics used for shape feature extraction technique. Textural features of a magnetic resonance imaging were represented with first (mean, variance, skewness, kurtosis) and second order statistical (contrast, correlation, homogeneity, energy) based feature extraction techniques. Gray and white regions were extracted using k-means algorithms. Local features were extracted from these regions by shape and texture methods. Global features were extracted with second order statistics which is called gray level co-occurrence method. The most important attribute was determined by using principal component analysis. The experiments were conducted on a full training dataset including 26 instance and 5 fold cross validation was adopted for randomly sampling training and test sets. ADHD is successfully classified with 100 % accuracy by using the proposed method. The outcome of our study will reduce the number medical errors by informing physicians in their efforts of diagnosing ADHD.**

Keywords — classification; naive bayes; image preprocessing techniques; feature extraction, principle component analysis.

I. INTRODUCTION

Attention deficit hyperactivity disorder (ADHD) is a psychiatric condition that affects millions of children and many times last into adulthood [1]. Although symptoms of ADHD can differ from person to person, three basic characteristic define attention-deficit hyperactivity disorder (ADHD) – inattention, hyperactivity and impulsivity.

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The World Health Organization (WHO) predicted that almost 11 % of children, ages 4 to 17 (6.4 million), have been diagnosed with ADHD in 2011. The percentage of children with an ADHD increase from year to year. ADHD may impact on personal, social, academic and familial functioning. Children with ADHD often experience with social difficulties, social denial, and interpersonal relationships problem. According to statistics, almost 50-60% of ADHD children experience denial by group of their friends. Children diagnosed with ADHD experience more problems with schools. For example, children with ADHD score lower on reading and arithmetic achievement tests than controls.

Although many people have been diagnosed with ADHD, some people with ADHD are still misdiagnosed. Many parents think that their children are struggle with inattention and assume that they must have ADHD. Sometimes, psychiatrist and pediatricians prescribe stimulant medication to children who appear to have ADHD, but most times actually do not! Because the symptoms of ADHD actually overlap with other disorder, a correct ADHD diagnosis is more difficult than it may seem. There is no single test that can show whether a person has ADHD. The symptoms of ADHD vary from person to person. Therefore, it is hard to diagnose ADHD contrary to many physical illnesses. ADHD needs careful medical evaluation. Healthcare professional like a pediatrician or psychologist ask parents and teacher about the child's behavior in different places; such as at home or school. Many tests are done by experts. Specialist collects test data for diagnosis. Tests analysis is very time consuming for experts. Our aim is to create methods to minimize human effort and increase accuracy of diagnosis of ADHD.

Our method can be a solution to this problem by producing rules from enormous datasets that can be used in analyzing ADHD data. Also, our aim of this study is to use different classification techniques in order to find the best one for helping diagnosis of ADHD.

II. RELATED WORK

There are a few studies in the field of diagnosing ADHD. In this section, we discuss studies about diagnosing ADHD based on the literature review.

To classify ADHD, Some studies use traditional method which has many deficiencies. Therefore they did not create correct model for diagnosing ADHD. To overcome deficiency and create effective, rapid and accurate model, Xiao long Peng and Pan Lin studied about machine-based classification of ADHD using structural MRI data in the year of 2013. So they collected MR images from 110 subjects: 55 controls and 55 diagnosed with ADHD. They calculated multiple brain measure (cortical thickness) using a fully automated procedure and extracted 340 feature using MRI images. To find optimal feature F-score and SFS method were used. Support Vector Machine (SVM) and Extreme Learning Machine (ELM) were evaluated. [2].

In 2012, Ani Eloyan and Johns Hopkins conducted a study on diagnoses of attention deficit hyperactive. In this study, they review diagnostic impacts of the research and show the results and predictability of ADHD. They collected resting-state fMRI and Structural magnetic resonance imaging (MRI) from 776 subjects: 491 controls and 285 children diagnosed with ADHD. Their final prediction algorithm had an external test set specifity of 94 % with sensivity 21 %. [3].

Other researches focused on same issue. Matthew R. G. Brown et. al., studied about diagnosing ADHD using personal characteristic data can outperform resting state fMRI measurements. They participated ADHD-200 Global Competition which includes a large data set of 973 participants including healthy controls and ADHD. ADHD-200 data set includes an rs-fMRI scan, demographic information and diagnostic data. Their training set consist of three class: ADHD combined (ADHD-C), ADHD inattentive (AHDH-I) type and healthy control. Classification accuracy rate was very low 62.52 %. Their model was not robust because of having low accuracy rate [4].

Rubi Hammera and Gillian E. Cooke tried to find neurobiological markers for ADHD. So fMRI data collected from 40 subjects: 20 boys with ADHD and 20 boys healthy group. They used multimodal analysis based on brain images. Features were extracted and best features were selected using principal component analysis, which is way of finding out which features are important. Logistic regression was used as a classifier. This accuracy level is 92.5%. In this study, there is some limitation. The first is that their data set size was so small. Another limitation is that they only used one classification algorithm. They could be used other machine learning algorithm like neural network and decision tree [5].

Che-Wei Chang, Chien-Change Ho and Jyh-Horng Chen, in the year of 2012, conducted on an ADHD classification by a texture analysis of anatomical brain MRI data. In this study, they used 436 male subjects from ADHD - 200 Global Competition which provides an excellent opportunity for building diagnostic classifiers of ADHD based on rs-fMRI and sMRI: 210 with ADHD and 226 controls. “They used isotropic local binary patterns on three orthogonal planes (LBP-TOP) in order to extract to feature from MR brain images. They used support vector machines (SVM) in order to develop classification models”. The accuracy that they achieved was 0.69[6].

III. METHODOLOGY

Magnetic resonance images of 26 individuals were obtained from NPIstanbul Neurophysiology Hospital. In the image pre-processing phase, the gray and white regions were reached using the k-means algorithm. By using shape and texture feature extraction techniques, the data was best characterized. The features that would adversely affect the classification model were identified with principal component analysis. Naive Bayes and K nearest neighbors algorithm was applied to classify magnetic resonance images. The flow diagram of the proposed method is shown in detail in Figure 3.

A. Image Acquisition

Our Data is recorded in NPIstanbul Neuropsychiatric Hospi tal, Istanbul, Turkey. We collected Structural Magnetic Resonance Imaging (MRI) from 26 subjects: 11 controls and 15 children diagnosed with ADHD. Images from the NPIStanbul NeuroPsychiatric hospital were obtained using a 1.5 tesla philips mri scanner. T1-weighted high-resolution, fast magnitude of the slope prepared by 3D magnetization was obtained by using gradient eco method. The parameters of the magnetic resonance image are as follows. Acuisition matrix:256x256x140; TR:2.8 s; T.E: 4.0 s; flip angle : 8°; field of view: 240mm; voxel size=0.937 x 0.937 x 1.2 mm resolution.

Figure 1. Adhd

Figure 2. Control

B. Image Pre-Processing

Some unrelated data in image can be removed using image pre-processing technique. K-means algorithm can be used as a pre-processing step. We want to extract local features from gray and white matter region in an axial plane. The reason is why Gray and white matter plays important roles in brain. Changes in these substances cause psychiatric illness. Therefore, it was extracted local features from these regions. Before this step, it is needed to segment gray and white matter in axial plane. K-Means was applied to partition these regions.

1) Segmentation

Image segmentation is a process, which partitions a digital image into multiple regions based on similarity criterion. In this study, we used clustering based segmentation.

1.1) K means Clustering Technique

K means is the algorithm of segmenting a group of data points into a small number of clusters.

Figure 3. shows axial image. To obtain gray matter and white matter separately, we use k-means algorithm.

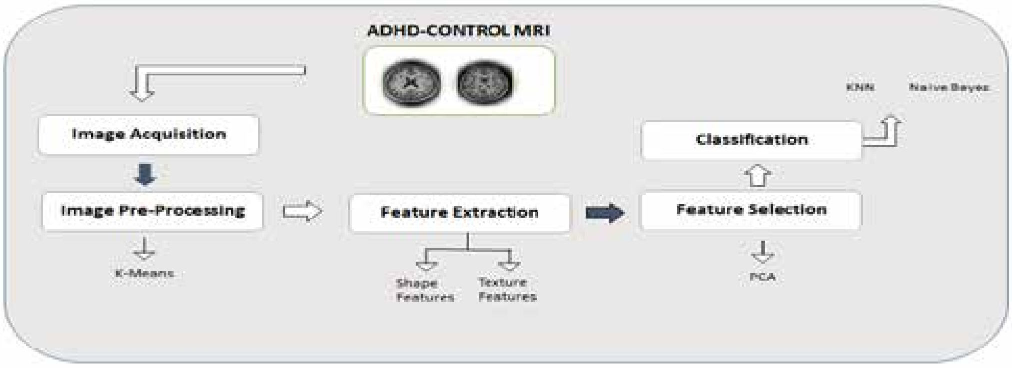

Figure 3. A Framework for Diagnosing ADHD-CONTROL MRI

Figure 4. Axial MRI

Figure 5. Segmented MRI

As seen Figure 5, there are 3 different areas; black, gray and white regions. So the value of k should be 3. Figure 6. shows three regions together.

Figure 6. Three Cluster

Figure 7. shows three regions that are divided with k means separately. We extracted white region from the first and the gray matter from the middle cluster.

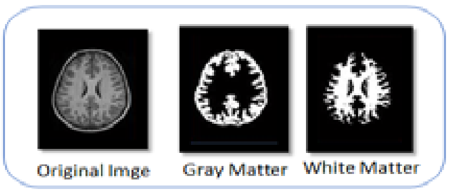

Figure 7. Original Image to Desired Image

Figure 7. shows original image, gray region and white region.

To acquire white matter and gray matter, we do following operations sequentially.

1. Apply K means algorithm
2. Separate three clusters
3. Decide which cluster is white matter and gray matter
4. Use connected component analysis to label the pixels
5. Acquire white and gray regions.

C. Feature Extraction

In this study, shape and texture feature extraction technique was implemented to extract local and global features. To acquire local features, Gray and white matter region in axial plane was segmented with k-means algorithm. After segmenting, shape features and first order statistical features extraction techniques was applied on those regions to get local features. To acquire global features, we used second order statistic based technique which is called gray level co-occurrence method.

1) Shape Feature Extraction Techniques

The Shape features extracted and used on local region are area, perimeter, eccentricity, equivDiameter, major axis length, minor axis length and orientation.

2) Texture Feature Extraction Techniques

Image texture is defined as a function of the spatial variation in pixel intensities (gray values). In this study, First and second order statistical based feature extraction method was implemented. The first order features used and extracted on a local region (gray and white matter) are mean, variance, kurtosis and skewness. The second order features used and extracted on a global region are contrast, correlation, energy and homogeneity by creating gray level co-occurrence matrix. Using the gray level co-occurrence matrix function, texture of image is extracted by calculated how often a given pair of pixels in a given spatial relationship.

D. Feature Selection

Feature Selection is a process of reducing dimension of a data set. In this study, principle component analysis is used to reduce the dataset and find the most important features.

E. Classification Algorithm

1) K Nearest Neighbor Algorithm

K nearest neighbor algorithm that is one of the successful classification techniques is a very simple algorithm, which stores all available instances and classifies new instance based on a similarity measure [10]. As a formula:

$$\boldsymbol{E}(\boldsymbol{x},\boldsymbol{y}) = \sqrt{\sum_{i=0}^{n}(\boldsymbol{x_i}-\boldsymbol{y_i})^2} \tag{1}$$

Table I. The Detailed Performance Measure for Three Different Dataset

	Accuracy			Sensivity			Specifity		
Feature Extraction Technique	Shape	First Order	Second Order	Shape	First Order	Second Order	Shape	First Order	Second Order
KNN with all attributes	0.72%	0.54%	0.50%	0.93%	0.20%	0.36%	0.45%	1%	0.60%
KNN with selected attributes	0.85%	0.62%	1%	1%	0.33%	1%	0.63%	1%	1%
Naive Bayes with all attributes	0.54%	0.42%	0.41%	0.80%	0.06%	0.%	0.18%	0.90%	0.71%
Naive Bayes with selected attributes	0.50%	0.42%	0.23%	0.36%	0.20%	0.%	0.60%	0.72%	0.45%

2) *Naive Bayes*

Other classification algorithm used in this study is Naive Bayes which supposed independence between the variables. The classes of data in training set are known. Probabilistic operation by using training dataset. According to result, the class of test data is found.

$$P(C|A) = \frac{P(A|C)P(C)}{P(A)} \tag{2}$$

IV. EXPERIMENTAL RESULTS

As aim of this study is to improve diagnosis of ADHD using machine learning techniques. Local features were extracted using these regions. Shape and texture feature extraction technique was used. Area, Perimeter, Eccentricity, EquivDiameter, Major Axis Length, Minor Axis Length, Orientation are characteristics used for shape feature extraction technique. Textural features of a magnetic resonance imaging were represented with first (mean, variance, skewness, kurtosis) and second order statically (contrast, correlation, homogeneity, energy) based feature extraction techniques. Gray and white matter regions from axial plane were segmented with k-means algorithm to extract local features, which were extracted with shape and first order statically based feature techniques. Global features were extracted with second order statistics method.

Then, feature selection is applied whether to learn if any dimension is unrelated. Lastly, classification was performed to improve diagnosis of ADHD. Naive Bayes and K-nearest neighbor classification algorithms are used in order to build the models on Matlab computation environment.

As seen in tables, the classification performance of the naive bayes is low. The high accuracy of classification in Naive Bayes is due to the large number of objects in the training set. The number of data in the training set is not sufficient for these algorithms. At the same time, the presence of noise data in the dataset can affect the performance of model. However, the new data set is obtained by removing irrelevant attribute by using basic principal component analysis. If the nearest neighbor algorithm is applied to the obtained data set, classification accuracy gives the highest results. These results were given in Table I.

V. CONCLUSION

The aim is to design predictive model for improving diagnosing of attention deficit hyperactivity disorder. Misdiagnosis or non-diagnosis of this disease can lead to life-threatening complications. Therefore, the approach to be used in diagnosis should be an objective and reliable model. So, Magnetic resonance imaging was collected from NPIstanbul Neuropsychiatirc Hospital including 26 instances for this study. Gray and White matter were segmented with k-means algorithm. Local features were extracted using these regions.

Shape and first order statistical based features were obtained from these regions. The performances of the models were evaluated using sensivity and specifty.5 Fold Cross validation was adopted for training and testing set. The most effective model is k nearest neighbor algorithm with principal component. Classification accuracy of that model is 100 %.

This study showed that image processing and machine learning techniques can be used to create model for diagnosing of attention deficit hyperactivity disorder. This tool can be beneficial for medical mentor.

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