Review on Analysis and Quantification of Specific Learning Disability (SLD) with fMRI using Image Processing Techniques

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ABSTRACT
Specific learning Disabilities (SLD) is a generic term that refers to a heterogeneous group of disorders manifested by significant, unexpected, specific and persistent difficulties in the acquisition and use of efficient reading *(Dyslexia),* writing *(Dysgraphia)* or math *(Dyscalculia)* abilities despite conventional instructions, intact senses, normal intelligence and adequate education. Conventional methods for the diagnosis of SLD are subjective of nature. This paper proposes an objective view towards the quantification of SLD features with Functional Magnetic Resonance Imaging (fMRI) using image processing techniques. Research works on brain imaging points that dyslexia, dysgraphia and dyscalculia represents fMRI brain signal activities in specific regions of the brain that are distinguishable from healthy brain fMRI's. The analysis of features extracted from the pre-processed fMRI images quantifies the classification of SLD, depth of severity, degree of recovery and post doctoral therapy.

Keywords
Specific Learning Disability (SLD), Dyslexia, Dysgraphia, Dyscalculia, fMRI, Feature detection, Feature extraction.

1. INTRODUCTION
1.1 Specific Learning Disability (SLD)
The human brain function is determined by activation and interaction mechanisms of the millions of neurons from which it is constituted. Their oscillatory activity is increasingly thought to get synchronized during physiological or pathological brain states, at stimulation or during the performance of certain tasks [1]. Developmental brain disorders represent one of the most interesting and challenging research areas in neuroscience. Dyslexia, Dysgraphia and Dyscalculia are the most complicated developmental brain disorders that affect the behavior and learning abilities of children [2] [3]. 30 – 50% of the population has undiagnosed learning disabilities (Source: National Institute for Literacy). Specific learning disabilities have increased 22% over the past 25 years. In the past decade, the number of students ages six to 21 years identified with specific learning disabilities has increased by 38% (Source: National Institutes of Health, 2003). 48% of those with learning disabilities are out of the workforce or unemployed. (Source: Bridges to Practice). SLD is particularly insidious since a large number of dyslexics, dysgraphics and dyscalculics are very intelligent and many are well endowed with the ability for abstract thinking

1.1.1 Dyslexia – reading disability
Dyslexia is characterized by the failure to develop appropriate reading skills [4]. Dyslexia constitutes a specific reading disability, a condition characterized by severe difficulty in the mastery of reading despite normal intelligence or adequate education. Electrophysiological studies have shown that there are physiological deficits in dyslectic subjects [5]-[6], which may affect cognitive functions of the brain such as selective attention, working memory, audio or language process. The importance of accurate early diagnostics of dyslexia that severely affects the learning abilities of children cannot be overstated. A typical characteristic of the dyslexic's reading impairment is his difficulty in recognition and recall of the orientation of letters and the order of letters in words [7] [8]. Reading involves many interrelated sub tasks namely, Phonological Processing, Orthographic Processing, Sound-Symbol Connection, Word Meaning etc (see Figure 1).

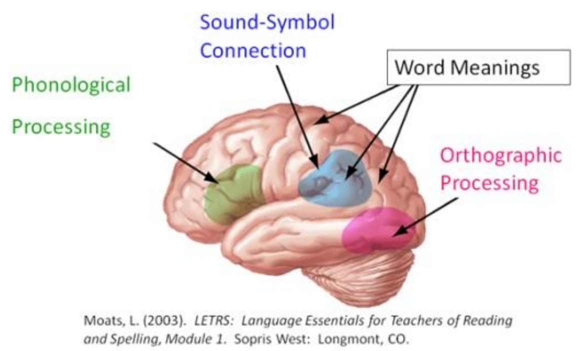

Figure 1. How brain reads?

1.1.2 Dysgraphia – Writing disability
Dysgraphia is a learning disability that affects writing abilities. Most common difficulties with Dysgraphia are spelling, poor handwriting and trouble putting thoughts together on paper. Dysgraphia is a processing disorder. Dysgraphia is the term applied to those difficulties confined to the fine motor skills required for handwriting. Handwriting is a complex human activity that entails an intricate blend of cognitive, kinesthetic, perceptual motor components (Bonny, 1992) including visual perception, eye-hand coordination, visual-motor integration, kinesthetic perception, motor planning, dexterity and manual skills (Tseng & Cermak, 1993). The study of handwriting has importance beyond the issues of basic human perceptual-motor control. Handwriting is considered to be proficient when legible text is produced at a minimum of effort [15].

1.1.3 Dyscalculia – Mathematical disability
Dyscalculia is characterized by qualitative difficulties in performing mathematic calculations of certain types [17]. Numeracy problems impact more negatively on job prospects than literacy problems. Dyscalculia is a condition which affects the ability to acquire arithmetical skills [18]. Dyscalculic learners may have difficulty understanding simple number concepts, lack an intuitive grasp of numbers, and have problems learning number facts and procedures (DfES - 2001). Dyscalculics shows difficulty in understanding concepts or place value, quantity,

number lines, positive and negative value, and carrying and borrowing, difficulty in understanding and completing word problems difficulty with adding, subtracting, multiplying, or dividing, difficulty using steps involved in math operations and even difficulty in handling money [19].

1.2 fMRI - Functional Magnetic Resonance Imaging

Experimental approaches towards the study of the brain functions often involve the detection of the brain regions that respond differently to external stimuli [20] [21]. Magnetic Resonance Imaging (MRI) provides superior brain anatomic images with high contrast of soft tissues and spatial resolution and is widely used in clinical practices. Functional MRI (fMRI) is often used to explore the brain function by detecting the hemodynamic change induced by specified cognitive or sensorimotor tasks [22] (see Figure 2).

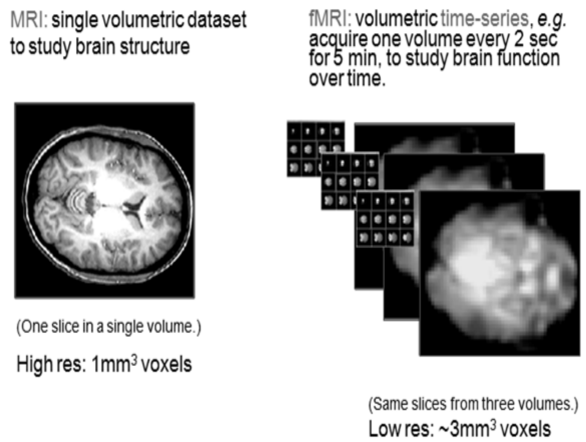

Figure 2. Difference between MRI and fMRI data

In fMRI, the increased blood flow to the activated areas of brain is detected. Here, a series of images of the brain are acquired at short intervals exploiting the dephasing effect that paramagnetic deoxyhaemoglobin in blood has on the MR signal [23]. Activation of groups of neurons in processing stimuli implies increase in oxygen consumption, blood flow and volume, resulting in a net decrease in deoxyhaemoglobin concentration close to the activated region. This leads to an increase in the intensity of the MR signal relative to the baseline state, and provides a source of endogenous contrast, which has been used to study a vast range of sensory, cognitive and emotional brain functions over the past two decades [24] [25].

For each subject j we can represent an fMRI image time-series as a spatiotemporal matrix Y of dimensions M x N, where M is the number of time samples and N is the number of voxels [26]. Based on a series of multi-slice images of the brain, fMRI provides the information for detection and analysis of functionally different part of the brain.

fMRI and magnetic brain stimulation during active task execution hold the potential to identify and visualize networks of brain areas that are functionally related to specific cognitive processes (see Figure 3). A hierarchical method that applies an optimization algorithm based on modified maximum correlation model (MCM) that can detect small variations across the two study groups hypothesize that dyslexia might represent fMRI brain signal activities in specific regions of the brain that are distinguishable from healthy brain fMRI's [22]. Nowadays, fMRI can determine that when people with dyslexic fMRI and magnetic brain stimulation during active task execution fMRI and magnetic brain stimulation during active task execution hold the potential to identify and visualize networks of brain areas that are functionally related to specific cognitive processes.

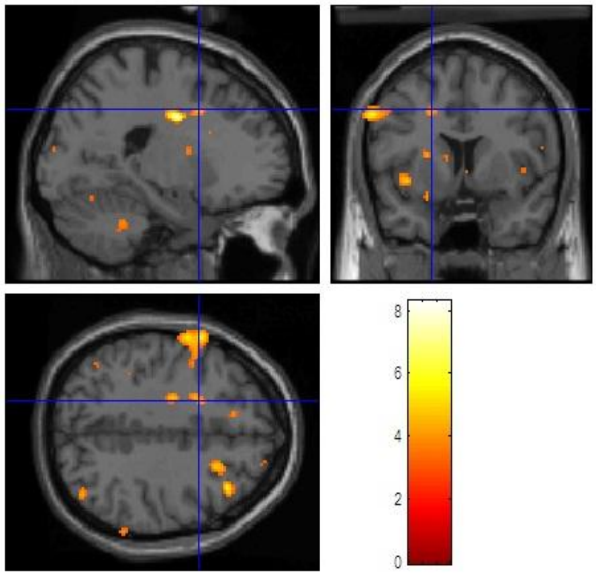

Figure 3. fMRI data showing brain activity

1.3 Image processing techniques

Image processing seeks to modify and reaper pixel values of fMRI images to produce a form that is more suitable for subsequent diagnosis application. For instance, Ohnishi [27] shows that the classification of morphologic changes in the brain with normal aging and Alzheimer disease are different [28]. Gallaghera [29] provides functional imaging studies on 'theory of mind' in verbal and non-verbal to identify distinct active region. Nicola [30] states that stroke patients show a different type of hemodynamic response function (HRF) compared to that of the healthy subjects. In our method, we first pre-process the images, then extract features, analyze the relationships among these features using image processing techniques to explore the differences across the four groups and finally quantify the class of disability, depth of severity, degree of recovery and post doctoral therapy.

2. LITERATURE REVIEW

'A Modified Maximum Correlation Modeling Method for fMRI Brain Mapping; Application for Detecting Dyslexia' by Soo-Yeon Ji and Kayvan Najarian - 978-1-4244-2890-8/08/$25.00 ©2008 IEEE.

In this paper, they have designed a hierarchical method that applies an optimization algorithm based on modified maximum correlation model (MCM) that can detect small variations across the two study groups. Based on the proposed method, they also hypothesize that dyslexia might represent fMRI brain signal activities in specific regions of the brain that are distinguishable from healthy brain fMRI's. In this paper, they have presented a model to detect the brain activation using a hierarchical optimization algorithm. In particular, an optimization algorithm is applied to the specific regions of the brain identified by SPM to find patterns that are significantly different across two groups of subjects. The method was specialized for optimal brain fMRI filtering and signal detection in noisy images. A limitation of this study was the small size of the dataset used to identify the fMRI brain activity. Even though the dataset was small sized, the method successfully processed active raw time series in both dyslexic and healthy subjects in order to distinguish regions differentially activated in the two groups.

'Brain mapping and detection of functional patterns in fMRI using wavelet transform; application in detection of dyslexia' by Soo-Yeon Ji, Kevin Ward and Kayvan Najarian - BMC Medical Informatics and Decision Making 2009, 9(Suppl 1):S6 doi:10.1186/1472-6947-9-S1-S6.

In this paper, the capability of a hierarchical method that performed an optimization algorithm based on modified maximum model (MCM) was evaluated by the researchers. The optimization algorithm was designed by adopting modified maximum correlation model (MCM) to detect active regions that contain significant responses. The optimization algorithm was examined based on two groups of datasets, dyslexia and healthy subjects to verify the ability of the algorithm that enhances the quality of signal activities in the interested regions of the brain. After verifying the algorithm, discrete wavelet transform (DWT) is applied to identify the difference between healthy and dyslexia subjects. They found that DWT based features can identify the difference between healthy and dyslexia subjects. Apart from evaluating the improvement of filtering with the hierarchical optimization algorithm, they have also applied a signal processing strategy to identify two subjects, healthy and dyslexia subjects. In this paper, they have presented the utility of practical optimization based on FD and DWT features. They describes that wavelet based features may useful to differentiate two groups, healthy and dyslexic subjects, of fMRI time series. In this study, they have concluded that the wavelet transform is an appropriate non-stationary signal analysis method, which may be suitable for differentiating two different conditions.

'Neural mechanisms involved in the comprehension of metaphoric and literal sentences: An fMRI study' by Midori Shibataa, Jun-ichi Abea, Atsushi Teraoa, and Tamaki Miyamotob - brainresearch1166 (2007)92–102.

In this study, the researchers have investigated the neural substrate involved in the comprehension of novel metaphoric sentences by comparing the findings to those obtained with literal and anomalous sentences using event-related fMRI. In this work, the stimuli consisted of 63 copula sentences ("An A is a B") in Japanese with metaphorical, literal, or anomalous meanings. Thirteen normal participants were made to read these sentences silently and their responses, as to whether or not they could understand the meaning of each sentence, were studied. They found that, when participants read metaphoric sentences in contrast to literal sentences, higher activation was seen in the left medial frontal cortex - Brodmann's area, the left superior frontal cortex, and the left inferior frontal cortex. The literal sentences in contrast to metaphoric sentences, gave higher activation in the precuneus and the right middle. In this study, the data were smoothed using an 8-mm full-width-athalf- maximum Gaussian kernel. Functional data were analyzed in an event-related design, and the reaction time that was collected while the participants performed the task in the scanner was entered in these analyses as a regressor. A high-pass filter was used to remove low-frequency noise. Statistical parametric maps were generated for each contrast of the t statistic on a voxel-by-voxel basis. The resulting statistical maps were height-thresholded and clusters of 10 or more contiguous voxels were reported in this paper. The complete data set was transformed into Talairach space. The findings from these clusters are used to suggest that metaphor comprehension is involved in specific neural mechanisms of semantic and pragmatic processing which differ from those in literal comprehension.

'Top-down and bottom-up modulation of language related areas – An fMRI Study' by Tomme Noesselt, Nadim Jon Shah and Lutz Jancke - BMC Neuroscience 2003, 4:13 - 1471-2202/4/13.

In this paper fMRI is used to investigate the interaction between stimulus and task driven neural modulation in the human brain. The researchers have corrected for motion artifacts, co-registered, resliced, normalized and smoothed using an 8 mm full-width-athalf- maximum Gaussian kernel. The data were analyzed in the context of the general linear model approach of SPM99. In this paper, the statistical analysis corresponded to a random effects analysis. They have firstly estimating the subject specific contrasts of interest for each condition (semantic classification and passive and then entered these contrast-images into a second level analysis to produce parametric maps of the T statistic. The contrasts at the first level contained parameter estimates pertaining to each of the conditions. These conditions were then modeled with box-car stimulus functions convolved with a hemodynamic response function. Voxels showing significant interaction effects were excluded from the analysis of main effects. The resulting sets of voxel values for both main effects and the interaction constitute statistical parametric maps of the T statistic which was then transformed to the unit normal distribution. Significant activations were thresholded and a spatial extent criterion was proposed for multiple comparisons. In this work, a lenient statistical threshold is applied between frontal brain regions and the inferior frontal areas.

'The representation of the verb's argument structure as disclosed by fMRI' by Ramin Assadollahi, Marcus Meinzer, Tobias Flaisch, Jonas Obleser and Brigitte Rockstroh - BMC Neuroscience 2009, 10:3 doi:10.1186/1471-2202-10-3.

This fMRI study served to verify the neural structures involved in the processing of German verbs with different argument structure. The paper reveals that reading of isolated one-argument verbs produced stronger BOLD responses than three-argument verbs in the inferior temporal fusiform gyrus of the left hemisphere. Here, the pre-processing included correction for slice-time differences and spatial alignment to the first volume of the image series to adjust for head movements. The functional volumes were smoothed with a Gaussian Kernel of 8 × 8 × 9 mm full-width-at-half maximum (FWHM). Pre-processed data were submitted to statistical analysis implementing the General Linear Model (GLM). Before estimating the modeled regressors, a high pass filter was applied to the data. Then the planned contrasts-of-interest were calculated for each subject. Then the comparisons were carried out between isolated verbs. Maximally activated voxels within significant clusters were reported.

'The Neural Basis for Category-Specific Knowledge: An fMRI Study' by Murray Grossman, Phyllis Koenig, Chris DeVita, Guila Glosser, David Alsop, John Detre and James Gee - NeuroImage 15, 936–948 (2002)-doi:10.1006/nimg.2001.1028.

In this paper, fMRI was used to monitor regional cortical recruitment patterns while subjects were exposed to printed names of Animals, Implements, and Abstract nouns. The paper depicts that both Implements and Abstract nouns were related to recruitment of left posterolateral temporal cortex and left prefrontal cortex, and Abstract nouns additionally recruited posterolateral temporal and prefrontal regions of the right hemisphere. Animals were associated with activation of ventral-medial occipital cortex in the left hemisphere. The work suggests a neural model of semantic memory that reflects the processes common to understanding Implements and Abstract nouns and a selective sensitivity, possibly evolving from adaptive pressures, to the overlapping, intercorrelated visual characteristics of Animals. In this paper, the raw image data were reconstructed using a 2D FFT. Here the algorithm combined raw difference images from individual subjects into a statistical t map using the intersubject variance. Then the data were analyzed parametrically using t test comparisons converted to Z scores for each compared voxel. The paper proposes a conjunction analysis, a technique for identifying voxels significantly recruited in common across pairs of contrasts. The analyses included a contrast of each category minus the pseudoword baseline with a "statistical mask" involving the contrast of all words minus the pseudoword baseline. This revealed areas of activation for the category of interest within a statistically determined region. This paper reports the differences between conditions that are statistically significant.

'An fMRI study of the differential effects of word presentation rates (reading acceleration) on dyslexic readers' brain activity patterns' by A. Karnia, I.A. Morocza, T. Bitana, S. Shaulc, T. Kushnirb, Z. Breznitza.

This paper reveals that the word reading rate can be considered as an independent variable which influences comprehension as well as accuracy in reading. The study explored the fact that readers of various levels of reading proficiency, as well as clearly impaired readers (dyslexics), if made to read faster than their normal (routine) reading rate, can increase their decoding accuracy and comprehension. In brief, the procedure included: creating a mean image for each subject (anatomical and EPI data); zero padding with a two-voxel layer in the coronal plane; spatial co-registration using mutual information, re-slicing, calculation of a new mean image and smoothing with a Gaussian kernel. Here, a box-car model, convoluted with the standard hemodynamic response function was used to contrast any given condition to its baseline as the first level analysis. To contrast between the two groups or between stimulus presentation rates within a task or between different tasks, a second level analysis was performed based on a paired t-test. Then a small volume correction (SVC) based on the Gaussian Random Field theory was applied defined by the following ROIs: left and right peri-sylvian language area, bilateral extra-striate visual areas, bilateral cunei and pre-cunei.

'An fMRI study of multimodal semantic and phonological processing in reading disabled adolescents' by Nicole Landi, W. Einar Mencl, Stephen J. Frost, Rebecca Sandak & Kenneth R. Pugh – Springer - DOI 10.1007/s11881-009-0029-6.

This paper investigated the multimodal (visual and auditory) semantic and unimodal (visual only) phonological processing in reading disabled (RD) adolescents and non-impaired (NI) control participants using fMRI. The work concludes that the reduced activation for RD relative to NI in a number of left-hemisphere reading-related areas across all processing tasks regardless of task type or modality. The y found that the activation differences in these regions, which included the inferior frontal gyrus, the superior temporal gyrus, and the occipitotemporal region, were largely independent of in-scanner performance in our auditory semantic task. Here the functional images were first sinc-interpolated to correct for slice acquisition time, corrected for motion and spatially smoothed with a Gaussian filter. For each subject, an affine transformation to the standardized space was obtained. For each subject and voxel, linear regression was used to compare the mean signal during each experimental condition to the baseline condition, generating regression parameter estimates for each activation condition. First-, second-, and third-order temporal trends and run-to-run mean offsets were additionally included in the model. Across subjects, these values were entered with planned comparisons for main effects of group, task type, word type and modality and their interactions, conducted on a voxel-wise basis.

'Disrupted neural responses to phonological and orthographic processing in dyslexic children: an fMRI study' by Elise Temple, CA Russell, A. Poldrack, Joanna Salidis, Gayle K. Deutsch, Paula Tallal, Michael M. Merzenich and John D. E. Gabrieli - BRAIN IMAGING- 0959-4965 & Lippincott Williams & Wilkins- Vol 12 No 2 12 February 2001.

The main aim of this paper was to study the brain images for relating brain activity to phonological and orthographic performance in dyslexic and control children. They revealed that the dyslexic children had impaired performance on a phonological task that correlated with their reading scores and those children failed to exhibit the left temporo-parietal activation seen in normal-reading children during phonological processing. In this work the images were motion corrected and the Root mean-squared motion was estimated across all three directions and all time points. Images were smoothed with a Gaussian filter. Data were best fitted at every voxel using a linear combination of the effects of interest (multiple regression). Group analysis was performed with random effects model using contrast images normalized to the stereotaxic space using tri-linear interpolation. The statistical threshold was set with a cluster size threshold of 20 voxels. Two sample tests were used to determine group differences. For region of interest analysis, scaled, normal contrast images were interrogated in a specified sphere to extract parameter estimates from the multiple regression for each subject.

'A Nonparametric Bayesian Approach to Detecting Spatial Activation Patterns in fMRI Data' by Seyoung Kim, Padhraic Smyth, and Hal Stern-

In this paper, a mixture-based response-surface technique for extracting and characterizing spatial clusters of activation patterns from fMRI data is presented. The work reveals that each mixture component models a local cluster of activated voxels with a parametric surface function. A novel aspect of approach is used by implementing Bayesian nonparametric methods to automatically select the number of activation clusters in an image. They have described an MCMC sampling method to estimate both parameters for shape features and the number of local activations. They have shown that infinite mixtures of experts can be used to locate local clusters of activated voxels in fMRI data and to model the spatial shape of each cluster, without assuming a priori how many local clusters of activation are present. Then the characteristics of spatial activation patterns (shape, intensity, relative location) are extracted directly and automatically from the clusters.

3. LITERATURE REVIEW CONCLUSION

The image enhancement techniques like rotation, cropping, contouring and background subtraction will be employed to focus on the region of interest. Prior to analysis, the data were spatially normalized, resampled and smoothed. The primary process is to examine overall patterns of activation for each group and between groups. Thresholding is one of the pre processing employed to enhance the image. Thresholding means Remove lighting effects from the acquire image and converting it to a binary image using a threshold. Image segmentation is defined as one process that partitions a digital image into disjoint (non-overlapping) regions. It tries to group pixels together into regions of similarity. While the task of image segmentation hardly has a counterpart in human visual experience, it is a nontrivial task in digital image analysis. The literature survey reveals three types of segmentation for digital images. Generic Image Segmentation tries to separate regions according to some discontinuity in an image. Texture Segmentation locates texture and non-texture area or regions containing different types of texture. Application-Specific Segmentation appears usefully for special applications, such as contour segmentation of domain specific features for image retrieval.

Feature extraction is a complex image processing problem that can be approached from different directions. It is closely linked to other problems as image segmentation or image classification. It consists of identifying, in a digital image, groups of pixels belonging to the same entity from the real world (feature). This extraction can be automatic to a certain level. Fully automatic feature extraction algorithms exist, but they are very limited (they are designed for a very specific type of image and for a very specific feature). The semi-automatic approach tries to extract as much as possible from the image using a few parameters provided by the user, who will choose them depending on the target feature. In image processing Feature extraction is a special form of dimensionality reduction. Feature extraction is a general term for methods for constructing combinations of the variables, but still describes the data sufficiently accurately. Medical images of different categories can be distinguished via their homogeneousness or feature characteristics. Therefore, it may be useful to extract features for image classification. The general features extracted from the medical images are Energy, Entropy, Contrast, Homogeneity, Maximum probability, Inverse difference moment, and correlation. The other extracted features are Mean, Median, Standard deviation, Root mean square, Frequency, Number of objects, Sum of local variance, Sum of edges, Minimum value, Range of intensity, Color, Texture, Edges, Gradient, and Histograms etc.

The main purpose of feature selection is to reduce the number of features used in classification while maintaining acceptable classification accuracy. Feature selection is a preprocessing technique, commonly used on high-dimensional data, that studies how to select a subset or list of attributes or variables that are used to construct models describing data. Wide data sets, which have a huge number of features but relatively few instances, introduce a novel challenge to feature selection. In any classification task, there is a possibility that some of the extracted features might be redundant. These features can increase the cost and running time of the system, and decrease its generalization performance. In this way, the selection of the best discriminative features plays an important role in this work.

The detected features are to be selected, extracted and analyzed by an expert system to conclude into some quantitative results. The decision making system will classify the new image as normal, dyslexic, dysgraphic or dyscalculic. This objective and quantified classification reduces the amount of error in diagnosing specific learning disability. Subjects with SLD will get a smart quantified idea about the severity of disability, which is an outcome of our work. The quantified depth of diversity in brain functions is another outcome of the proposed method which helps the Neuro - Physicians while diagnosing specific learning disability. The subjective errors and non-quantified conclusions about the degree of recovery of the patient, present in conventional diagnosis of dyslexia, dysgraphia and dyscalculia are avoided in our work through Objective and quantified results.

4. PROPOSED WORK

The proposed work consists of acquisition of the data, analyzing data sets, pre-processing, feature detection, feature extraction and its analysis and finally designing the decision making system which provide the quantitative outcomes of the work (see Figure 4).

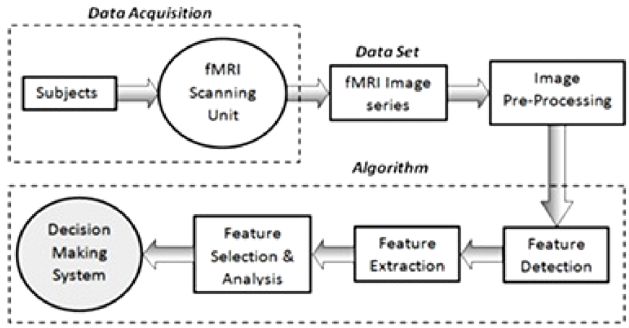

Figure 4. Block diagram of the proposed work

The aim of our algorithm is to detect the subtle differences between the scan sets. The BOLD fMRI signal is often found to vary considerably between scanning sessions and between subjects, and research studies recommends to invoke random effects models where the fMRI signal is modeled with two components: The between-scan within-session/subject variation and the between-session/subject variation.

5. EXPECTED OUTCOME OF THE WORK

The detected features are to be selected, extracted and analyzed by the proposed expert system to conclude into some quantitative results. The decision making system will classify the new image as normal, dyslexic, dysgraphic or dyscalculic. This objective and quantified classification reduces the amount of error in diagnosing specific learning disability. Subjects with SLD will get a smart quantified idea about the severity of disability, which is an outcome of our work. The quantified depth of diversity in brain functions is another outcome of the proposed method which helps the Neuro - Physicians while diagnosing specific learning disability. The subjective errors and non-quantified conclusions about the degree of recovery of the patient, present in conventional diagnosis of dyslexia, dysgraphia and dyscalculia are avoided in our work through Objective and quantified results. An objective algorithm will be designed in MATLAB for the diagnosis of SLD using fMRI with the help of image processing techniques. Real time images acquired through fMRI BOLD method are subjected to image processing. The significant features are detected, extracted, selected from these images. Analysis of these vital features results in quantified outcomes of our work as following:

1. Classification of normal, dyslexic, dysgraphic and dyscalculic subjects.
2. Degree of severity.
3. Depth of abnormality in brain functions.
4. Degree of recovery.
5.

6. REFERENCES

[1] Tung-Kuang Wu, Shian-Chang Huang and Ying-Ru Meng. Identifying and Diagnosing Students with Learning Disabilities Using ANN and SVM. 2006 International Joint Conference on Neural Networks, Vancouver, BC, Canada July 16- 21, 2006, 0-7803- 9490- 9/06/©2006 IEEE.

[2] Roberto Tuchman. The Treatment of Learning Disabilities. International Pediatrics/Vol. 15/No. 2/2000

[3] John R. Anderson, Dana Byrne, Jon M. Fincham and Pat Gunn. Role of Prefrontal and Parietal Cortices in Associative Learning. Cerebral Cortex April 2008; 18:904 — 914 doi:10.1093 / cercor / bhm123 Advance Access publication August 3, 2007

[4] BERNARD SKLAR, JOHN HANLEY, AND WILLIAM W. SIMMONS. A Computer Analysis of EEG Spectral Signatures from Normal and Dyslexic Children. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. BME - 20, NO. 1, JANUARY 1973.

[5] M. L. Bonte, L. Blomert, Developmental dyslexia: ERP correlates of anomalous phonological processing during spoken word recognition , Brain Res Cogn Brain Res, vol. 21, issue 3, pp. 360-376, 2004.

[6] Alexander T. Sack, Axel Kohler, Sven Bestmann, David E. J. Linden, Peter Dechent, Rainer Goebel and Juergen Baudewig. Imaging the Brain Activity Changes Underlying Impaired Visuospatial Judgments: Simultaneous fMRI, TMS, and Behavioral Studies. Cerebral Cortex Advance Access published March 3, 2007.

[7] E. Grikorenko, Developmental Dyslexia: An Update of Genes, Brains and Enviroment, J. Child. Psychol. Psychiat., vol. 42, no. 1, pp. 91 – 125, 2001.

[8] A. El-Baz, M. Casanova, G.Gimel'farb, M. Mott, A. Switala, E. Vanbogaert, and R. McCracken. Dyslexia diagnostics by 3D texture analysis of Cerebral White Matter gyrifications. 78-1-4244-2175-6 / 08 ©2008 IEEE.

[9] Richards, T., Berninger, V., Winn, W., Swanson, H. L., Stock, P., Liang, O., & Abbott, R. Differences in fMRI activation between children with and without spelling disability on 2- back/0- back working memory contrast. Journal of Writing Research,1 (2), 93-123, Educational Psychology, University of Washington, Seattle, WA 98195- 353600 USA (2009).

[10] E. Boder, Developmental dyslexia, a new diagnostic approach based on the identification of three subtypes, J. School Health, vol. 40, pp. 289-290, June 1970.

[11] M. Critchely, The Dyslexic Child. Springfield, Ill.: Charles C. Thomas, 1970.

[12] J. Money, On learning and not learning, in The Disabled Reader, J. Money, Ed. Baltimore, Md.: Johns Hopkins Press, 1966, pp. 21-40.

[13] Ioannis I. Andreadis, Giorgos A. Giannakakis, Charalabos Papageorgiou, and Konstantina S. Nikita. Detecting Complexity Abnormalities in Dyslexia Measuring Approximate Entropy of Electroence phalographic Signals. 31st Annual International Conference of the IEEE EMBS Minneapolis, Minnesota, USA, September 2-6, 2009

[14] Xiu-Li Zheng, Fei Luo, Chun-Lei Shan, Wen-Gang Yin. A Novel Cognitive Model of Reading: Neuropsychology Research on Internal Processing of the brain. Proc. 7th IEEE Int. Conf. on Cognitive Informatics (ICCI'08), 978-1-4244-2538-9/08/$25.00 ©2008 IEEE

[15] Richard P. W. Loose more, Gordon D. A. Brown and Frances L. Watson. A Connectionist Model of Alphabetic Spelling Development and Developmental and Acquired Dysgraphia. Proceedings of the Thirteenth Annual Conference of the Cognitive Science Society, 61-66. Hillsdale, New Jersey: Lawrence Erlbaum.

[16] Joy Hirsch, Functional Neuroimaging. Basic and Clinical Neurosciences 28th Annual Postgraduate Review Course December 3, 2005, through March 11, 2006.

[17] Karl H. S. Kim, Norman R. Relkin,Kyoung-Min Lee and Joy Hirsch. Distinct cortical areas associated with native and second languages. NATURE |VOL 388 | 10 JULY 1997, Nature © Macmillan Publishers Ltd 1997

[18] Yue Wang & Lotus Lin & Patricia Kuhl & Joy Hirsch. Mathematical and Linguistic Processing Differs Between Native and Second Languages: An fMRI Study. Brain Imaging and Behavior (2007) 1:68–82, Springer.

[19] John R. Anderson, Mark V. Albert, and Jon M. Fincham. Tracing Problem Solving in Real Time: fMRI Analysis of the Subject- paced Tower of Hanoi. Journal of Cognitive Neuroscience 17: 8, pp. 1261–1274, 2005.

[20] Karla L. Miller, Brian A. Hargreaves, Jongho Lee, David Ress, R. Christopher deCharms and John M. Pauly. Functional Brain Imaging with BOSS FMRI. Proceedings of the 26th Annual International Conference of the IEEE EMBS, San Francisco, CA, USA - September 1- 5, 2004.

[21] Camille G´omez-Laberge, Andy Adler, Ian Cameron, Thanh Binh Nguyen, and Matthew J. Hogan. Selection Criteria for the Analysis of Data-Driven Clusters in Cerebral fMRI. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 55, NO. 10, OCTOBER 2008.

[22] Soo-Yeon Ji and Kayvan Najarian. A Modified Maximum Correlation Modeling Method for fMRI Brain Mapping; Application for Detecting Dyslexia. 978-1-4244-2890-8/08/$25.00 ©2008 IEEE.

[23] A Primer on MRI and Functional MRI (version 2.1, 6/21/01), Douglas C. Noll, Ph.D., Departments of Biomedical Engineering and Radiology University of Michigan.

[24] Chia-Wei Lee, Der-Yow Chen, Chang-Wei Wu, Jyh-Horng Chen. Comparing The Spatial and Temporal Reproducibility of Brain Activation Using Three fMRI Techniques: BOLD, FAIR, and VASO. Proceedings of NFSI & ICFBI 2007 Hangzhou, China, October 12- 14, 2007.

[25] Yue Wang, Joan A. Sereno, Allard Jongman, and Joy Hirsch. fMRI Evidence for Cortical Modification during Learning of Mandarin Lexical Tone. Journal of Cognitive Neuroscience 15:7, pp. 1019–1027, © 2003 Massachusetts Institute of Technology.

[26] N. Soldati, S. Robinson, C. Persello, J. Jovicich and L. Bruzzone. Automatic classification of brain resting states using fMRI temporal signals. ELECTRONICS LETTERS 1st January 2009 Vol. 45 No. 1.

[27] T. Ohnishi, H. Matsuda, T. Tabira, T. Asada, and M. Uno. Changes in brain morphology in Alzheimer disease and normal aging: Is alzheimer disease an exaggerated aging process? American Journal of Neuroradiolgy, 22:1680–1685, 2001.

[28] S. Y. Bookheimer, M. H. Strojwas, M. S. Cohen, A. M. Saunders, M. A. Pericak-Vance, J. C. Mazziotta, and G. W. Small. Patterns of brain activation in people at risk for alzheimer's disease. The New England Journal of Medicine, 343:450–456, 2000.

[29] H. Gallaghera, F. Happe, N. Brunswicka, P. Fletchera, U. Frithc, and C. Fritha. Reading the mind in cartoons and stories: an fmri study of'theory of mind' in verbal and nonverbal tasks. Neuropsychologia, 38:11–21, 2000.

[30] A. D. Nicola, M. Caulo, C. D. Gratta, A. Ferretti, A. Tartaro, and G. Romani. A new processing method in fmri for detecting activated regions in patients after subcortical stroke. In IEEE EMBS, 2003.