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Detection Of Dyslexia From Eye Movements Using *Anfis* & *Bbwpe* Feature Extraction Methods

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ABSTRACT - *The control of attention orienting was studied in children with specific reading disorder (SRD) or dyslexia, and it was compared with that of normal readers. The main goal of the study was to propose and implement new feature extraction method for extracting the features efficient from the signals and it is classified using the classifier from eye movement signal. Eye movements of 76 school children were measured using videooculographic (VOG) technique during one reading and four nonreading tasks. Videooculographic (VOG) is used to measure the Eye movement's signals of children through single reading and four non reading tasks. Time and frequency domain features were extracted and various feature selection methods were performed to select subsets of significant features. The best basis-based wavelet packet entropy method (BBWPE) is proposed in this research for extracting the features from the eye movement signal. The improved ANFIS based on PSO is used as a classifier. The parameters used for finding accuracy of the proposed methodology are sensitivity, specificity and p-value. The Experimentation confirmed that the proposed ANFIS with BBWPE model has good detection results than ANFIS with MAR and ANN model in terms of parameters like sensitivity, specificity, detection accuracy and p-value.*

KEYWORD *- Learning disability, Feature Extraction, Classification, Adaptive Neuro-Fuzzy Inference System (ANFIS), Best Basis-based Wavelet Packet Entropy method (BBWPE).*

I. INTRODUCTION

Learning disability [LD] denotes to a neurological condition which disturbs an individual's ability to think and remember. It is established in disorders of listening, thinking reading writing spelling or arithmetic [1]. These individuals are not attributed to medical, emotional or environment causes despite having normal intellectual abilities [2]. LD can be broadly classified into three types. They are difficulties in learning with respect to read (Dyslexia), to write (Dysgraphia) or to do simple mathematical calculations (Dyscalculia) [3] which are often termed as special learning disabilities. Krik [1] stated that, children with special learning disabilities exhibit a disorder in one or more of the basic psychological processes involved in understanding or in using spoken or written language. These may be manifested in disorders of listening, thinking, talking, reading, writing, spelling or arithmetic. They include conditions which have been referred to as perceptual handicaps brain injury minimal brain dysfunction dyslexia development aphasia etc. and they do not include learning problems which are due primarily to visual hearing or motor handicaps to mental retardation emotional disturbance or to environment deprivation. In that dyslexia is one of the important disability which affects the children in preschool stage itself.

Developmental dyslexia is traditionally defined as a discrepancy between reading ability and intelligence in children receiving adequate reading tuition. Since the definition is entirely behavioral [4], it leaves open the causes for reading failure. It is now well established that dyslexia is a neurological disorder with a genetic origin, which is currently being investigated. The disorder has lifelong persistence, reading retardation being merely one of its manifestations. Dyslexia difficulty is normally differentiated by using the following problems during learning process such as how to spell each letter differently, how the words are read correctly and their confidence level of each word [5].

Dyslexia is, however, often associated with abnormal movements of the eyes. Although many people suggest that these are merely a consequence rather than a cause of reading difficulties, perhaps arising from children's inability to make sense of what they see, it is now clear that many dyslexics have unusual eye movements even when they are not trying to read.

There are several techniques are used for monitoring of eye position from video [6]. One of the important and recent techniques used for monitoring the eye movements is videooculographic. It is mainly used for recording of eye movement and it is a highly effective non-invasive technology for evaluating eye movement.Several diagnosing systems are introduced in the past decade for identifying the dyslexia children's from normal ones. Although these algorithms give better results, it is not efficient one and diagnosing of dyslexia is still under progress. In order to solve these issues the recorded eye movement signals are analyzed using word length and frequency effects in a teach reading disorder with wordnet tool. Eye movement signals of each child are recorded using Videooculographic technology. Totally there are 76 students eye movement signals are recorded using iView 3.0 videooculography systems at the Department of Neurology. The recorded eye movement signals are analyzed using wordnet tool, then most important features for analyzing eye movement signals are extracted using Best Basis-based Wavelet Packet Entropy (BBWPE) and learning of extracting features for dyslexia detection through improved Adaptive Neuro-Fuzzy Inference System (ANFIS) with PSO algorithm. Finally measure the detection rate of dyslexia between existing ANFIS model and Improved ANFIS model from feature extraction results for each eye movement signal.

II. RELATED WORK

Learning disabilities (LD) have been much attracting the interest in various applications areas such as scientific regulation, together with therapy, neuroscience, psychology, knowledge, and sociology. Since learning disabilities are generally imagine and understood if both becomes under the similar scientific regulation, can offer facts for the complication under different category [7]. In earlier work several learning academic activities [8-9] have been carried out to discover the dyslexia children who have actually suffers from LD difficulty, the major causes of the learning disability majorly affects the following actions such as thinking, listening, concentration, and, mainly significantly The study of official disclosure [10] is used to identify the learning disability problem adopted by the Saudi department of Education. Since it says that reading is a complex task that needs many skills for its mastery. Therefore, identification of skills for success reading is also very significant. Recently, Behrmann et.al [11] developed a word-based length examination to detect the results of pure alexia. Pure alexia is known as reading disorder that happen from a low-level unimportant destruction in the graphematics system detection of letter character. In Word processing point of view, if the quantity of information increases, and its morphological complexity also simultaneously increases [12] at a time and which it is directly proportional with more letters. For all the above specified reasons conclude that the word length becomes one of the important part to analysis the results of eye movements signals based on fixation time.

Analysis of the eye movement’s signals becomes one of the interesting research areas and the modeling’s of information for eye movement’s signals are straightforwardly associated with mental states of each reader. The meaning of each word read by child is measured by using eye fixations [13]. Eye movements are well-known to be there cognitively-controlled [14]. It consists of information about low-level behavioral examination of interactive tasks [15] and well-matched task to characterize the textual information acquisition process throughout exploration tasks .Much of the existing science information works concentrate an eye tracking methods based on the number of eye fixations, for example to discover which information is most ranked in search results pages [16-17] .

III. PROPOSED METHODOLOGY

Based on the investigation and learning researches from earlier work, the assessment of eye movement’s signals plays major imperative role in experimental reading investigation. Our work majorly focuses on the analysis of eye movement signals based on their information reader by each child, since so since none of the research work mainly focuses on the analysis of the eye movement signals with word length their corresponding frequency property. The major aim of this study is to discover different sequential and spatial parameter away from entire fixation time .The number of fixation time is used to examine the word - based performance period and neighborhood fixation pattern is used to distinguish among the several learning disorders for dyslexic detection .From this analyzed eye movement’s signal from wordnet based similarity measure to extract most important features such as frequency and time domain features of eye movement signals to perform dyslexia detection results using best basis-based wavelet packet entropy method. Proposed a Improved Adaptive Neuro-Fuzzy Inference System (ANFIS) with PSO algorithm for dyslexia detection. Word length and lexical frequency become one of the most significant factors are used to analysis the results of eye movements. Word length verifies the values of fixation time and measures the number of fixation time for each reading along with the number of words read by children. If the word length becomes longer, more number of fixations are required to complete reading task. To measure the word length of the eye movement signals in this work uses a wordnet based similarity measure where each child's word is considered as input from eye movement signals. Each and every one of the children word length is separated into two parts such as medium (6-7) and long letters (13-14) .Shorter word length is not considered for analysis of eye movement signals, since it consist of less fixation time with patients , it becomes hard to analysis the eye movement signals with less fixation time . Each and every one of the child's eye movement signals words is compared by measuring the similarity among words it the similarity levels of each reader reaches medium at long time is considered as dyslexia affected students.

Word Net, each meaning of a word from eye movement's readers is characterized by a unique wordsense of the word, and a synset consists of group of wordsenses that having the similar meaning for eye movement's signal. It consists of two third of nodes in WordNet it is known as synsets. Made following assumption to analysis the eye movements signals using wordnet with edge lengths of the shortest path: (i) the relation type of edge-edge nodes in the wordnet; (ii) the total number of word at end nodes (iii) the depth level of end nodes for each nodes in the tree, and (iv) the maximum number of nodes in depth level for entire tree structures.

$$wt(c,p) = \left(\beta + (1-\beta)\frac{\bar{E}}{E(p)}\right)\left(\frac{D}{d(p)}\right)^{\alpha} T(c,p) \tag{1}$$

where c is a node on the shortest path in the entire word sentence of single eye movement user signal, p is the parent node of c ,$\bar{E}$ is the average local density results of dyslexia user of entire eye movements signals, $E(p)$ is the local density of p ,D is the maximum depth level analysis of dyslexia and non dyslexia of hierarchy structure that c and p are in $d(p)$ is the depth of p, α , depth factor, β density factor, and $T(c,p)$ edge type factor, correspondingly,the relateness between the words from eye movement signals c and that parent node p of that word from eye movements signals , (c,p) is calculated by following equation,

$$Related(x,y) = \frac{\max\{\log f(x), \log f(y)\} - \log\ f(x,y)}{\log N - \min\{\log f(x), \log f(y)\}} \tag{2}$$

where $f(x)$, $f(y)$, and $f(x,y)$, are the numbers of word length readied by children from eye movements signals that contain x, y, and both x and y, correspondingly. x & y is different word of children ,N is a normalising factor its value is greater than $f(x)$ and $f(y)$. The semantic relatedness among two attributes words in the same eye movement signal can be calculated by the following equation:

$$rel(c_1, c_2) = \sum_{n \in \{S(c_1,c_2) - sol(c_1,c_2)\}} wt(n, parentOf(n)) \tag{3}$$

where $S(c_1,c_2)$ is the set of different nodes features in the shortest path among $c_1$and c_2,that corresponds to same user eye movement signal $Sol(c_1,c_2)$ is the set of different nodes features in the shortest path without parent , n represents the number of nodes considered by $S(c_1,c_2)$.

Feature extraction using Best Basis-based Wavelet Packet Entropy (BBWPE)
WPT representation of EEG signals
The wavelet packet transform (WPT) can be viewed as a generalization of the classical wavelet transform, which provides a multi-resolution and time–frequency analysis for eye movement signal. The wavelet packet transform generates the full decomposition tree, as depicted in Fig. 1.

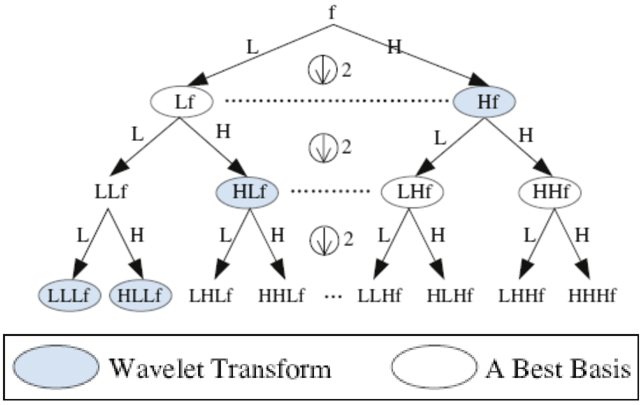

Fig. 1. Illustration of the wavelet packet decomposition.

The wavelet transform basis is indicated by gray ovals. The orthogonality of the basis functions allows the use of an additive cost function to determine the optimal basis for data compression. An example of a possible best basis is shown using white ovals. A low (L) and high (H) pass filter is repeatedly applied to the function f, followed by decimation by 2, to produce a complete subband tree decomposition to some desired depth. The low- and high-pass filters are generated using orthogonal basis functions [18]. Because WPT not only

decomposes the approximations of the signal but also details, it holds the important information located in higher frequency components than WT in certain applications.
A wavelet packet is represented as a function (Shinde & Hou, 2004):

$$\psi^{i}_{j,k}(t) = 2^{-j/2}\psi^{i}(2^{-j}t - k) \quad (4)$$

where i is the modulation parameter, j is the dilation parameter and k is the translation parameter. $i = 1,2,\ldots,j^{n}$, and n is the level of decomposition in wavelet packet tree.
The wavelet ψ^{i} is obtained by the following recursive relationships:

$$\psi^{2i} = \frac{1}{\sqrt{2}}\sum_{-\infty}^{\infty} h(k)\psi^{i}\left(\frac{t}{2} - k\right) \quad (5)$$

$$\psi^{2i} = \frac{1}{\sqrt{2}}\sum_{-\infty}^{\infty} h(k)\psi^{i}\left(\frac{t}{2} - k\right) \quad (6)$$

Here ψ^{i} is called as a mother wavelet and the discrete filters $h(k)$ and $g(k)$ are quadrature mirror filters associated with the scaling function and the mother wavelet function.
The wavelet packet coefficients $c^{i}_{j,k}$ corresponding to the signal $f(t)$ can be obtained as,

$$c^{i}_{j,k} = \int_{-\infty}^{\infty} f(t)\,\psi^{i}_{i,k}(t)\,dt \quad (7)$$

provided the wavelet coefficients satisfy the orthogonality condition. The wavelet packet component of the signal at a particular node can be obtained as

$$f^{i}_{j}(t) = \sum_{k=-\infty}^{\infty} c^{i}_{j,k}\,\psi^{i}_{i,k}(t)\,dt \quad (8)$$

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency.
Wavelet packet entropy and best basis selection
The number of decompositions from a signal in different ways may be very large. An exhaustive search for the optimal decomposition is not feasible, given the large number of possible binary subtrees decompositions. Therefore, it is necessary to find an optimal decomposition by using a convenient algorithm. The best basis selection provides a means for choosing the features which are best for classification based on various criteria. The selection process is based on either (1) best representation of a given class of signals, or (2) best distinction between classes [19]. Entropy is a common method in many fields, especially in signal processing applications. Commonly, there are several useful entropy types such as Shannon, log energy, sure, threshold, etc. [20] for calculating the lowest cost basis. Here only one of the most attractive cost functions Shannon entropy was employed which is a measure of signal complexity to wavelet coefficients generated by WPT where larger entropy values represent higher process uncertainty and therefore higher complexity. In wavelet entropy can provide useful information about the underlying dynamical process associated with the signal. The entropy 'E' must be an additive information cost function such that E(0) = 0 and

$$E(s) = \sum_{i} E(S_i) \quad (9)$$

The entropy for the observed signal in lp norm with pP1 can be expressed as

$$E(S_i) = |S_i|^{p} \quad (11)$$

And

$$E(s) = \sum_{i} |S_i|^{p} \quad (12)$$

The Shannon entropy is defined as

$$E(s) = -\sum_{i} S_i^{2}\log(S_i^{2}) \quad (13)$$

where s_i represents coefficients of signal s in an orthonormal basis. If the entropy value is greater than one, the component has a potential to reveal more information about the signal and it needs to be decomposed further in order to obtain simple frequency component of the signal. By using the entropy, it gave a useful criterion for comparing and selection the best basis.

The procedure of feature extraction

Given the signals, the best basis-based wavelet packet entropy feature extraction is obtained by performing the following steps:

1. Select a wavelet function W and specify the decomposition level L
2. Calculate the sample mean SM
3. Decompose SM at the specified level with the selected wavelet function, and return a wavelet packet tree T. Let Bl,k be the set of WPT basis vector, $0 \leq l < L, 1 \leq k \leq 2^{L} - 1$
4. Calculate energies $E_{l,k}$ for all subbands using
5. Set the initial basis $B = \{B_{L-1,1}, \dots, B_{1,k}, \dots, B_{L-1,2^{L-1}}\}$ related to the subbands at the bottom level.
6. Compare the entropy of a parent node $E_{l,k}$ with the sum of the entropy of two child nodes $E_{(l+1,2k-1)} + E_{(l+1,2k)}$. If $E_{l,k} \leq E_{(l+1,2k-1)} + E_{(l+1,2k)}$ then replace $B_{l+1,2k-1}$ and $B_{l+1,2k+1}$ by $B_{l,k}$ in B else set $E_{l,k} = E_{(l+1,2k-1)} + E_{(l+1,2k)}$ i.e., assign the sum of the children's entropy to the parent node.
7. Repeat (f) for the next higher level until the root is reached.
8. Select a sample from training set.
9. Decompose the sample to L using W.
10. Calculate wavelet coefficients in the corresponding best basis B.
11. Calculate the wavelet coefficients to form a features
12. Repeat steps (8)–(11) for all samples.

Improved ANFIS model for Dyslexia detection

The proposed improved ANFIS model to detects dyslexia for each feature extraction results from Wavelet packet entropy and best basis selection models. Generally Adaptive Neuro-Fuzzy Inference System (ANFIS) consists of five layers such as input layer, fuzzy layer, product layer; defuzzify layer and output layer it was used in earlier work [20] for several classification tasks. The training and testing of the parameters for dyslexia detection becomes one of the major important issues in detection task, since the ANFIS parameters are based on gradient function, it becomes hard to update the values of gradient function to each step of dyslexia detection. In order to overcomes these problems proposed methods uses swarm intelligence based optimization method PSO(Particle swarm optimization) to optimist the parameters values of ANFIS to enhance the detection rate of dyslexia in antecedent part and consequent parameters of ANFIS model is optimized using RLS. The proposed improved ANFIS model is used to discover dyslexia detection for extracted features results from MAR. In this work we use Takagi-Sugeno-Kang type fuzzy model [21] for dyslexia detection. It consists of two major parts such as antecedent and consequent parts and the structure of ANFIS model is shown in Figure 2.

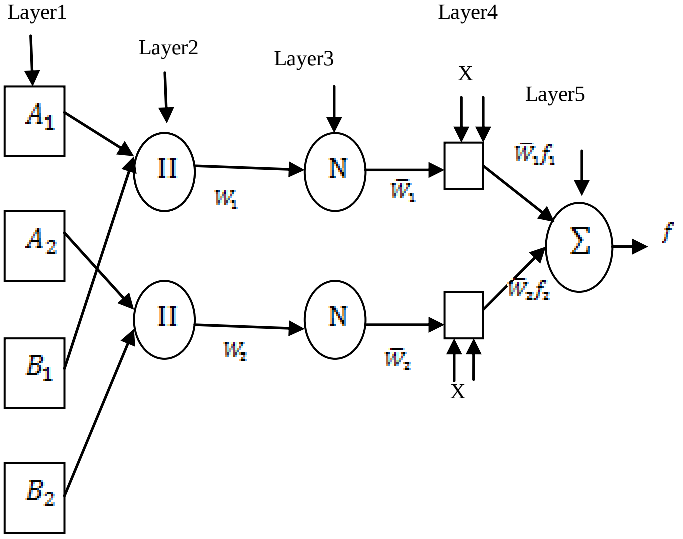

Figure 2 Adaptive neuro-fuzzy inference system

Representation of ANFIS model is carried out using fuzzy if-then rules and it is characterize in the following way:

R_i if x_1 is A_{i1} and x_2 is A_{i2} then x_1 is y_i is $f_i(x)$ (14)

where x_1 and x_2 are the input variables feature extraction results from best basis-based wavelet packet entropy to the ANFIS. $A_{i1}, \dots A_{in}$ be the fuzzy membership set function to each rule $(i = 1, 2, \dots, n)$ and y_i is the dyslexia detection classification results for ith rule. Fuzzy set A_{ij} at layer for each feature vector result from MAR and it has the form,

$$A_{ij}(x) = \exp\left\{-\left(\frac{x_j - m_{ij}}{\sigma_{ij}}\right)^2\right\} \tag{15}$$

where m_{ij} denotes centre and σ_{ij} be the measurement of A_{ij} correspondingly to detect the results of Dyslexia. These parameters are known as antecedent parameters. Dyslexia detection results of ANFIS is obtained by weighting the parameters values of subsequent parts of n rules through the equivalent membership evaluation,

$$\hat{y} = \sum_{i=1}^{n} \overline{w}_i f_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{16}$$

Where

$$w_i = \prod_{j=1}^{n} A_{ij}(x_i) \tag{17}$$

$$y_i = f_i(x) = (a_i x_1 + b_i x_2 + c_i) \tag{16}$$

Where (a_i, b_i, c_i) is the parameter set of ANFIS objective function and it is named as consequent parameters. As discussed above the optimization of parameters values becomes one of the important problems in ANFIS model to reduce the results of dyslexia, in order to overcome these problems the resultant part of parameters is optimized using Dynamic spread factor PSO (DSF-PSO) is used in this paper [22]. The weight values of layer 2 and layer 3 are decreased linearly starting 0.9 to 0.4 during dyslexia detection process. Since the appropriate choice of the weight value only provides a best detection results among dyslexia and non-dyslexia children. The illustration of DSF-PSO to optimize consequent parts of ANFIS is mathematically specified as,

$$x_{id_{new}} = x_{id} + v_{id_{new}} \tag{18}$$

$$v_{id_{new}} = (w * v_{id}) + c_1(\mathrm{rand}_1(p_{id} - x - id)) + c_2(\mathrm{rand}_2(p_{gd} - x_{id})) \tag{19}$$

where , c_1 and c_2 are given by

$$w = \exp\left(-iter/(spread\_factor \times \max\_iteration)\right) \tag{20}$$

$$spread_{factor} = 0.5(spread + deviation)$$

$$c_1 = 2(1 - iter/\max\_iteration)\ \&\ c_2 = 2$$

where x_{id} and v_{id} represent the location vector and velocity vector value for every parameters of ANFIS model through d-dimensional investigate space correspondingly. In equation (18) represents the velocity of each parameter in ANFIS models which present adequate information to optimize ANFIS parameters through the examination in solution search space. There are two major parts presented in equation (20) ,there are first and second parts .The initial part of the equation is used for approximation of the result of current feature vectors for dyslexia detection, the second parts move towards to achieve best optimized ANFIS parameters for entire training samples. From this optimized parameters dyslexia detection accuracy is enhanced in terms of parameters like sensitivity, specificity and detection accuracy. The optimized ANFIS parameters results from SFPSO are measured using spread factor with improved dyslexia detection rate than normal ANFIS model.

Similarly antecedent parts such as $m_{ij} \& \sigma_{ij}$ in ANFIS model for dyslexia detection is optimized through RLS in(16). From (14) it is known that,

$$\overline{w}_1 f_1 + \overline{w}_2 f_2 + \cdots + \overline{w}_n f_n = \hat{y}_1 + \hat{y}_2 + \cdots + \hat{y}_n \tag{21}$$

$$\begin{bmatrix} \overline{w}_1 x_1 & \overline{w}_1 x_2 & \overline{w}_1 \\ \overline{w}_2 x_1 & \overline{w}_2 x_2 & \overline{w}_2 \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \overline{w}_n x_1 & \overline{w}_n x_2 & \overline{w}_n \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \cdot \\ \cdot \\ \cdot \\ \hat{y}_n \end{bmatrix}$$

Where

$$\varepsilon(t) = y(t) - \varphi^T(t)\theta(t-1) \quad (22)$$

In this work use of non-weighted RLS to approximate the parameters (a_i, b_i, c_i) are specified by

$$P(t) = P(t-1) - p(t-1)\varphi(t)(I + \varphi^T(t)P(t-1)\varphi(t))^{-1}\varphi^T(t)P(t-1) \quad (23)$$

$$\theta(t) = \theta(t-1) + P(t)\varphi(t)(y(t) - \varphi^T(t)\theta(t-1))$$

A Gaussian membership function $\theta(t)$ measures the results of ANFIS model according to the fuzzy rule in(12). A swarm with number of dyslexia features determination depends on the number of membership function for each dyslexia feature vector data x_1 and x_2 used to obtain best possible number of rules for Dyslexia detection. Therefore, the number of eye movements signals features in each particle determination depends on possible number of antecedent parameters. In PSO algorithm the parameter values of ANFIS are optimized based on the fitness function value. The parameter of the ANFIS model is predictable based on the mean squared error function (MSE) for each eye movements signal features, it is represented as,

$$f(x) = \frac{1}{s}\sum_{t=1}^{s}(y(t) - \hat{y}(t))^2 \quad (24)$$

IV. EXPERIMENTAL RESULTS

In order to perform experimentation in this work the eye movement signals of 76 female students were recorded by using iView 3.0 videooculography system in dept of Neurology, Charles University. The measured results have been implemented in dark area. To measure the eye movement's signals of each student the screen is placed away from 1 meter to each student. It is motivated to both verbal and four non-verbal tasks. Non verbal task consists of browsing during period, taking an inspection of a movie. A verbal task belongs to reading a particular text or information. To analysis the results of eye movement signals , additionally consider a set of stimulus words that consists of information about word knowledge and word length which is one of the normally used methods in now a day of examination the results of eye movement signals for continuous reading. During this process each children were asked to study a high loudly words in each sentence reading to examine the results of eye movements signals .At the same time to measure the results of detection accuracy we use the following parameters such as sensitivity and specificity [23].

To evaluation performance of the ANFIS with BBWPE, ANFIS with MAR and ANN system the parameters discussed below plays most important role to make final decision.

T_p = True positive denotes when the results of experimentation is positive for a subject with dyslexia.

F_p =false positive denotes when the results of experimentation is negative for a subject with dyslexia

T_n = true negative denotes when the results of experimentation is negative for a subject without dyslexia

F_n = false negative denotes when the results of experimentation is positive for a subject without dyslexia

Sensitivity

Sensitivity is also known as true positive rate (TPR), which estimate the percentage of actually classified data corresponds to positive which are dyslexic subject's class .The sensitivity is defined as below:

$$Sensitivity = \frac{T_p}{T_p + F_n} \quad (25)$$

Specificity

Specificity is also known as true negative rate (TNR) which estimates the percentage of actual classified data corresponds to negatives which are nondyslexic subject's class. It measures the accuracy results of non-dyslexic subjects and defines the percentage of appropriately classified nondyslexic subjects.

$$Specificity = \frac{T_n}{T_n + F_p} \quad (26)$$

Accuracy

Accuracy is defined as the percentage of corrected class of the model and is summation of actual classification parameters, $(T_p + T_n)$ separated by the total number of classification parameters $(T_p + T_n + F_p + F_n)$

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \quad (27)$$

P value estimation

The p-value estimation is used to analysis the results of classification that were the actual class which are correctly classified as correctly dyslexia, make assuming that null hypothesis is true. A most of the investigator rejects these values; their resultant p-value belongs to 0.05 or 0.01. It shows that the p-value of the proposed ANFIS with BBWPF model is less than 0.01; detection rate of the proposed system is high than existing ANFIS with BBWPE and ANN model. The above mentioned parameters results are shown in the Figures 3, 4,5 and 6 .

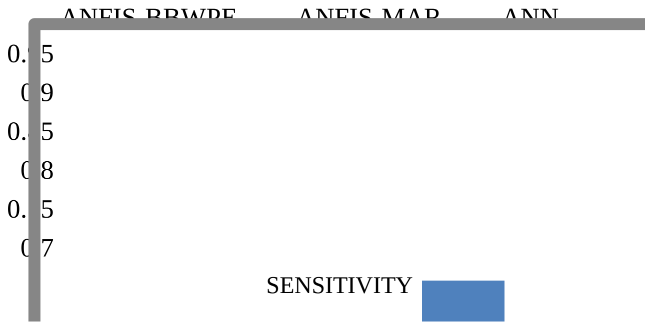

Figure 3: Sensitivity of dyslexia detection with classification

Figures 3 shows the sensitivity results of detection methods such as ANN, ANFIS with MAR and ANFIS with BBWPE methods, it shows that proposed ANFIS-PSO have higher sensitivity rate than the existing ANFIS and ANN , because of word length examination of eye movement signals.

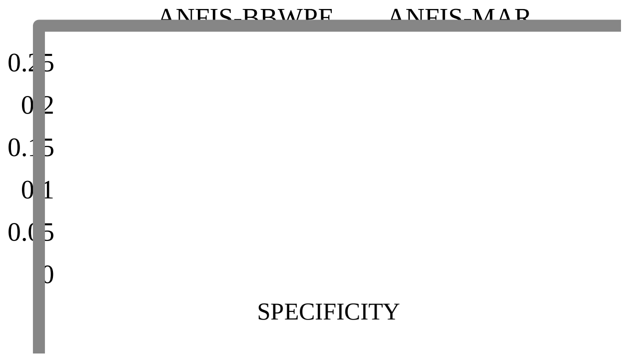

Figure 4: Specificity of dyslexia detection with classification

Figures 4 shows the specificity results of detection methods such as ANN, ANFIS with MAR and ANFIS with BBWPE, it shows that proposed ANFIS with BBWPE have lesser negative rate results than the existing ANN and ANFIS with MAR, because of word length examination of eye movement signals.

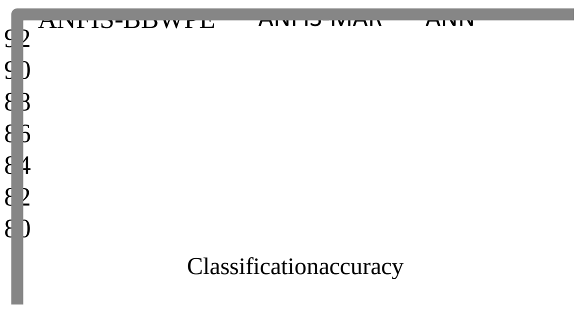

Figure 5: Dyslexia detection with classification accuracy

Figure 5 measures detection accuracy rate of entire system between detection methods such as ANN, ANFIS with MAR and ANFIS with BBWPE. Experimentation results shows that proposed ANFIS with BBWPE have higher dyslexia detection results than existing ANN and ANFIS with MAR, because of word length examination of eye movement signals.

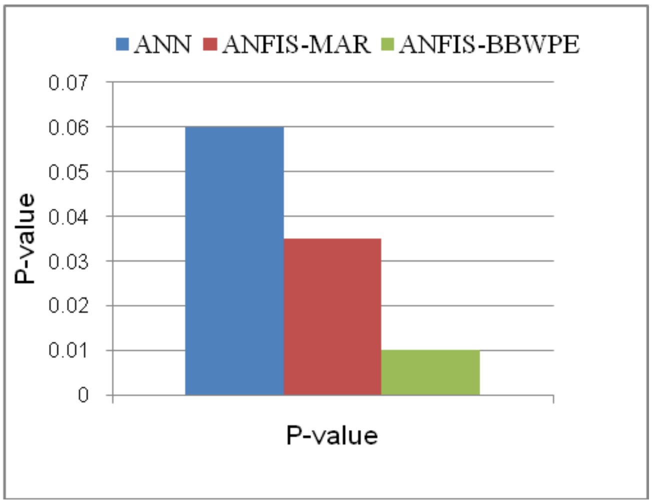

Figure 6: Dyslexia detection With P-value

The p-value estimation is used to analysis the results of classification that were the actual class which are correctly classified as correctly dyslexia, make assuming that null hypothesis is true. A most of the investigator rejects these values; their resultant p-value belongs to 0.05 or 0.01. Proposed ANFIS with BBWPE is nearly 0.01 , so the detection rate of proposed ANFIS with BBWPE is high when compared to existing ANN and ANFIS with MAR.

V. CONCLUSION

Identification of dyslexia affected students turn into one of the major significant medical analytical problem in now days; principally due to not have of the appropriate identification method. Without an analysis of eye movement signals also simultaneously reduces the detection accuracy rate of dyslexia. In order to overcome these problem current study uses as wordnet tool based similarity measure to analysis dyslexic reading from eye movement analyses. The eye movement's signals of each subject are measured based on word length measurement with wordnet tool. Reading is distinguished through the original fixations landing on the start of a word; it is carried out from the left position of the word to the center position of the word. Once the reading eye movement's signals are analyzed then proposed best basis-based wavelet packet entropy method to extract features of dyslexia for each student data, and then perform dyslexia detection framework. ANFIS with BBWPE has been modeled for dyslexia detection with a reduced number of rules in the membership function. Experimentation confirmed that the proposed ANFIS with BBWPE model has good detection results than ANFIS with MAR and ANN model in terms of sensitivity, specificity, accurateness and P-value. Hence, proposed improved ANFIS with BBWPE methods optimize the number of generated rules to enhance dyslexia detection rate.

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