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Research Article

An Efficient Feature Extraction Approach with Improved ANFIS Model for Detection of Dyslexia from Eye Movements

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Abstract: There is lakhs and millions of children suffered from the Learning Disability (LD) Dyslexia problem across the world. Based on the characteristics of dyslexia, the detection or identification of dyslexia students becomes one of the main significant issues in now a day. The eye movement signals of each child are recorded and detection methods are applied to recorded signals. So the eye movement's signal plays majors important role in dyslexia detection. So the analysis of eye movements has become one of the most important problems in Learning Disability. All of the existing work only focuses on identification of children suffering from dyslexia only without measuring eye movement signals results. Up to now still none of the work analyzes eye movements signals based on their word length. The goal of this study was to analysis the eye movement's signals using word net tool. Then Multivariate autoregressive model (MAR) is proposed for feature extraction. Finally proposed an Improved Adaptive Neuro-Fuzzy Inference System (ANFIS) which combines particle swarm optimization for dyslexia detection. Video Oculo Graphic (VOG) is used to measure the Eye movement's signals of children through single reading and four non reading tasks. Experimentation confirmed that the proposed ANFIS-PSO model has good detection results than ANFIS and ANN model in terms of parameters like sensitivity, specificity, detection accuracy and p-value.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS), classification, dyslexia, feature extraction, Learning Disability (LD), Particle Swarm Optimization (PSO), Recursive Least Squares (RLS)

INTRODUCTION

Dyslexia is a one of the most significant usually preceding condition in hospital and educational backgrounds. To detection of dyslexia students in homogenous groups make use of randomized examination; educators routinely deal with children who have occurs with several numbers of developmental problems. Several numbers of investigations required to study this type of complex cases and take an action immediately to solve a dyslexia problem to each child in earlier stage to achieve sufficient learning (Grigorenko, 2001).A child who actually suffers from dyslexia problem required a specific educational strategies to increase reading skills., it is not a ‘‘short-lived developmental lag’’(Shaywitz and Shaywitz, 2005; Coltheart, 2006). The frequency in the Czech school population is predictable to 2-3% (Lerner, 2000), which are significantly lesser results when compared to the usual English language country. This gives more chance to the detection of dyslexia students in the early stage itself and applies specialized training skills to improve reading capability. 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.

Dyslexia detection is carried out to each eye movement's signal. Generally there are two possible categories of eye movement signals such as small and big. The quicker process eye movements between fixation points is known as Saccades, which allow binocular rotating to one more fixation points. The direction of each eye movement's signal and scale of the eye movement's signals becomes mainly significant parameters used to characterize saccades signal results. The direction reading of each person starts from left to right accordingly it is known as forward saccades. The opposite of this reading is known as regressions. The fixation time consists of three types of eye movement's signals such as small, micro saccades eye movement's signals and tremor eye movement signals. The fixation time consists of three types of eye movement's signals such as small, micro saccades eye movement's signals and tremor eye movement signals. Several numbers of

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computation methods Kavale and Forness (2003) have been proposed in earlier work to account the results of various dyslexia types. The Dual Route Cascaded (DRC) model (Ziegler *et al*., 2001) presumes that two different categories of reading tasks are self-determining from each other to a different language.

The aim of this study focuses on the detection of medicinal analytical difficulty among eye movement signals and dyslexia. This problem is studied in several works in literatures, though these methods should not provide exact detection results since recorded eye movement signals are not analyzed using specific methods. 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 word net 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 multiple autoregressive models (MAR) 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.

LITERATURE REVIEW

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 (Kavale and Forness, 2003). In earlier work several learning academic activities (Kavale and Forness, 2003; Reid and Valle, 2004) 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 (Ferri *et al*., 2004) 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*. (2001) 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. If the quantity of information increases and its morphological complexity also simultaneously increases (Bertram and Hyönä, 2003) at a time and which it is directly proportional with more letters in word processing point of view. 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 modelings 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 (Staub *et al*., 2010). Eye movements are well-known to be there cognitively-controlled (Findlay and Gilchrist, 2003). It consists of information about low-level behavioral examination of interactive tasks (Terai *et al*., 2008) 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 (Pan *et al*., 2007; Brumby and Howes, 2008).

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 word net 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 a Multivariate Autoregressive Model (MAR). 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 study 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 (Ziegler *et al*., 2001; Lerner, 2000) and long letters (Staub *et al*., 2010; Findlay and Gilchrist, 2003). 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.

WordNet, 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:

- The relation type of edge-edge nodes in the word net
- The total number of word at end nodes
- The depth level of end nodes for each nodes in the tree
- The maximum number of nodes in depth level for entire tree structures

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

where,

c = A node on the shortest path in the entire word sentence of single eye movement user signal

p = The parent node of c

E = The average local density results of dyslexia user of entire eye movements signals.

E(p) = The local density of p

D = 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 relatedness between the words from eye movement signals c and that parent node p of that word from eye movement's signals

(c, p) = Calculated by following equation:

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

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:

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

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 $S(c_1, c_2)$.

Global information service Feature extraction based on Multivariate Autoregressive Models (MAR): The most significant features of dyslectic children detection /classification were extracted using Multivariate Autoregressive Models (MAR) models. A proposed MAR model extracts time and frequency domain features from eye movement signals for individual children, therefore feature vector values of current children is represented as a linear summation of earlier activities. Let us consider d be the time series eye movement signals from wordnet tool results with d attributes within a system is considered as functional network and where m be the order of MAR(m) model for time and frequency feature extraction, y_n is linear summation of different m feature vector results, it is represented as:

$$y_n = \sum_{i=1}^{m} y_{n-i}A(i) + e(n) \qquad (4)$$

where, $y_n = [y_n(1), y_n(2), \ldots, y_n(d)]$ is the n^{th} sample of a d-dimensional eye movement extracted feature signals results at various stages, A(i) is a $d-by-d$ weight matrix values for each eye movements signals from wordnet tool. Then $e_n = [e_n(1), e_n(2), \ldots, e_n(d)]$ is represented as preservative Gaussian noise for each eye movement signals with consideration of zero mean value and covariance R. Here the Gaussian additive noise assessment is used to approximation of eye movements features signals results from MAR. General illustration of MAR model for feature extraction is represented as follows:

$$y_n = x_nW + e_n \qquad (5)$$

where, $x_n = [y_{n-1}, y_{n-2}, \ldots\ldots, y_{n-m}]$ represents the m previous feature vector results from multivariate model for each eye movements signals, W is a $(m \times d)$ −by-d matrix of MAR coefficients. If the n^{th} rows of eye movements signal Y with X and E are respectively

y_n, x_n and e_n, where $n = 1..N$ eye movements training samples can be written as:

$$Y = XW + E \quad (6)$$

where, Y is an $(N - m)$ -by-d matrix, X is an $(N - m)$ -by-$(m \times d)$ matrix and E is an $(N - m)$-by-d matrix. In equation (6) MAR model is not effectively extract all features in eye movements signals. In order to overcome these problem perform reformulation operation to MAR model, through the Maximum Likelihood (ML) result for each eye movement's signal along with MAR coefficients:

$$\widehat{W} = (X^T X)^{-1} X^T Y \quad (7)$$

The maximum Likelihood (ML) feature extraction results for eye movement's signal(S_{ML}), can be expected as follow:

$$S_{ML} = \frac{1}{N-k}(Y - X\widehat{W})^T (Y - X\widehat{W}) \quad (8)$$

where, $k = m \times d \times d$. Define weight values based feature (eye movements) vector coefficient values as $\widehat{w} = vec(\widehat{W})$ where vec denotes the total number of column weight values feature vector for each eye movement signals. To correctly re-estimate the values of matrix $\widehat{W}$ just simply restore the values of $\widehat{w}$ in Eq. (7) and maximum likelihood results of feature vector weighted coefficient matrix $\widehat{w}$ is given as:

$$\widehat{\Sigma} = S_{ML} \otimes (X^T X)^{-1} \quad (9)$$

where, $\otimes$ represents the Kronecker product. The best values of m can be selected using Minimum Description Length (MDL) (Neumaier and Schneider, 2002). It is also improves the performance results of Bayesian structure (Penny and Roberts, 2002). The ML feature extraction from eye movement's signal along with MAR coefficients is considered as initialization to Bayesian scheme. The Bayesian structure accurately analysis the results of feature extraction results for eye movements signal $N(0, Q^{-1})$ with mean bc and precision b^2c. Also, $Ga(b, c)$ is the represented as gamma distribution along with the parameters b and c. The Bayesian structure makes use of the probabilities to estimate feature extraction results for each eye movement signal:

$$\begin{aligned} &p(W|m) = N(0, \alpha^{-1} I) \\ &p(\alpha|m) = N(0, \alpha^{-1} I) \\ &p(\Lambda|m) = |\Lambda|^{-(d+1)/2} \end{aligned} \quad (10)$$

where,

m = The order value of MAR model

α = The precision value of weights feature vector which drawn randomly

Λ = The noise precision matrix posterior likelihood value for each eye movements signals distributions are specified by:

$$\begin{aligned} &p(W|Y, m) = N(\widehat{W}_B, \widehat{\Sigma}_B) \\ &p(\alpha|Y, m) = Ga(\hat{b}, \hat{c}) \\ &p(\Lambda|Y, m) = Wi(s, B) \end{aligned} \quad (11)$$

Improved ANFIS model for dyslexia detection: The proposed called as improved ANFIS model to detect dyslexia for each feature extraction results from MAR models. Generally Adaptive Neuro-Fuzzy Inference System (ANFIS) consists of five layers such as input layer, fuzzy layer and product layer; defuzzify layer and output layer it was used in earlier work (Mashrei, 2012) 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 study we use Takagi-Sugeno-Kang type fuzzy model (Jacquin and Shamseldin, 2006) for dyslexia detection. It consists of two major parts such as antecedent and consequent parts and the structure of ANFIS model is shown in Fig. 1.

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

$$\begin{aligned} &R_i \text{ if } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \\ &\text{then } x_1 \text{ is } y_i \text{ is } f_i(x) \end{aligned} \quad (12)$$

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

$$A_{ij}(x) = exp\left\{-\left(\frac{x_j - m_{ij}}{\sigma_{ij}}\right)^2\right\} \quad (13)$$

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:

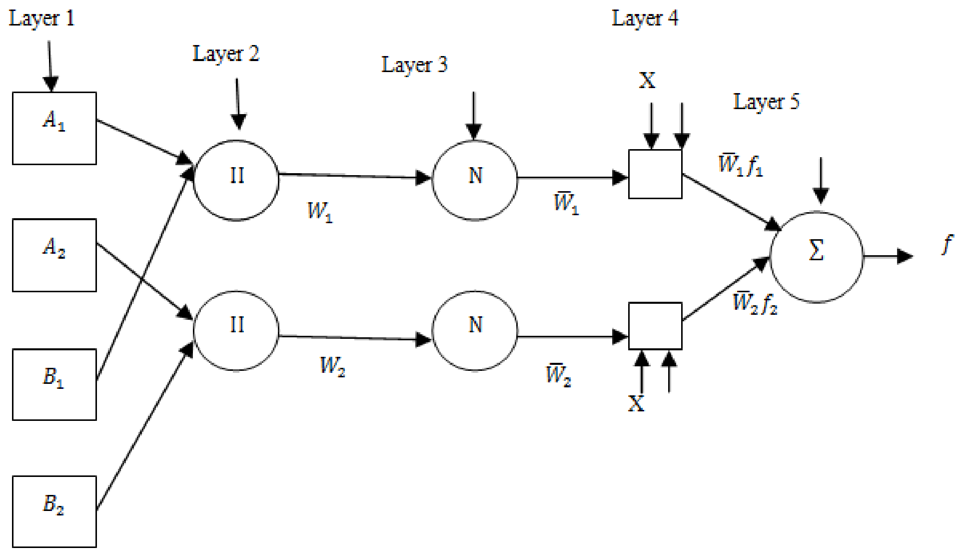

Fig. 1: Adaptive Neuro-fuzzy inference system

$$\hat{y} = \sum_{i=1}^{n} \overline{w}_i f_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{14}$$

where,

$$w_i = \prod_{j=1}^{n} A_{ij}(x_i) \tag{15}$$

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

where, $(\mathrm{a_i}, \mathrm{b_i}, \mathrm{c_i})$ 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 study (Latiff Abd and Tokhi, 2009). 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:

$$x_{id_{new}} = x_{id} + v_{id_{new}} \tag{17}$$

$$v_{id_{new}} = (w * v_{id}) + c_1(rand_1(p_{id} - x - id)) + c_2(rand_2(p_{gd} - x_{id})) \tag{18}$$

where, c_1 and c_2 are given by:

$$\begin{gathered} w = \exp\left(-iter/(spread\_factor \times \max\_iteration)\right) \\ spread_{factor} = 0.5(spread + deviation) \\ c_1 = 2(1 - iter/\mathrm{max\_iteration})\ \&\ c_2 = 2 \end{gathered} \tag{19}$$

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 Eq. (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 Eq. (18), 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. The procedure of the SFPSO methods to optimize the consequent part of ANFIS parameters is shown in Fig. 2.

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

$$\overline{w}_1 f_1 + \overline{w}_2 f_2 + \cdots + \overline{w}_n f_n = \hat{y}_1 + \hat{y}_2 + \cdots + \hat{y}_n \tag{20}$$

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

where,

$$\varepsilon(t) = y(t) - \varphi^T(t)\theta(t-1) \tag{21}$$

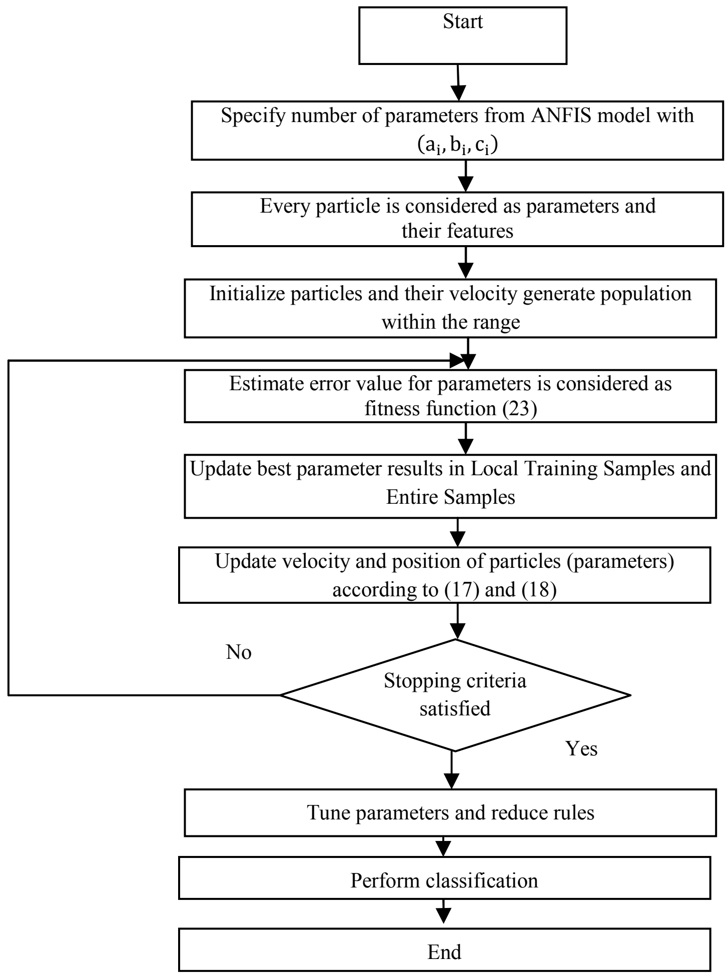

Fig. 2: Parameter tuning using SFPSO for ANFIS model

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

$$\begin{aligned} &P(t) = P(t-1) - p(t-1)\varphi(t)(+\varphi^T(t) \\ &P(t-1)\varphi(t))^{-1}\varphi^T(t)P(t-1) \\ &\theta(t) = \theta(t-1) + P(t)\varphi(t) \\ &(y(t) - \varphi^T(t)\theta(t-1)) \end{aligned} \tag{22}$$

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:

$$f(x) = \frac{1}{s}\sum_{t=1}^{s}(y(t) - \hat{y}(t))^2 \tag{23}$$

EXPERIMENTAL RESULTS AND DISCUSSION

In order to perform experimentation in this study 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 movement's signals. At the same time to measure the results of detection accuracy we use the following parameters such as sensitivity and specificity (Rangayyan, 2002).

To evaluation performance of the Improved ANFIS, ANFIS 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 resutls of experimentation is negative for a subject with dyslexia

T_n = True negative denotes when the resutls of experimentation is negtaive for a subject without dyslexia

F_p = 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:

$$Sensitivity = \frac{T_p}{T_p+F_n} \tag{24}$$

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:

$$Specificity = \frac{T_n}{T_n+F_p} \tag{25}$$

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 $(T_p + T_n + F_p + F_n)$:

$$Accuracy = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \tag{26}$$

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 Improved ANFIS model is less than 0.01; detection rate of the proposed system is high than existing ANFIS and ANN model. The above mentioned parameters results are shown in the Fig. 3 to 6.

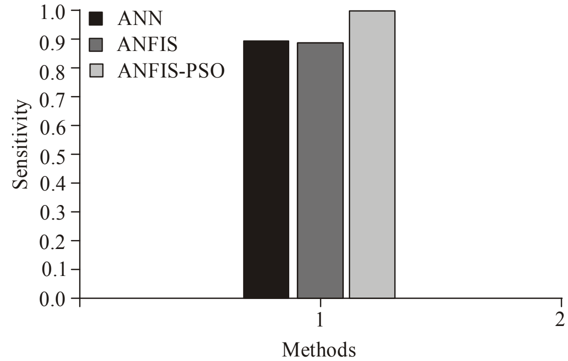

Fig. 3: Sensitivity of dyslexia detection with classification

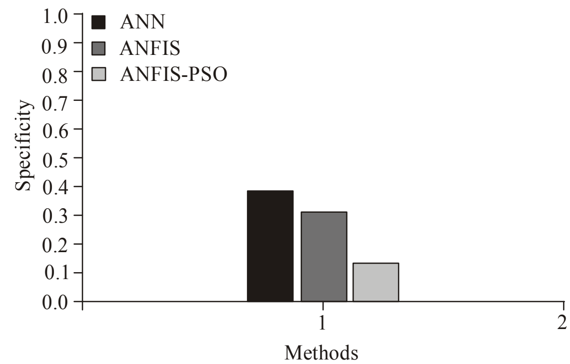

Fig. 4: Specificity of dyslexia detection with classification

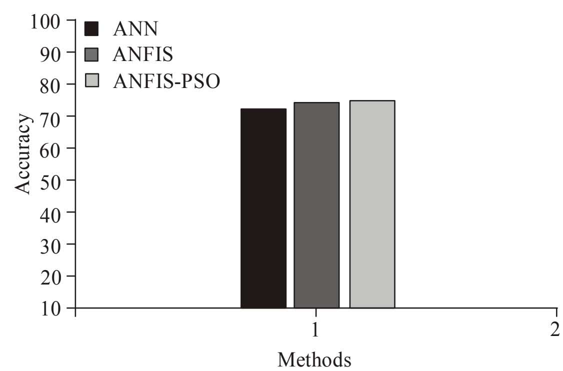

Fig. 5: Dyslexia detection with classification accuracy

Figure 3 shows the sensitivity results of detection methods such as ANN, ANFIS and ANFIS-PSO 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 shows the specificity results of detection methods such as ANN, ANFIS and ANFIS-PSO methods, it shows that proposed ANFIS-PSO have lesser negative rate results than the existing ANFIS and

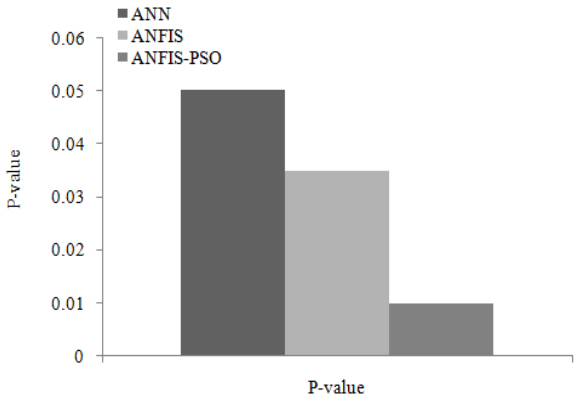

Fig. 6: Dyslexia detection with p-value

ANN, because of word length examination of eye movement signals.

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

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-PSO is nearly 0.01, so the detection rate of proposed ANFIS-PSO is high when compared to existing ANFIS and ANN Methods.

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 a Multivariate Auto Regressive model (MAR) to extract features of dyslexia for each student data and then perform dyslexia detection framework. ANFIS-PSO has been modeled for dyslexia detection with a reduced number of rules in the membership function. Experimentation confirmed that the proposed ANFIS-PSO model has good detection results than ANFIS and ANN model in terms of sensitivity, specificity, accurateness and P-value. Hence, proposed improved ANFIS-POS methods optimize the number of generated rules to enhance dyslexia detection rate.

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