P-1

CASE STUDY ON TRI-PHASE NATURE INSPIRED MODELS FOR UNCERTAINTY HANDLING IN EARLY PREDICTION OF DYSLEXIA AMONG CHILDREN

Dr. J LOVELINE ZEEMA*, Dr. VIGNESH RAMAMOORTHY H #

**Assistant Professor, Department of Computer Science, Sri Krishna Adithya College of Arts & Science, Coimbatore, Tamil Nadu, India*

 # Assistant Professor, Department of Information Technology, Sri Krishna Arts and Science College, Coimbatore, Tamil Nadu, India

j.lovelinezeema@gmail.com*, hvigneshram@gmail.com #

ABSTRACT

The learning disability in children's due to neurological related processing issues which affect writing and reading comprehension is known as Dyslexia. Discovering such learning disabilities at the earliest may improve the children's academic knowledge. This paper focuses on conducting a case study about learning disabilities among school children to detect the presence of dyslexia in the early stages. This study collects students details from both parents and teachers of four different centers within Tamil Nadu state. The prediction is done using three different models they are Quantum Particle Swarm Optimization Enabled Intuitionistic Fuzzy Artificial Neural Network, Neutrosophic Clustering with Artificial Bacterial Foraging and Paraconsistent Neutrosophic With Whale Optimization-based rule pruning. These three models, performance is analyzed based on the collected information to detect the presence of dyslexia at their earlier stages.

Keywords: Dyslexia, Foraging, Neutrosophic, Paraconsistent, and Quantum.

1. INTRODUCTION

There are no reliable statistics on the number of dyslexic children in India. However, it is roughly estimated that minimum 10% of the school going children could be affected by the learning disability[1]. Dyslexia is often undetected owing to its subtle neurological condition which escapes easily from identification. As per World Federation of Neurology, dyslexic is referred as a disorder manifested by learning difficulties, difficulty in intelligence and socio-cultural opportunity. It reports that dyslexia are prevalent among boys than girls with the rough estimated ration of 4:1[2]. This is a case study, and only male and female students from elementary schools were chosen as the sample of students from four different institutions that provide specific teaching methodologies for students with learning disabilities. In this study, two distinct types of questionnaires were created to obtain feedback from both parents and teachers about the children.

The parent questionnaire has 20 questions about their child's behaviour, issues during birth, reading and listening difficulties, day-to-day activities, and family history of learning difficulties. The questionnaire for teachers has 12 questions about the student's phonological awareness skills, issues learning letters and sounds, decoding and word recognition challenges, reading fluency in a context or from a material, spelling difficulties, and reading comprehension , and so on. The three different prediction model's results reveal that the dyslexic child is facing issues in almost every area of study at the primary level, especially in reading. The difficulties faced by the dyslexic child can be alleviated, to some extent, with the help of a cooperative attitude and positive approach by parents and teachers. Some psychiatrist sessions and speech therapy will help the dyslexic child to overcome the learning abilities.

2. RELATED WORK

This section discusses some of the current research in the field of dyslexia detection. Jothi and Bhargavi et al[3] conducted a thorough investigation of many facets of Alzheimer detection studies. They examined numerous dyslexia detection methods that used machine learning methods, design validation, image processing and many tools to assist the prediction of non-dyslexic and dyslexic children. Shahriar[4] in their findings, reported about the contribution of machine learning models using EEG, MRI, eye tracking and facial image acquisition for early detection of dyslexia. They have also observed the negative emotions of dyslexic children that occurred as a consequence of dyslexia such as anger, frustration and low self-esteem. Vani and Meenatchi[5] investigated the effects of neurological disorders on reading, writing, and comprehension. Eye movement used in their study to detect dyslexia using machine learning.

In their work, VaThomais et al[6] developed a DysLex machine learning model for detecting dyslexia using Support Vector Machine. The children's eye movement is tracked while they are silently reading. As a result, students' reading disorders are identified. Rezvani et al[7] created a dyslexia detection model that uses a neurobiological classifier to distinguish between dyslexic and non-dyslexic children. The weighted connection of the matrix is computed using EEG data, and the classification models employed in this study are k-NN and SVM. Opeyemi et al[8] conducted a comprehensive analysis of several machine learning algorithms, emphasizing the relevance of deep learning in achieving acceptable accuracy levels. Biomarkers used as the main factor in the deep understanding of dyslexia in children.

3. METHODOLOGY OF TRI-PHASE NATURE INSPIRED MODELS FOR UNCERTAINTY HANDLING IN EARLY PREDICTION OF DYSLEXIA AMONG CHILDREN

This research work was carried out in three phases. All the phases focus on detecting dyslexia in children at an early stage. This procedure uses data from four distinct institutes in Tamilnadu, India. Rashmika Centre for

Learning & Counselling Coimbatore, Sankalp The Open School Chennai, School Readiness Programme (SRP) Centre Udumalpet and Seagull Training & Study Centre Trichy in the 71 students between the age group of 6 and 10.

The first phase addresses the issue of vagueness and imprecision in the dataset by introducing intuitionistic fuzzy fused cognitive learning, which outperforms fuzzy-based models when compared[9].

The second phase works as an optimized unsupervised model. In this phase, the instances under investigation are unlabeled. So this the instances were clustered using neutrosophic c-means clustering and the centroid for forming clusters were selected by the bacterial foraging approach. In addition, this phase concentrates on enhancing the dyslexia dataset by imputing the missing values using boosted decision tree[10].

The third phase provides a classification model based on the neutrosophic inference system that enriches its activity by introducing paraconsistent logic to establish favourable and unfavourable rules, which are then trimmed using the whale optimization approach[11]. As a result, all of these process work together to create an intelligent model for detecting dyslexia in children at an early stage.

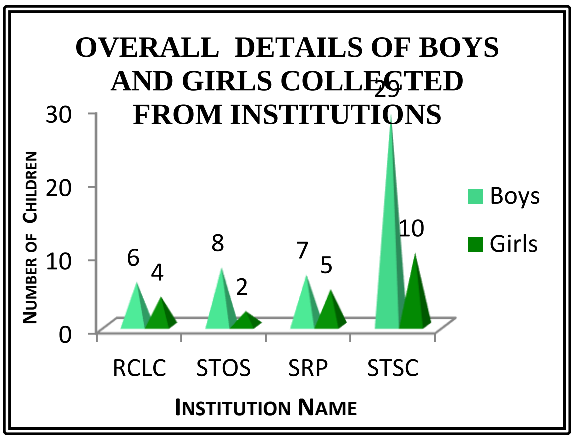
4. RESULTS AND DISCUSSIONS

This section discusses about the performance analysis of four different models using Quantum Particle Swarm Optimization based Intuitionistic fuzzy artificial neural network (QPSO-IFANN)[9], Optimized Neutrosophic C Means clustering using behavioral inspiration of Artificial Bacterial Foraging (ONCMC-ABF)[10] and Whale Behavior based Rule Optimization on Paraconsistent Neutrsophical Classification (WBRO-PNC)[11] for dyslexia prediction. The detailed explanation is as shown in the following subsections. This case study gathers data for 71 children under the age group of 6 to 10 from 4 separate institutions. From the Rashmika Center for Learning & Counselling Coimbatore 6 Boys and 4 Girls students, Sankalp the Open School 8 Boys and 2 Girls students, 7 Boys and 5 Girls students from the Madathukulam Center for School Readiness Program (SRP) and 29 Boys and 10 Girls from the Seagull Training & Study Center Trichy are collected. Totally there are 50 Boys and 21 girls. The ratio of boys and girls is 5:2.It is observed that the proportion of boys is higher than that of girls according to information collected from four different institutions. Table1 and Graph1 shows the information collected from the four institutions.

This case study collects the dataset of 71 students under the age group of 6 to 10 from 4 different institutes. The table 1 and the figure 1 shows that from Rashmika Centre for Learning& Counselling, Coimbatore, 6 male and 4 female students' information are gathered from both parents and teachers. From Sankalp The Open School, Chennai consist of 4 male students and 2 female students' information. From School Readiness Programme (SRP) Centre, 7 male students and 5 female students' details are collected. From Seagull Training & Study Centre, 29 male students and 10 female students' information are collected. According to the information collected from four different institutes it is observed that proportion of male students is higher than the female students were 50 boys and 21 girl students which is approximately 5:2 ratio. In this case study, the sample was taken from the primary school children of four different institutions. Such organizations give special teaching methodologies to those students with learning disabilities. Two different formats of questionnaires were prepared to collect feedback about the students from both parents and their teachers. The screening questionnaire[1] for the child's parent is based on a 1998 research published in the British Journal of Occupational Therapy which says scoring 7 or more "YES" suggests that the children need further assistance with their learning impairment. The teacher Observation Questionnaire[2] was adapted from the Dyslexia Teacher Observation Questionnaire, Texas Scottish Rite Children's Hospital Texas.

Table 1: Overall details of Boys and Girls Collected from 4 Institutions

Name of the Institutions	Boys	Girls
Rashmika Center for Learning & Counselling, Coimbatore (RCLC)	6	4
Sankalp The Open School, Chennai (STOS)	8	2
Center for School Readiness Programme (SRP), Madathukulam, Udumalpet	7	5
Seagull Training & Study Centre, Trichy (STSC)	29	10
Total	**50**	**21**



Graph 1: Overall details of Boys and Girls collected from 4 Institutions

Table 2: Personal information of children collected from parents

S.No	Attributes	Description
1	MPP	Medical Problems during Pregnancy
2	BBAT	Born Before / After Term
3	CAB	Complications at Birth
4	ED	Extremely Demanding in first 6 months of Life
5	MOC	Miss out on Crawling
6	SLW	Slow Learning to Walk(normally 12 to 16 months)

7	SD	Speech Difficulties
8	ENTP	Ear/Nose/Throat Problem
9	LDTS	Difficulty in Learning to Dress / Tie Shoelace
10	BW	Bedwetting after 5 years of age
11	RCF	Difficulty in Reading Clock Face
12	LRB	Difficulty in Learning to Ride Bike
13	CB	Difficulty in Catching Ball
14	DSS	Difficulty to Sit Still
15	ORS	Over React for sudden noise
16	RD	Reading Difficulty
17	WD	Writing Difficulty
18	CD	Copying Difficulty
19	WOD	Work Organizing Difficulty
20	HRDF	History of Reading Difficulties in Family

The parents' questionnaire consists of 20 questions related to their child's behaviour, difficulties in their time of birth, difficulties in reading and listening, day-to-day activities and family history of learning difficulties. The teachers' questionnaire consists of 12 questions related to the phonological awareness skills of the students', difficulties in learning letters and learning sounds, difficulties in decoding and recognition of words, fluency in reading a context or material, difficulty in spelling and reading understanding. The table 2 lists the 20 attributes collected from parents about their children. The data obtained in reading disabilities are linked to their birth information cognitive behavior, communication and reading skills and genetic issues.

Statistics on personal information of children

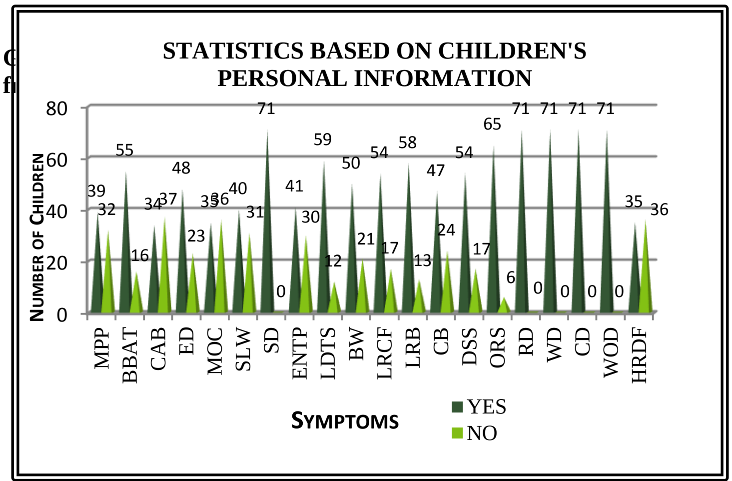
The table3 and graph2 demonstrate the presence or absence of 20 different metrics used by 71 children to determine the presence or absence of dyslexia. From table3 it is clearly shown that most of the children are affected by the following symptoms. The details are listed below. Graph3 illustrates these learning disability symptoms that affect children to understand the presence or absence of dyslexia based on information obtained from parents for this case study. These symptoms are associated with skills in phonology, motor ability, and concentration.

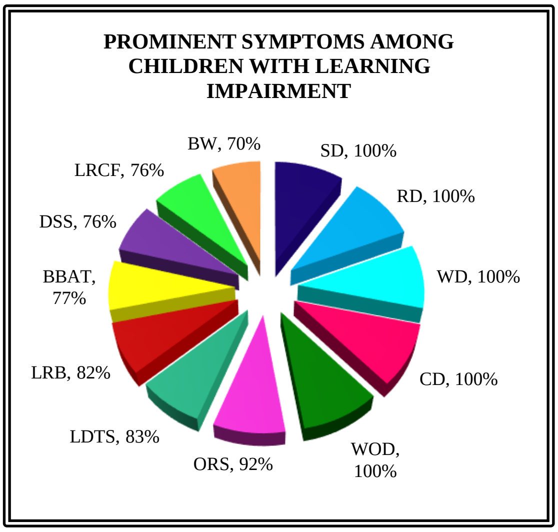
-

Table 3: Statistics based on personal information of children collected from Parents collected from parents

S.No	Attribute	Description	YES	NO
1	MPP	Medical Problems during Pregnancy	39	32
2	BBAT	Born Before / After Term	55	16

3	CAB	Complications at Birth	34	37
4	ED	Extremely Demanding in first 6 months of Life	48	23
5	MOC	Miss out on Crawling	35	36
6	SLW	Slow Learning to Walk (normally 12 to 16 months)	40	31
7	SD	Speech Difficulties	71	0
8	ENTP	Ear/Nose/Throat Problem	41	30
9	LDTS	Difficulty in Learning to Dress / Tie Shoelace	59	12
10	BW	Bedwetting after 5 years of age	50	21
11	LRCF	Difficulty in Reading Clock Face	54	17
12	LRB	Difficulty in Learning to Ride Bike	58	13
13	CB	Difficulty in Catching Ball	47	24
14	DSS	Difficulty to Sit Still	54	17
15	ORS	Over React for sudden noise	65	6
16	RD	Reading Difficulty	71	0
17	WD	Writing Difficulty	71	0
18	CD	Copying Difficulty	71	0
19	WOD	Work Organizing Difficulty	71	0
20	HRDF	History of Reading Difficulties in Family	35	36





Comparative study on affected boys and girls

According to the parent’s information in table3 about their wards’ response to the learning impairment symptoms, the table4 is constructed. The table4 and graph4 describe the number of boys and the number of girls with “YES” response to the symptoms. From the analysis it is observed that

1. The following symptoms are found to be *more common in Boys than Girls*

Medical problems during pregnancy (MPP) [56%-28 Boys | 52%-11 Girls]. Born before/after term (BBAT)[80%-40 Boys | 71%-15 Girls] .Complications at birth (CAB)[50%-25 Boys | 43%-9 Girls]. Extremely demanding in first 6 months of life(ED)[70%-35 Boys | 62%-13 Girls]. Slow learning to walk (SLW)[60%-30 Boys | 48%-10 Girls]. ENT problem (ENTP)[62%-31 Boys | 48%-10 Girls]. Learning to read clock face (LRCF)[78%-39 Boys | 71%-15 Girls]. Difficulty in catching ball (CB)[68%-34 Boys | 62%-13 Girls]. Difficulty in sit still (DSS)[80%-40 Boys | 67%-14 Girls]. Over react to sudden noise (ORS) [94%-47 Boys|86%-18 Girls].

2.* The following symptoms are found to *be more common in Girls than Boys

Difficulty in learning to dress / tie shoelace (LDTS)[80%-40 Boys | 90%-19 Girls] , Bedwetting after 5 years of age (BW)[66%-33 Boys | 81%-17 Girls], Difficulty in learning to ride bike (LRB)[80%-40 Boys | 86%-18 Girls]

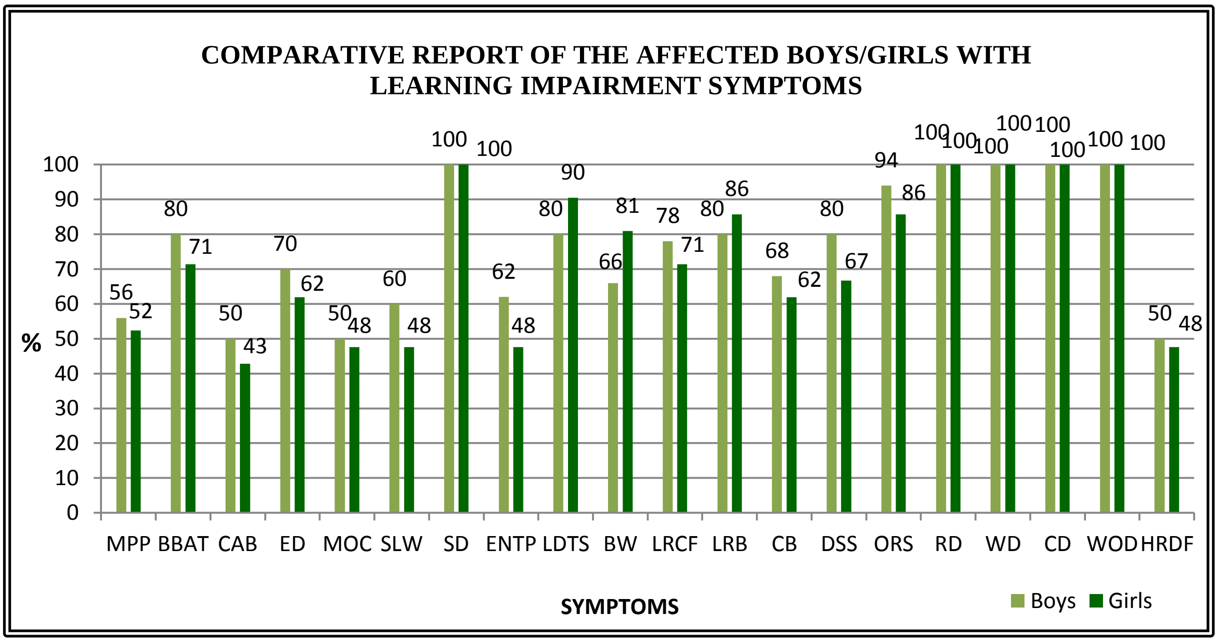
3. Girls and boys are approximately *equally affected* with the following symptoms

Miss out on crawling (MoC)[50%-25 Boys | 48%-10 Girls], History of reading difficulty in family (HRDF)[50%-25 Boys | 48%-10 Girls]

4. **Both boys and girls *experience 100%*in the below mentioned symptoms**

Speech difficulty (SD) , Reading Difficulty (RD), Writing difficulty (WD), Copying difficulty (CD), Work organizing difficulty (WOD)

Symptoms of dyslexia are more widespread in boys than girls. The condition may be developed or hereditary or acquired. Cognitive and neurological disabilities are responsible for developmental dyslexia. External factors such as birth complications, early childhood illness and decreased care and balance & coordination problems are responsible for acquired dyslexia. Dyslexia usually involves difficulty in reading, writing, spelling, arithmetic, memory, direction and, time.



Graph 4: Comparative report of the affected boys/girls with symptoms of

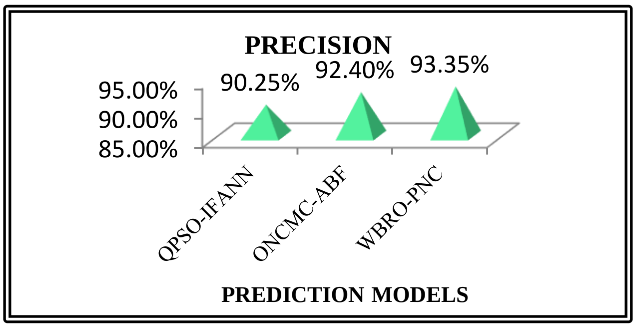
dyslexia based on the information collected from parents

Performance Analysis of 3 Proposed Prediction Models

This section explains the performance analysis of three proposed dyslexia prediction models.

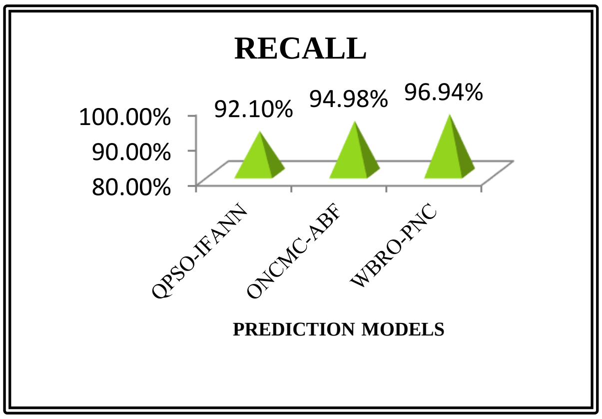
S.NO	MODEL	QPSO-IFANN	ONCMC-ABF	WBRO-PNC
1	Precision	90.25%	92.40%	93.35%
2	Recall	92.10%	94.98%	96.94%
3	F-Measure	91.17%	93.67%	95.11%

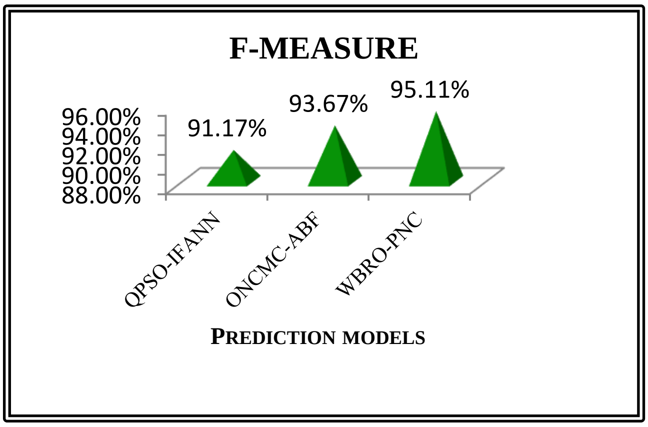
Table 4: Performances analysis of 3 different prediction models to detect dyslexia among children



Graph 5: Performance Analysis based on precision of 3 proposed models

The table 8 shows the performance of three different proposed models namely Quantum Particle Swarm Optimization based Intuitionistic fuzzy artificial neural network (QPSO-IFANN), Optimized Neutrosophic C Means clustering using behavioural inspiration of Artificial Bacterial Foraging (ONCMC-ABF) and Whale Behavior based Rule Optimization on Paraconsistent Neutrosophic Classification (WBRO-PNC) based on precision, recall and F- Measure. The performance of ONCMC-ABF and WBRO-PNC produces better results because of their ability to handle impreciseness, vagueness, inconsistency and uncertainty with the knowledge of Neutrosphical problem solving. Graph7, graph8 and graph9 show the precision, recall and f-measure values of three separate QPSO-IFANN, ONCMC-ABF, and WBRO-PNC models. It is found that QPSO-IFANN's performance produces minimal accuracy relative to two other models because it cannot handle the situation when the prediction of dyslexia is unpredictable, unacceptable and inadequate. Comparatively ONCMC-ABF performs less than WBRO-PNC due to the presence of inconsistency in clustering the other cognitive impairment symptoms The WBRO-PNC has neutrosophic & paraconsistent ability. It prunes the rules with whale behaviour optimization also. There by slightly increasing the rate of detecting accuracy.





Graph 6: Performances analysis based on Recall of 3 proposed models

Graph 7: Performances analysis based on F-Measure of 3 proposed models

5. CONCLUSION

This paper conducted a case study. It is observed that the dyslexia child faces issues in academics with a large margin while comparing to non-dyslectic children or students. Dyslexic child needs five times more effort than the non-dyslexic student with the assistance of teachers with special materials and techniques. The early prediction of dyslexia may help the dyslexic student to overcome this problem with proper guidance and support. This case study investigated the detection of dyslexia among school children's in Tamil Nadu by collecting the details from four different institutions. As the nature of dataset is impreciseness, and ambiguous when multiple symptom of cognitive impairments is detected by neutrosophic models both in supervised and non-supervised machine learning paradigm produces better result compared to the standard clustering or classification models. The performance results demonstrate the ability of the three newly developed models of dyslexia prediction substantially help parents to identify signs of dyslexia in their children, and also recommends that they should take their children with such symptoms to the experts in the field for clinical assistance.

REFERENCES

1. Asha Krishnakumar, India's National Magazine from the publishers of THE HINDU, Volume 16 - Issue 8, Apr. 10 - 23, 1999
2. https://wfneurology.org/world-congress-of-neurology-2019
3. Jothi Prabha A., Bhargavi R. (2019) Prediction of Dyslexia Using Machine Learning—A Research Travelogue. In: Nath V., Mandal J. (eds) Proceedings of the Third International Conference on Microelectronics, Computing and Communication Systems. Lecture Notes in Electrical Engineering, vol 556. Springer, Singapore
4. Shahriar Kaisar, Developmental dyslexia detection using machine learning techniques : A survey , ICT ExpressVolume 6, Issue 3, September 2020, Pages 181-184
5. Vani Chakraborty, Meentachi Sundaram, Machine learning algorithms for prediction of dyslexia using eye movement Third National Conference on Computational Intelligence (NCCI 2019) Journal of Physics: Conference Series1427 (2020
6. ThomaisAsvestopoulou, Victoria Manousaki, AntonisPsistakis, IoannisSmyrnakis, Vassilios Andreadakis, Ioannis M. Aslanides, Maria Papadopouli, DysLexML: Screening Tool for Dyslexia UsingMachine Learning, CoRR, abs/1903.06274, 2019
7. Rezvani, Z, Zare, M. Žarić, G., Bonte, M., Tijms, J, Van der Molen, M.W, Fraga González G, Machine learning Classification of Dyslexic Children based 1on EEG Local Network Features, bioRxiv , Mar 6, 2019

8. Opeyemi Lateef Usman, Ravie ChandrenMuniyandi, Khairuddin Omar, Mazlyfarina Mohamad, Advance Machine Learning Methods for Dyslexia Biomarker Detection: A Review of Implementation Details and Challenges, Vol 9, pp 36879- 36897, 2021
9. Ana M. Palacios, Luciano Sanchez, Ines Couso, Diagnosis of dyslexia with low quality data with genetic fuzzy systems, International Journal of Approximate Reasoning 51 (2010) 993– 1009
10. F.Bin, Z. Wang, J. Sun, Niche quantum-behaved particle swarm optimization with chaotic mutation operator, Comput. Appl. Software 26 (1) (2009)50–52.
11. V. Georgopulos, A fuzzy cognitive map to differential diagnosis of specific language impairment, Artificial Intelligence in Medicine 29 (2003) 261–278.
12. Hoeft, F., McCandliss, B.D., Black, J.M., Gantman, A., Zakerani, N., Hulme, C., Lyytinen, H. Whitfield-Gabrieli, S., Glover, G.H., Reiss, A.L., Gabrieli, J.D.E., 2011. Neural systems predicting long-term outcome in dyslexia. Proc. Natl. Acad. Sci. U. S. A. 108, 361–366.
13. Krassimir T. Atanassov, Fuzzy Sets and Systems, North-Holland, Volume 20 (1986), pages 87-96, ISSN 0165-0114
14. Luz Rello & Miguel, Ballesteros Detecting Readers with Dyslexia Using Machine Learning with Eye Tracking Measures, W4A '15 Proceedings of the 12th Web for All ConferenceArticle No. 16, ACM digital library, 2015
15. Vipul Sharma S.S. PattnaikTanuj Garg, A Review of Bacterial Foraging Optimization and Its Applications, National Conference on Future Aspects of Artificial intelligence in Industrial Automation, Proceedings published by International Journal of Computer Applications, NCFAAIIA, pp 1-12, 2012
16. Passino KM, "Biomimicry of Bacterial Foraging", IEEE Control System Magzine, Vol. 22, 2002, pp. 52-67
17. Francisco Gallego Lupianez, Another Note on Paraconsistent Neutrosophic Sets, Symmetry, , pp 1-4, 2017
18. Aggarwal, Swati, Ranjit Biswas, and A. Q. Ansari. "Neutrosophic modeling and control". Computer and Communication Technology (ICCCT), 2010 International Conference on. IEEE, (2010(:718-723.
19. M. David, Kannan Balakrishnan: "Machine Learning Approach for Prediction of Learning Disabilities in School Age Children", Int. J. of Computer Applications, ISSN-0975-8887, 9(10), Nov. 2010, pp 7-14
20. Kohli, M., Prasad, T.V, "Identifying Dyslexic Students by Using Artificial Neural Networks", Proceedings of the World Congress on Engineering, London, U.K, vol. 1(2010).
21. Vignesh Ramamoorthy H and et. al., Prediction based Cognitive Topology Control in MANET, International Journal of Emerging Trends in Engineering and Development (IJETED), 7(2), November 2012, pp.301-308, ISSN: 2249-6149, https://rspublication.com/ijeted/nov12/33.pdf.