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NEUTROSOPHICAL MULTIPLE REGRESSION ENRICHED CHAOS DEEP BELIEF NETWORK FOR DYSLEXIA PREDICTION

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ABSTRACT

Children with dyslexic can use the appropriate resources and specialised software to enhance their skills when problem is diagnosed early. Deep learning and machine learning techniques analyze dyslexia-related datasets from healthcare and educational sources, yet conventional models struggle with the inherent vagueness of dyslexia data, often represented in intervals. In this paper, generalized model of fuzzy and intuitionistic fuzzy known as neutrosophic multiple regression model is used for determining the degree of dependency among the independent and dependent variables of dyslexia dataset. In neutrosophic concept, each attribute is defined with the truthiness, falsity and indeterminacy membership, and are independent to each other. The correlation among the attributes are determined using neutrosophic least square error method. In existing deep neural networks using gradient based optimization ends up with the local minimum and results in early convergence. The proposed work deep belief network hyperparameters are scrutinized with chaos synchronization for classification. This work used two datasets, Dyslexic 12-4 dataset from Keel software repository and real time dataset collected from dyslexia schools of various districts are applied for performance comparison, the results proved that the proposed neutrosophic regression model produced highest rate of detection rate in dyslexia prediction compared with existing models. This study leverages advancements in AI to address the complex task of early dyslexia diagnosis. By employing neutrosophic multiple regression models alongside chaos deep belief networks, it achieves high prediction accuracy and handles data uncertainties effectively. This work significantly contributes to improve educational and healthcare outcomes for dyslexic children, underscoring the role of IT in learning disability interventions.

Keywords: *Dyslexia, Uncertainty, Chaos Theory, Neutrosophic Multiple Regression, Deep Belief Network*

1. INTRODUCTION

IT research has transformed diagnostics in healthcare and education, especially in addressing learning disabilities through predictive modeling. With innovative models like neutrosophic multiple regression, this study effectively handles data vagueness typical in dyslexia diagnosis, offering a significant IT contribution. The research utilizes a novel approach to manage uncertainty and improve dyslexia prediction, which is critical for early intervention in educational settings. A statistical technique involved in determining the strength and relationship between a dependent variable with one or two independent variables, finding significant dependent variables, how these variables are influence to one another, and which variables can be ignored is processed by regression analysis. Different assumptions, such as linearity, no multicollinearity, normality and error independence, must be met when using multiple linear regression to assess the influence of a single dependent factor with many independent features. But most of the real time applications comprised of inconsistent, incomplete, vague and uncertain information to be processed especially while dealing with disease prediction. The concept of uncertainty theory plays a vital role for handling the uncertain information using linguistic terms instead of crisp values. Uncertainty regression methods greatly helps to tackle unclear, hesitancy, vague details of disease diagnosis method. Based on

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this Zadeh [1] and Attanasova [2] developed Fuzzy and Intuitionistic fuzzy theories respectively, for representing the vague information with the ability of few uncertainty conditions.

This challenging issue is measured as the primary issue which affects the detection rate of disease diagnosis at its early stage. By considering it, Smarandache [3] introduced a generalization of many multi-valued uncertainty theories known as neutrosophic concept. The neutrosophic tools and functionalities is applied in many real-world applications even with incomplete information. A powerful method for determining the connections among the variables that are independent and dependent as well as prediction of the uncertainty of observational data is the neutrosophic regression approach which is mentioned in literatures [4].

The neurological condition known as dyslexia causes barriers and challenges in learning, particularly in reading. People with dyslexia typically struggle with poor reading, writing, spelling, and language skills. These issues, though, have nothing to do with their IQ. Children who are dyslexic can use the right resources and specialised software to enhance their skills if this problem is diagnosed early [5].

In order to identify dyslexia, artificial intelligence and machine learning methods were used to a variety of dyslexia-related datasets that have been collected from educational and healthcare organisations. It is imperative that learning disorders like dyslexia are identified early on [6].

The ability of a pupil to write and read can be significantly impacted by dyslexia. Students with dyslexia may endure avoidable and persistent educational, social, and financial challenges if they do not acquire these crucial language abilities. Early detection of dyslexic among children is crucial because it increases the possibility that the child may benefit from efficient intervention programmes and improve his or her skills [7].

The conventional certainty-based techniques investigated by the researchers find difficult to handle the vague dataset, with intervals as their values to predict the dyslexia. Hence, in this paper, to predict the dyslexia at its early stage the optimizing the training phase is carried by constructing a novel interval neutrosophic multiple regression predictor that handles vague nature of dyslexia data more prominently compare to other uncertainty logics.

In section 2, related work about the dyslexia prediction is discussed, followed by section 3 which explains the proposed methodology, its working principle and its step by step procedure in detail. In section 4, result and discussion about the performance outcome of the proposed interval neutrosophic multiple regression is explained. Finally, the work concludes the overall findings of the proposed work Interval Valued Neutrosophic multiple regression for dyslexia prediction at its early stage.

2. RELATED WORK

This study stands out by using a chaos deep belief network combined with neutrosophic regression for dyslexia prediction, which differs from other recent approaches like random forest and decision tree models. Compared to works such as those by Gilles Richard et al. [9] using traditional ML for dyslexia screening, the present model better manages uncertainty, offering improved performance in early diagnosis.

Alqahtani et al [8] conducted a deep investigation of recognising dyslexia at their early stages. The phonological dyslexia are considered as the key element for discovering the severity of dyslexia. They used support vector machine and grid-based CV for predicting normal kid and dyslexic kid.

Gilles Richard et al [9] developed an artificial intelligence-based dysgraphia or dyslexic child by using different forms of dataset. To discriminate the normal children from the dyslexic or dysgraphia children the audio recording, pictures of handwritten text are used. Machine learning algorithms are used for prediction and to conduct preliminary screening of reading disability, the authors stated that the recommended datasets are very effective.

Mahalakshmi et al [10] constructed a screening technique for early diagnosis of dyslexia presence among individuals. The authors used brain images, to analyse the high severity of dyslexia by applying the classification models. Unlike the dyslexia prediction using the psychology test, image processing or machine learning, this work examines the normal and dyslexic brain using the random forest and decision tree algorithms.

Andrea et al [11] developed a novel methodology to discover dyslexic individuals among university students. The supervised learning algorithms or classifiers are used for categorizing the normal and dyslexia students. Using the self-assessment questionnaire, the severity of dyslexia among the college students is determined.

Dębska et al [12] in their work conducted a detailed survey on the cognitive skills of children to determine the early dyslexia based on their reading skill. Four classification algorithms are used in this work to determine the cognitive skills of the students. This study helps to remediate the reading difficulties.

Appadurai et al [13] developed a novel velocity threshold algorithm for predicting the dyslexia presence using eye movement of child. They undergo investigation on 185 candidates and the hybrid model of support vector machine, Xtreme gradient boosting in particle swarm optimization is used for discovering the presence of dyslexia.

Gull et al [14] conducted a detailed survey on dyslexia prediction models using various machine learning approaches, image processing models, game-based approaches. The tools and the assessment methods conducted to determine the dyslexic person is also discussed in this work. the current problems, research gaps and the future challenges in accurate prediction or early diagnosis of dyslexia is conversed.

Several potential threats to validity exist in this study, including data limitations and biases that may impact generalizability. The selection of critique criteria, such as accuracy, sensitivity, and specificity, were chosen to directly address the complexities in dyslexia diagnosis, aligning with the need for precise and reliable detection methodologies.

3. CONTRIBUTION OF THIS WORK

After performing analysis on the existing algorithms, the information extraction from the features (i.e) independent variables and depend variables in dyslexia is still challenging. When the dataset comprised of uncertainty information, using the conventional algorithms, not beware of the importance of indeterminacy among the selection of attributes affects the detection rate of dyslexia prediction at its early stage. Hence, in this work a novel neutrosophic multiple regression model is constructed to understand the dependency among the dependent and independent variables are examined in detail. The deep belief network along with neutrosophic multiple regression information, the prediction of dyslexia in uncertainty conditions are discriminated effectively to improve the detection rate of dyslexia among children.

4. NEUTROSOPHIC SETS AND ELEMENTS

The neutrosophic set is defined as a set which explains about the indeterminacy and uncertainty in any facts or information. In neutrosophic set comprised of the degree of indeterminacy is introduced to understand about the knowledge of neutral thought and non-standard analysis. The neutrosophic sets are represented as

$$\wp = \frac{< \mathcal{T}_1, \mathcal{I}_1, \mathcal{F}_1 >}{\mathrm{Z}_1} + \frac{< \mathcal{T}_2, \mathcal{I}_2, \mathcal{F}_2 >}{\mathrm{Z}_2} + \cdots + \frac{< \mathcal{T}_n, \mathcal{I}_n, \mathcal{F}_n >}{\mathrm{Z}_n} \quad (1)$$

Where $\mathcal{T}_n, \mathcal{I}_n, \mathcal{F}_n$ signifies the three membership degree of truthiness, indeterminacy and falsity of Z_i, i= 1, 2,..,n and the union operation is represented using '+' symbol. The neutrosophic elements $\mathcal{T}_n, \mathcal{I}_n, \mathcal{F}_n$ are independent to each other. The neutrosophic model is signified based on the generalization of classical and characteristic features of the function of a set. The trapezoidal representation of neutrosophic elements is shown in the figure 1.

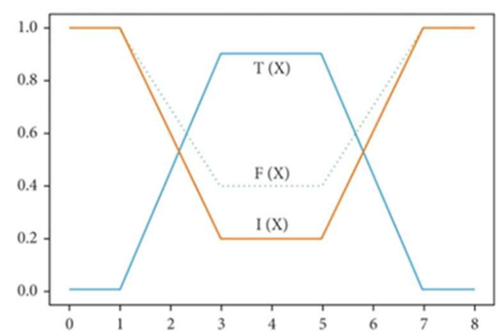

Figure 1. Neutrosophic Values representation in Trapezoidal form

4.1 Neutrosophic Multiple Regression Model

The general representation of classical multiple regression is

$$\mathrm{Y} = \rho_0 + \rho_1 \mathrm{Z}_1 + \rho_2 \mathrm{Z}_2 + \ldots + \rho_n \mathrm{Z}_n + \varepsilon \quad (2)$$

Where Z and Y denotes independent and dependent variables. The co-efficient or slopes are represented by $\rho_1, \rho_1, \rho_2, \ldots, \rho_n$ which determines the relationship of each dependent and independent variables and random error is denoted by ε. The coefficients are computing using least square error to minimize the sum of squared difference among actual and predicted value of the dependent variable.

4.2 Neutrosophic Multiple Linear Regression

Three different cases are considered to denote the neutrosophic multiple linear regression depending on the nature of dependent and independent variables.

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Case I:

$$\breve{N}_i = \rho_0 + \rho_i \breve{Z}_i + \epsilon_i \quad (3)$$

Here $\breve{Z}_i$ denotes the neutrosophic parameter, ρ_0 is the intercept and ρ_1 is the slope which holds crisp parameters of linear regression.

Case II:

$$\breve{N}_i = \breve{\rho}_0 + \breve{\rho}_1 Z_i + \epsilon_i \quad (4)$$

Here Z_i denotes crisp parameter, $\breve{\rho}_0$ is the intercept and $\breve{\rho}_1$ is the slope are neutrosophic parameters of linear regression.

Case III:

$$\breve{N}_i = \breve{\rho}_0 + \breve{\rho}_1 \breve{Z}_i + \epsilon_i \quad (5)$$

Here Z_i, $\breve{\rho}_0$ and $\breve{\rho}_1$ the predictors and other parameters are neutrosophic.

In neutrosophic multiple regression method is formulated as

$$\breve{N}_i = \breve{\rho}_0 + \breve{\rho}_1 \breve{Z}_{k1} + +\breve{\rho}_1 \breve{Z}_{k2} + \cdots + +\breve{\rho}_1 \breve{Z}_{kq} + \epsilon_i \quad (6)$$

The formula to determine the intercept value $\breve{\rho}_0$ for two independent variables in dyslexia dataset can be computed as follows

$$\breve{\rho}_0 = y - \breve{\rho}_1 \breve{Z}_1 - -\breve{\rho}_2 \breve{Z}_2 \quad (7)$$

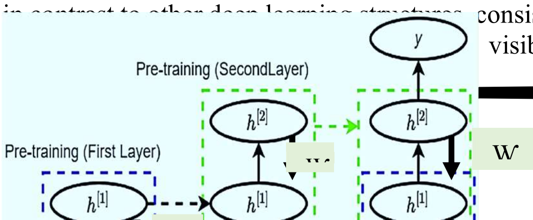
$$\rho_1 = \frac{\sum z_2^2 \sum Z_1 y - \sum Z_1 Z_2 \sum Z_2 y}{\sum z_1^2 \sum z_2^2 - (\sum Z_1 Z_2)^2} \quad (8)$$

$$\rho_2 = \frac{\sum z_1^2 \sum Z_2 y - \sum Z_1 Z_2 \sum Z_1 y}{\sum z_1^2 \sum z_2^2 - (\sum Z_1 Z_2)^2} \quad (9)$$

With the obtained information about the correlation of the dependent and independent variables, the acquired details is passed as input to the deep belief network. The prediction of the dyslexia presence is applied on the two different datasets and their performance are discussed in the result section.

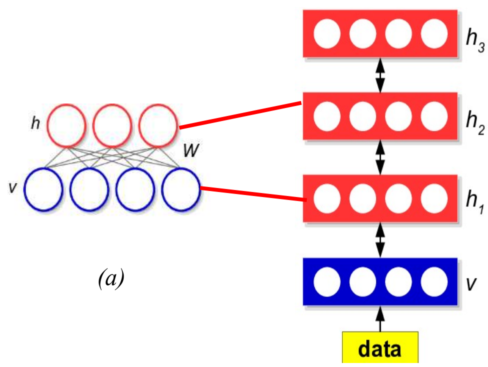
5. PREDICTION OF DYSLEXIA USING DEEP BELIEF NETWORK

Deep Belief Network (DBN) is a kind of deep learning structure that is built using a series of Restricted Boltzmann machines. The DBN structure, in contrast to other deep learning structures, consists visible



layer and the hidden layer, as shown in figure 2a, are the two layers that comprise up each RBM.

The input for the dyslexia dataset is gathered, provided to the visible unit of the RBM, and then transmitted to the hidden layer nodes, once the activation function has been applied to the input values. They operate as a self-directed strategy based on the contrasting diverse method. This process is continued till it gets to the last RBM in the stack having recognising the input patterns for the chosen variables as depicted in figure 2b). When the whole network has wrapped up its learning phase, it uses a supervised framework to identify children with dyslexia and those who do not.



(a) (b)

Figure 2 (a). RBM Visible and hidden variable (b) DBN formation by staked

The SoftMax layer functions as the supervised approach, classifying the input data as having normal or varying degrees of dyslexia severity. With the exception of the first and last layers, the middle layers of a DBN fulfil the dual roles of input layer for one RBM and hidden layer for another. Let's presume that x is the input dyslexia dataset for the two-layered RBM-based DBN shown in the figure 3. The initial RBM in the chain accepts it utilising the visible unit and learns details about the features employing the equation

$$\rho(v, W^{(1)}) = \sum_{h^{(1)}} \rho\left(X \middle| h^{(1)}; W^{(1)}\right) \rho\left(h^{(1)}; W^{(1)}\right) \quad (10)$$

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Figure 3 : Two layered RBM functionality

The 2nd RBM is computed once the output of the 1stRBM as input as shown is mathematical formulation

$$.\rho(h^{(2)}, W^{(2)}) = \sum_{h^{(2)}} \rho\left(h^{(1)}; h^{(2)}; W^{(1)}\right)\rho\left(h^{(1)}; W^{(1)}\right) \quad (11)$$

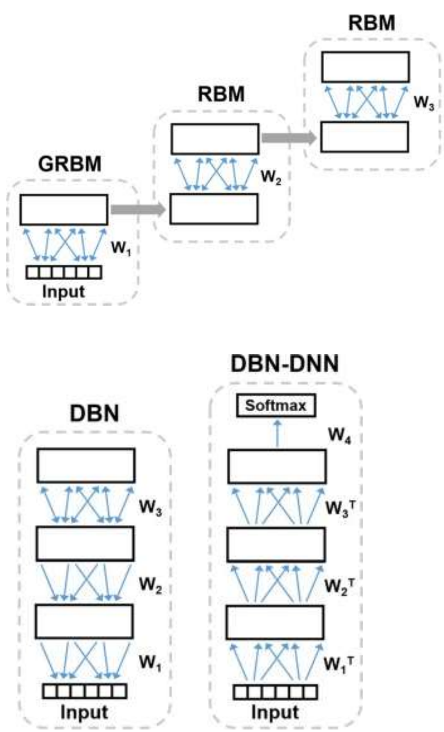

Figure 4. Structure of Deep Belief Network

As seen in figure 4, the higher weights are compelled to double those that descend weights while acquiring the variables of the initial layer "RBM". Intuitively, the initial absence of top-down feedback is made up for by utilising weights (W) twice while determining the condition of hidden units h(1). On the other hand, the falling weights are made to twice the ascending weights before the preliminary processing of the final "RBM" of the stack. When combining to create the DBN, the weight is divided in half in both directions for all intermediate RBMs.

S. No	Acronym	Feature Description
1	DR	Difficulty in Reading
2	DW	Difficulty in Writing
3	DC	Difficulty in Copying
4	DWO	Difficulty in Work Organizing
5	DHR	History of Reading Difficulties in
6	RDCF	Difficulties in Reading Clock Face
7	DCB	Difficulty in Catching Ball
8	DSS	Difficulty to Sit Still
9	OVR	Over React for sudden noise
10	MC	Miss out on Crawling
11	SLW	Slow Learning to Walk (generally 12 to 16 months)
12	DS	Difficulties in Speech
13	PENT	Problem in Ear/Nose/Throat
14	DLD	Difficulty in Learning to Dress up

5.1 CHAOS SYNCHRONIZATION WITH HYPERPARAMETERS OF DBN

Chaos theory is a study area in mathematics, which is functional in philosophy, economics, physics and biology. It is highly sensitive to initial conditions (so that its effect is referred as butterfly effect, in which a slight change in one state of deterministic nonlinear scheme can consequence in huge variances in a later state. The way of chaotic variable can travel at a maximum space of interest. Even though its variation resembles disorder they have a delicate inherent rule.

Therefore, in this present work chaotic deep belief network is applied to utilize unevenness and periodicity of variables involved in chaotic, to set the hyperparameters used by DBN. The chaotic maps greatly influence the prevention of premature convergence by gradient stochastic to overcome the local minimum.

The performance of DBN is greatly dependent on the hyper parameters such as number of hidden layers, learning rate, weight and random number generators. In first category the chaotic maps reinforced random number generators and variables deprived of any fundamental modifications in the algorithm. Because the performance of the stacked RBM is highly dependent on such variables and random number generators. In this work, due to the chaos effective performance, the performance of dyslexia prediction using deep belief network accomplished high rate of accuracy.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed model Neutrosophic multiple regressing classifier enriched chaos deep belief network (ENURGC-CDBN) for dyslexia prediction performance is discussed in this section. The ENURGC-CDBN is deployed using python software. In this work to predict the presence of dyslexia two different sources of datasets are used, one is collected from dyslexic-12_4 dataset and another dataset is the real time dataset collected from five different centres of various districts of Tamil Nadu state.

In dyslexic-12_4 dataset comprised of 1065 students with 6 features Vocabulary, Verbal orders, Colour, perception of shapes, Visual-motor coordination and Analysis of reading and writing. The real time dataset comprised of 100 students with the age group of 8-10 years. The features used for assessing the presence of dyslexia among the school children in the real time dataset is shown in the table 1.

Table 1: Real time dataset Features Description

In dyslexia dataset the children are classified using four different class labels such as No dyslexic, control and revision, dyslexic & inattention, hyperactivity or other problems. In real time dataset, the children are classified as mild dyslexic, moderate dyslexic, high dyslexic and other cognitive impairment. The Parameter settings of the RBM in Deep belief network is described in the table 2.

Table 2: Parameter setting of RBM in DBN for Dyslexia Prediction

RBM Parameters	***Values***
Layer Size	[8,6]
Training phase iteration	20
Batch size	100
Momentum	0
Learning rate	1
Size of the entire network	[10,8,6,2]
Activation function	sigmoid
Fine tuning -iteration	100
Fine tuning- batch size	100

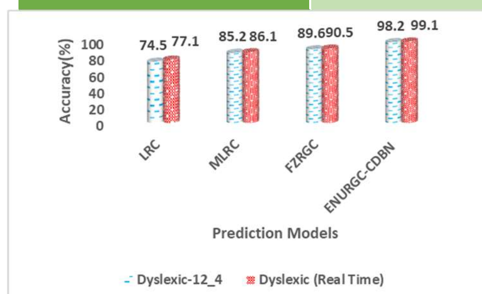

Figure 5. Evaluation based on Accuracy

Figure 5 illustrates the evaluation results of the four different prediction model based on their accuracy obtained on prediction of dyslexia in two different datasets. From the observed output it is shown that the performance of the proposed model enriched neutrosophic multilinear regression classifier empowered chaos deep belief network produced higher rate of accuracy 98.2% and 99.1% for dyslexic 12-4 dataset and real time dataset respectively. The neutrosophic theory denotes each instance in terms of belongingness towards truth value, falsity value and the indeterminacy value which improves the detection of dyslexic children at its early stage.

The deep belief network utilizes the neutrosophic regression data to improve the detection rate of dyslexia among children.

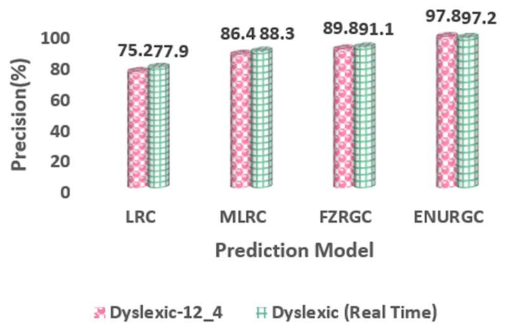

Figure 6. Evaluation based on Precision

Figure 6 displays the Dyslexia severity risk determination among children by examining the four different classification models. The performance of ENURGC is better compared to the other classification models as it has the ability to handle the uncertainty in both real time dataset and the Dyslexic 12-4 dataset. The Linear regression, multilinear regression and fuzzy linear regression suffers from the class imbalance and indeterminacy in classifying vague instances and the volume of handling dataset results in overfitting problem. Thus, the proposed ENURGC-CDBN achieved highest precision rate of 97.8% and 97.2% using dyslexic 12-4 dataset and dyslexic real time dataset correspondingly.

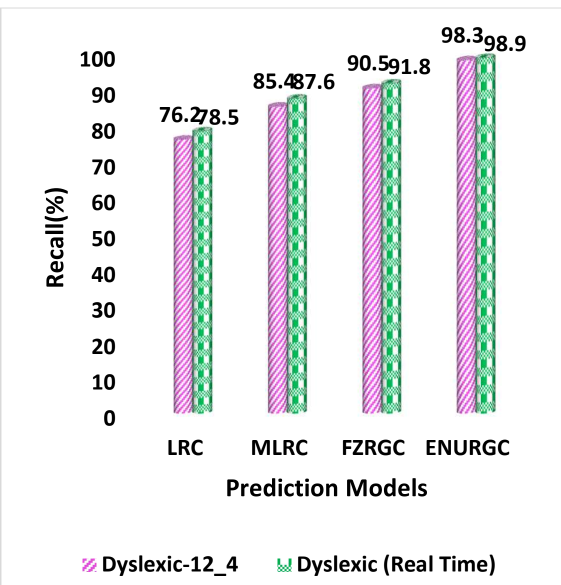

Figure 7. Evaluation based on Recall

The recall value obtained by the four classification models is depicted in the figure 7. The results show that ENURGC with the reduced feature subset selection using neutrosophic multiple regression model and using deep belief network it achieves better performance of recall value compared to other standard classification model. The fuzzy represent each feature only in the term of membership, whereas the neutrosophic represent the membership degree towards the truthiness, falsity and indeterminacy of the presence of dyslexia among children and classify their degree of severity. The recall rate of ENURGC-CDBN is higher than the other existing models as it attains the value of 98.3% and 98.9% respectively.

The primary strengths of this study include its high accuracy in dyslexia prediction and its unique approach to handling data uncertainty. However, the model's dependency on hyperparameter tuning may limit its adaptability, and there is a potential risk of overfitting due to the limited dataset. We believe that the presented model provides a valuable tool for early dyslexia diagnosis, which could greatly benefit educational institutions. Although the results are promising, there is room for further refinement to improve robustness and scalability in diverse settings.

7. CONCLUSION

The presence of uncertainty conditions in the dyslexia dataset makes the conventional machine learning or deep learning models more challenging and tough to conduct early stage prediction. This proposed work uses two stage approach to well understand the relationship among the independent and dependent attributes to perform an optimized dyslexia prediction. Hence, neutrosophical multiple regression model is used to understand the strength of the two attributes which are independent to avoid the redundancy and irrelevancy during dyslexia prediction. The coherence of the independent and dependent variable (or) class variable is discovered to conduct the depth understanding of the severity of the dyslexia child. Each records in dyslexia dataset is define in the triplet form, to focus on indeterministic symptoms which are considered as unknow patterns with the possibility of other cognitive disabilities. The deep belief network is used for prediction the dyslexia presence or absence, with the knowledge gained by the neutrosophic multiple regression. The scrutinization of hyperparameters in Deep belief network is accomplished using chaos mapping function. The performance of the proposed ENURGC-CDBN is tested with two different sources of dyslexia dataset. The dyslexia 12-4 is collected from keel software repository and the real time dataset is collected from five different centres of various districts of Tamil

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Nadu state. The proposed Empowered Neutrosophic multiple regression with chaos deep belief network produced highest accuracy rate of 98.2% and 99.1% for dyslexic 12-4 dataset and real time dataset respectively. Future studies should aim to expand the dataset size and diversity to enhance the model's generalizability. Additionally, exploring alternative neural network architectures or hybrid models may further improve accuracy while reducing the risk of overfitting. Addressing these limitations could help realize broader applications for dyslexia diagnosis and similar educational tools.

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