[1] Vinodh M. R.

[2]P. J. Arul Leena Rose

Intelligent Deep Adaptive Intuitionistic Fuzzy Classifier Based Dyslexia Prediction Among Children at its Early Stage

Abstract: - The inability of standard linear research to clearly define the role of cognitive abilities in reading difficulties is most likely due to the fact that reading and the components that are related to reading are both part of a system of factors. There are numerous interrelated and mitigating elements that conventional statistical models are unable to deal effectively. This work aims to increase dyslexia prediction accuracy by introducing two stage non-linear methodology which incorporate both deep learning and uncertainty theory. In the first stage, the pattern of dyslexic symptoms is learned by introducing deep adaptive neural network. During the training phase, the hyperparameters weight and learning rate are optimized using a metaheuristic algorithm called the fruit fly optimization algorithm. This algorithm imitates the behavior of fruit flies to search for the best set of values. The acquired knowledge is infused in the uncertainty inference model known as intuitionistic inference classifier. Each characteristic that defines an instance as dyslexic or non-dyslexic is represented in tristate degrees to precisely address the inconsistent or vague instance which neither or nor exhibit dyslexic symptoms by introducing the hesitancy factor. The simulation results support the proposed intuitionistic fuzzy rules prominently improves the accuracy rate of dyslexia prediction compared to the other existing state of arts.

Keywords: dyslexia, inconsistency, deep neural network, hyperparameter, fruit fly optimization algorithm, intuitionistic fuzzy

I. INTRODUCTION

In India there is no accurate details about number of children affected by dyslexia. Nonetheless, it is estimated that at least 10% of children enrolled in school may have a learning disability [1]. The subtle neurological condition of dyslexia makes it easy to miss because it goes undiagnosed a lot of the time. Dyslexia, as defined by the World Federation of Neurology, is a disorder characterized by challenges in learning, intelligence, and sociocultural opportunities [2]. It states that boys are more likely than girls to have dyslexia, with a rough estimated ratio of 4:1. [3]. A dyslexic child struggles with word recognition, decoding, and spelling. Phonological faults add to issues with unexpected disagreement, such as a lack of education, cognition, adequate perceptions and social context. These issues are frequently hidden in conjunction with other cognitive deficiencies [4]. The part of the brain involved in language processing is vulnerable because of the aberrant brain architecture seen in dyslexics. Depending on how the dyslexic uses language, different side effects may occur. It doesn't depend on a person's IQ and affects people of all ages. Analyzing the presence of dyslexia at its early stage is very challenging to the medical experts due to its uncertainty nature and it is very expensive. At the same time Children who have been diagnosed with dyslexia can be helped with specific teaching techniques and professional advice. Most of existing teaching aids are unable to meet these requirements because of limited finances, societal shame, and logistical issues [5].

Adopting the intelligence of data mining techniques greatly influence the process of detecting dyslexia among school children at its early stage. But improvising the percentage of detection accuracy is a toughest task while using conventional machine learning and data mining algorithms. The discrimination of varying factors among dyslexic and non-dyslexic is vague, inconsistent and indeterministic while using the certainty-based theories. Hence, in this paper to overcome the problem of indeterministic handling in the process of dyslexia detection is improvised by developing two stage analysing model.

[1,2]Department of Computer Science, Faculty of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur 603203, Tamil Nadu

First author email id: vinodhmr23@gmail.com

Corresponding Author: P.J.Arul Leena Rose

Corresponding author e-mail: leena.rose527@gmail.com

The main contribution of this proposed algorithm is to understand the depth pattern of discriminating factors among the clustered instances of dyslexia data obtained from our previous work [6]. The deep neural network model is used to extract the pattern of dyslexic, non-dyslexic and symptoms which other cognitive disabilities as hesitancy cases. The hyperparameters involved in DNN is optimized by the influence of fruit fly optimization algorithm. With the knowledge inferred from the deep neural network, the inconsistency, vagueness and uncertainty are handled by intuitionistic fuzzy inference model, which enriches its knowledge base using the DNN discovery about the patterns of dyslexia dataset. The rule generated by the intuitionistic fuzzy classifies the dyslexic and non-dyslexic with the increased detection rate.

II. RELATED WORK

This section discusses some of the current research on dyslexia prediction, as well as the difficulties in raising the prediction's accuracy rate.

Pralhad et al [7] developed a dyslexia perdition software tool using Grid search CV and Support vector machine to discover the dangerous situation that dyslexia children could face. The applied only the conventional models to accomplish the dyslexia prediction.

Appadurai et al [8] designed a predictive technique for dyslexia detection using machine learning algorithm. The authors used Apache SPARK framework to handle voluminous data while SVM is used for classification. The class imbalance during training phase affects the learning rate of SVM and inconsistent instances are not clearly defined.

Frid et al [9] derived a mathematical infused machine learning algorithm to identify complex attributes to discriminate normal readers and dyslexic readers. In order to support the hypothesis that the primary distinctions between skilled readers and individuals with dyslexia are primarily located in the left hemisphere of the brain.

Jothi et al [10] in their work differentiates dyslexics from non-dyslexics using eye movement, a prediction model based on mathematical methods has been proposed. Using an eye tracker, the eye movements are monitored. Principal Component Analysis with kernel SVM is used to extract the higher-level features to extract the essential characteristics of eye movement in dyslexia prediction.

Suhaila et al [11] defined a speed up robust features to discover significant characteristic in frontal face discovery. Then it is clustered as colour code book. The Naive bayes and two dissimilar kernels of SVM is used for dyslexic children.

Sofia et al [12] devised a set of pre-processing methods to recover the brain activity zones during three different reading tasks. A single model that allows for voxel comparison between each subject was created by converting the fMRI scans into Nifti volumes, correcting head motion, and applying normalisation and smoothing treatments to the patient brains. According to the study, it is possible to identify dyslexic children when they execute reading tasks that require phonological and orthographic knowledge using deep learning and functional MRI

From the existing research works it is observed that most of the work concentrates on the conventional way of improvising the dyslexia prediction accuracy. But the issue of vague data handling presented in dyslexia dataset is not highly focused and it is the main reason for unknown pattern understanding. When the data size increases or class imbalance occurs it cannot be handled by the conventional algorithms. Considering these issues, the present work developed a vague dataset understanding model using deep adaptive Intuitionistic fuzzy Classifier.

III. METHODOLOGY

Deep Adaptive Intuitionistic Fuzzy Classifier Based Dyslexia Prediction Among Children at its Early Stage:

The proposed work is a two-stage process, its objective is to understand the vague pattern of dyslexia dataset and to improvise the accuracy rate of dyslexia prediction in case of hesitancy or inconsistency. The raw dataset is collected from dyslexic-12_4 dataset [13]. The deep neural network is used in the first stage for understanding the vague information hidden among clustered dataset [6]. To accomplish the task of discovering such inconsistent instances, the hyper parameters such as weight and learning rate is fine-tuned by fusing fruit fly optimization algorithm. The foraging behavior of fruit flies is utilized to search for optimal values to assign to the hyperparameters during the training phase. The resultant knowledge is transferred to next stage. In second stage, the issue of inconsistency and abnormality in prediction of symptoms that exactly exhibits dyslexia is done by devising Intuitionistic fuzzy inference model, by adopting the knowledge acquired from deep neural network. By boosting the Intuitionistic fuzzy knowledge base, the result of predicting dyslexic and non-dyslexic accuracy rate is precisely improvised.

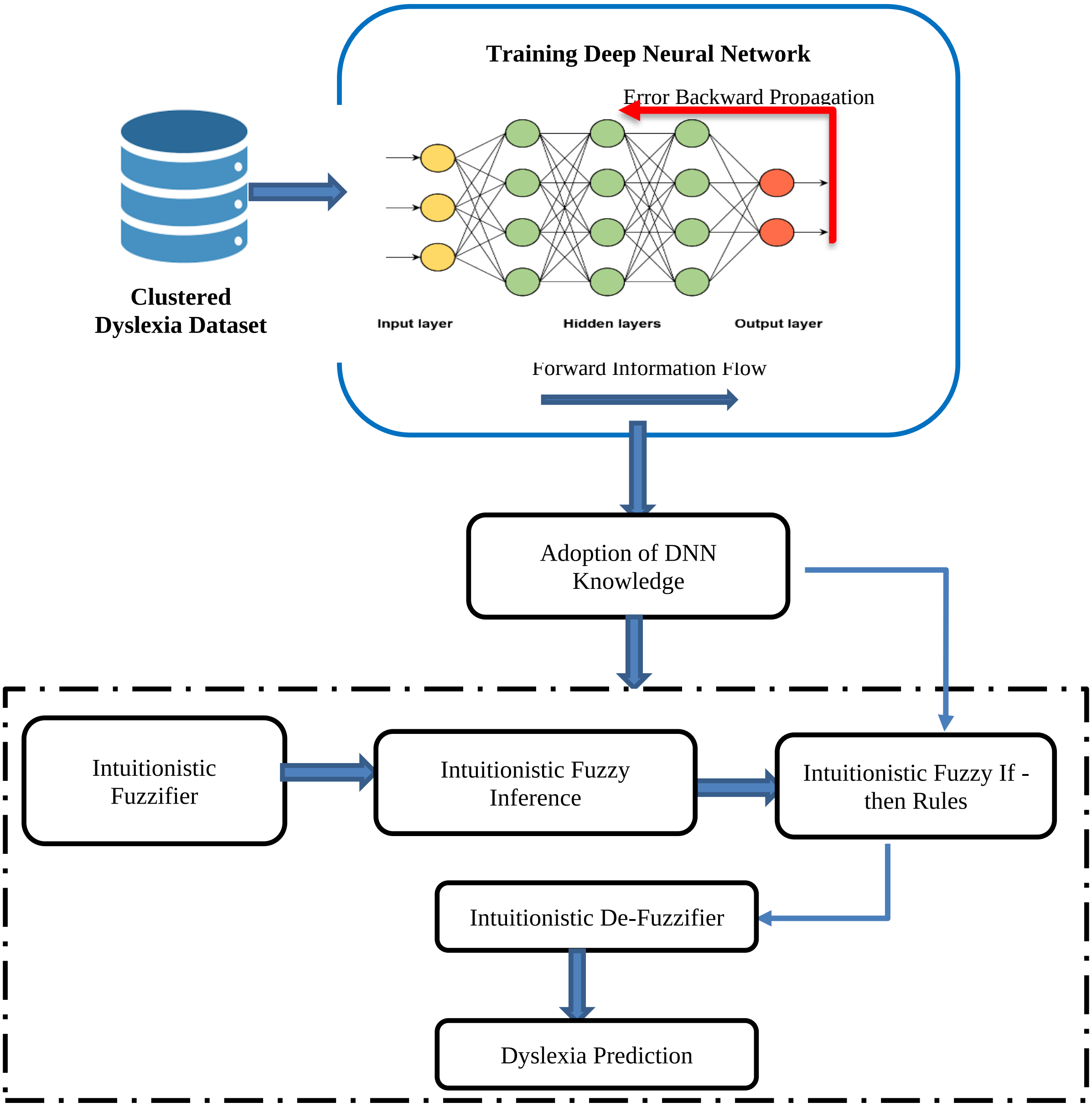

Figure 1: Overall Architecture of proposed Intelligent Deep Adaptive Intuitionistic Fuzzy Classifier Based Dyslexia Prediction Among Children at its Early Stage

Deep Neural Network

A deep neural network is a type of neural network that consists of multiple layers stacked on top of each other. It is a multilayer with man hidden layers and traverse only in forward direction [14]. The input attributes are matched with the output classes are matched with their corresponding input nodes and output nodes. The very essential elements in DNN are non-linear activation, weights, biases and backpropagation. Figure depicts the architecture of DNN with backpropagation.

In DNN the input layer comprised for four components namely IN-1, IN-2, IN-3, and IN-4. In order to distinguish between different outputs, it is necessary to identify one or more patterns among the entities of the input. Thus, several hidden units are created with activation functions to do that. The formation of an active hidden unit pattern involves the application of nonlinear activation functions.

For instances, let us consider that to activate output dyslexia, the hidden nodes HD-10, HD-12, HD-15, HD-21. HD-24, HD-27, HD-30, HD-34, HD-38 are needed to produce it. To accomplish this, modify the weights and biases so that the activation function activates certain hidden nodes. Biases and weights are generated at random. Thousands of inputs are then used to train the network. To change the weights and biases so that the hidden neurons are activated at the appropriate values, employ backpropagation of error. A feature set or kernel is the collection of weights and biases that will be used to distinguish one output from another.

Architecture of deep layered network

Multiple layers of computing are combined in deep neural networks. The calculation for a network with LN hidden layers is shown in equation:

$$\mathrm{HF}(\mathrm{x}) = \mathrm{HF}\left[\mathrm{a}^{(LN+1)}\left(\mathrm{HL}^{(LN)}\left(\mathrm{a}^{(L)}\left(\ldots\left(\mathrm{HL}^{(2)}\left(\mathrm{a}^{(2)}\left(\mathrm{h}^{(1)}\left(\mathrm{a}^{(1)}(x)\right)\right)\right)\right)\right)\right)\right)\right]$$

where $\mathrm{HL}^{(l)}(\mathrm{x})$ is the output of hidden layers.

$$\mathrm{a}^{(LN)}(x) = \mathrm{wt}^{(LN)}x + b^{(LN)}$$

$$\mathrm{a}^{(LN)}(\hat{x}) = \theta^{(L)}\hat{x}, LN = 1$$

$$\mathrm{a}^{(LN)}\left(\hat{h}^{(LN-1)}\right) = \theta^{(LN)}\hat{h}^{LN-1}, LN > 1$$

Every pre-activation function $\mathrm{a}^{(LN)}(x)$ is generally a linear operation combined with weight $\mathrm{wt}^{(LN)}$ and bias $b^{(LN)}$ that is combine to a parameter as θ.

Process of activation function

The activation functions significantly affect the network's effectiveness and learning process by altering the neurons' outputs. Every neuron in the network has a function connected to it that decides whether or not to fire depending on how significant an input is to the model's prediction. A few activation processes also aid in restoring the neurons' outputs to normal. The epochs and sign functions, among other binary activation functions used by early NNs, were not differentiable. The differentiable activation functions allow to employ straightforward as well as efficient training algorithms. For ease of use, a single neuron in a single layer's activation function and state are indicated as $\beta(.)$ and λ respectively.

Improvising Hyperparameters in DNN using Fruit Fly Optimization Algorithm

The fruit fly optimization algorithm (FOA) [15] is a metaheuristic technique that draws inspiration from the foraging behavior of fruit flies. FOA leverages the fruit fly's reliance on smell and vision to locate food sources, applying this strategy to solve optimization problems. FOA process begins with arbitrary generation of populations in the solution space, each fruit fly position is updated depending on their flight mode. During each iteration, the fruit flies unceasingly improves the fitness of the population.

Individual fruit flies in FFO are represented by their positions in a surface and are uniformly created around the historically optimal solution, also known as the present population position, it is formulated as:

$X_i = X_{pos} \pm \sigma * \mathrm{rnd}\ ()$

$Y_i = Y_{pos} \pm \sigma * \mathrm{rnd}\ ()$

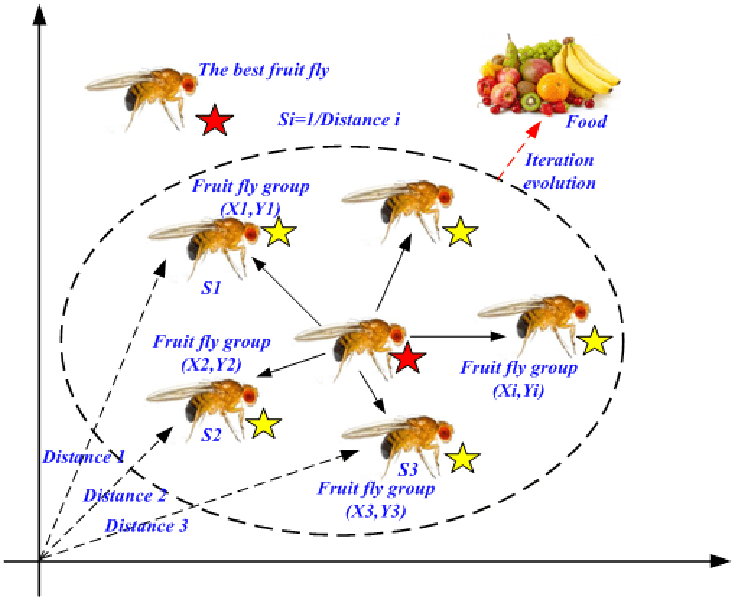

Figure 2: Fruit Fly food searching strategy

The global optimization is exhibited by FFO algorithm, which is utilised in searching of most appropriate values that can be assigned to the hyper parameters involved in classification of dyslexia data. In order to determine the most optimal fruit fly, the fitness of each individual fruit fly is assessed by evaluating its location. The fruit fly swarm position is updated based on the location of the best position, which has the highest fitness value. The fruit fly with best fitness value is computed iteratively to attain global optimization. Thus, the training phase of DNN reliably identifies the vague patterns more precisely to detect dyslexic and non-dyslexic instances.

Procedure: Fine tuning hyperparameters using Firefly Optimization Algorithm

Begin

- Initialize sm_bst = 1, pop = 100, iter = 1
- Initialize position ($X_{pos,}$ Y_{pos}) = (0,0)
- Update the coordinates of ($X_{pos,}$ Y_{pos}) of the nth fruit fly using equation
- $X_{pos(n)}$= $X_{pos(G)}$+SR(υ-0.50) $X_{pos(n)}$= $Y_{pos(G)}$+SR(υ-0.5)
- //Where N = 1,2,..pop, υ is the random direction and group position of firelfy $X_{pos(G)}$, swarm radius is SR.
- Compute distance (D_n), smell (sm_n), $C_{n,}\sigma_n$

$$\mathrm{DT}_n = \sqrt{X_{pos(n)}^2 + Y_{pos(n)}^2}$$

$$\mathrm{sm}_n = \frac{1}{DT}; \; C_n = 20\mathrm{sm}_n; \; \beta_{n\,=\,0.1}\mathrm{sm}_n$$

- Train the DNN model using C_n is the learning rate and β_n is the weight in DNN.
- Compute the fitness value

$$Sm_n = \frac{1}{4}\sum_{i=1}^{4}\left[\frac{1}{p}\sum_{j-1}^{p}\left(\hat{y}_{ij} - y_{ij}\right)^2\right]$$

- Find the minimum MSE among the firefly swarm

$$[bst\_Sm \quad bst\_Idx] = \min(Sm)$$

- find the best smell

$$Sm\_bst = bst\_Sm, X_{pos(G)} = X(bst\_Idx), Y_{pos(G)} = Y(bst\_Idx)$$

- Update the fruit fly swarm position
- Calculate the optimal value of C_n and σ_n

Intuitionistic Fuzzy

In fuzzy theory the elements are denoted only in the form of membership towards belongingness μ, of a particular situation and the non-belongingness is assumed to be 1 - μ. It is not true in all facts, hence in this research work, the theory which has the ability to define both belongingness and non-belongingness of a fact is deployed for improving the dyslexia prediction with the aid of intuitionistic fuzzy theory. The intuitionistic fuzzy system [16,17] represents every element or instance of the universe using two grades: one representing membership in a general subset and the other representing non-membership in that specific subset. The intuitionistic fuzzy is signified as $\{< E, \mu_E(z), \upsilon_E(z) > | z \in Z\}$. The lack of knowledge about an element in represented using hesitancy degree π.

$\pi_E(z) = 1 - (\mu_E(z), \upsilon_E(z))$

Intuitionistic Fuzzy Inference System (IFIS)

The clustered dyslexia data is translated by IFIS into an intuitionistic domain that labels all input according to true membership and non-membership or false membership functioning. The updating process is executed subsequent to acquiring the membership and hesitancy or non-membership functions, depending on the necessary inference procedure. The diagram illustrates the process of using an intuitionistic fuzzy inference system (IFIS) to identify hidden patterns in instances and determine whether a record belongs to the category of dyslexia, non-dyslexic, or exhibits indeterministic symptoms. This is achieved by employing various units within the IFIS.

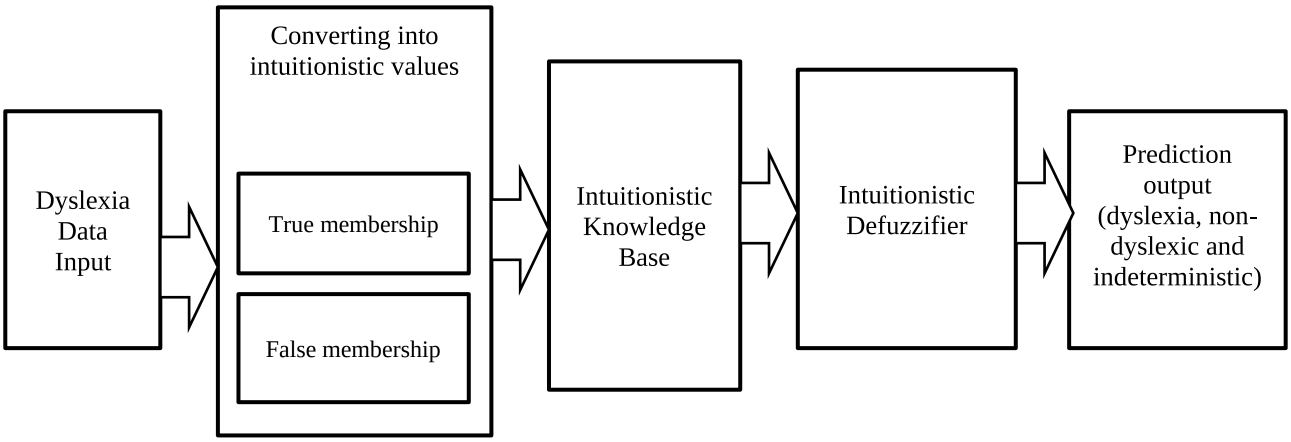

Figure 3: Overall Workflow of Intuitionistic Fuzzy Inference System

Process of Intuitionistic Fuzzy Inference System

1. Input value for clustered dataset of dyslexia was fed into the IFS system.
2. The intuitionistic fuzzification unit transforms the crisp value into the true membership and non-membership or false membership grades of representation.
3. To infer information about input values and produce intuitionistic rules, intuitionistic knowledge base is used.
4. The output value is intuitionistic defuzzifier, which involves in converting intuitionistic value to crisp value based on the rules generated and predicts the presence or absence of dyslexia.

Intuitionistic rule generation

Each instance of the dyslexia dataset contains three distinct class labels: dyslexia, no dyslexia, and degree of hesitation regarding dyslexia. Every dyslexic has n + 1 characteristics. The final feature determines the class to which the instance is assigned. while the first n attributes specify the characteristics of an instance. The intuitionistic classifier has three categories of rules: normal, abnormal, and hesitation. An intuitive classifier is determined by a collection of rules, and if there are n different classes, n rules are created.

Intuitionistic fuzzy Rule format

RUL1: IF cnd_1 THEN data is cls_1 . . .

RULn: IF cnd_n THEN data is cls_m

The observed variables are utilized to form the condition segment, while the categorization attribute is employed to delineate the conclusion segment.

A few instances of intuitionistic rules for membership criteria include,

RUL_N:

if id1 is low and id2 is high and id3 is low and id4 is low and id5 is low and id6 is medium and id7 is low and id8 is low and id9 is low and id10 is medium and id11 is low and id12 is medium

then child is normal [0.7]

RuL_A:

if id1 is high and id2 is high and id3 is high and id4 is high and id5 is high and id6 is high and id7 is medium and id8 is high and id9 is high and id10 is high and id11 is high and id12 is high

then child has dyslexic [0.8]

RUL_H:

if id1 is medium and id2 is medium and id3 is medium and id4 is medium and id5 is low and id6 is high and id7 is medium and id8 is medium and id9 is medium and id10 is medium and id11 is medium and id12 is medium **then** child has other-symptoms [0.9]

$$\text{Cls} = \begin{cases} \textbf{Normal: IF } TV(RL_N) > TV(RL_D) > TV(RL_H) \\ \textbf{Dyslexic: IF } TV(RL_D) > TV(RL_N) > TV(RL_H) \\ \textbf{Hesitancy: IF } TV(RL_H) > TV(RL_N) > TV(RL_D) \end{cases}$$

Where D: dyslexic, N: Normal and H: Hesitancy

IV. RESULTS AND DISCUSSIONS

The performance of the Deep Adaptive Intuitionistic Fuzzy Classifier (DA-IFC) for predicting the presence of dyslexia is discussed in this section. Python software is used to deploy the DA-IFC, and the dyslexic dataset—also referred to as the dyslexic-12_4 dataset—was gathered from Keel [13]. The performance evaluation of DA-IFC is compared with conventional intuitionistic fuzzy classifier, fuzzy inference system and rule induction classifier. To evaluate, accuracy, precision, recall and error rate are used as metrics.

$$Accuracy = \frac{\text{Number of instances accurately classified as dyslexic and non} - \text{dyslexic}}{\text{Total Number instances in dataset}}$$

$$Precision = \frac{\text{Number of instances accurately classified as dyslexic}}{\text{Total Number predicted as dyslexic children}}$$

$$Recall = \frac{\text{Number of instances accurately classified as dyslexic}}{\text{Total Number of dyslexic}}$$

Error rate = $\frac{1}{n}\sqrt{\sum_{i=1}^{n}(y(Act)_i - y(pred)_i)^2}$

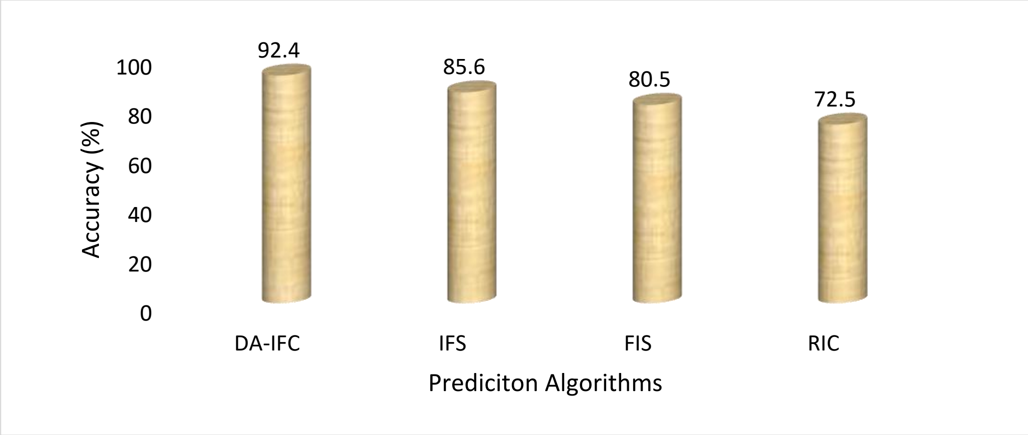

Figure 4: Comparative Analysis based on Accuracy

The efficacy of the proposed Dyslexia Assessment-Integrated Feature Classification (DA-IFC) algorithm in predicting dyslexia based on the accuracy rate is shown in the figure. The depth knowledge about the pattern of normal, dyslexic, hyperactivity, control and revision are inherited by the intuitionistic inference system by adopting deep neural network output. The fruit fly optimization algorithm is employed to optimize the hyperparameters in deep neural networks. The intuitionistic fuzzy represents each instance in the dyslexia dataset with the tristate grade to perfectly handle the indeterministic cases in dyslexia dataset. Thus, the proposed DA-IFC produced highest rate of accuracy in dyslexia prediction compared to the conventional fuzzy inference system and rule-based classifiers.

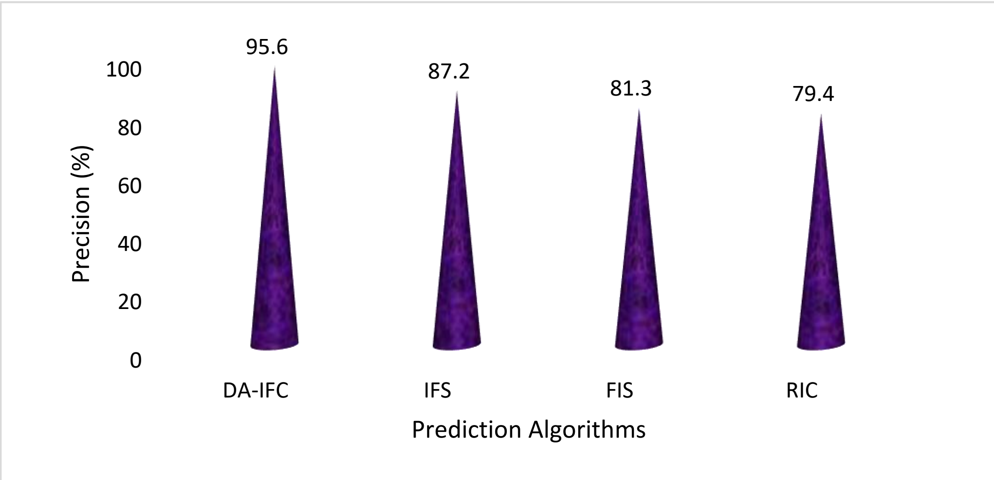

Figure 5: Comparative Analysis based on Precision

The figure presents the findings that investigate the effectiveness of the proposed deep adaptive intuitionistic fuzzy classifier based on the precision rate obtained compared with other three existing algorithms. The deep adaptive network model boosts the performance of intuitionistic fuzzy rule generator by extracting the variations of dyslexia and non-dyslexic persons during its training phase. The learning rate and weight values involved are optimized by metaheuristic algorithm known as FOA. The backpropagation algorithm optimizes performance of deep neural network to reach its best value by adjusting weight and learning rates depending on the incoming data. While using conventional intuitionistic fuzzy model, fuzzy inference model and rule Induction classifier they generate the rules based on their knowledge inferred by themselves. Thus, the validation of rule generation is not optimized in the existing models.

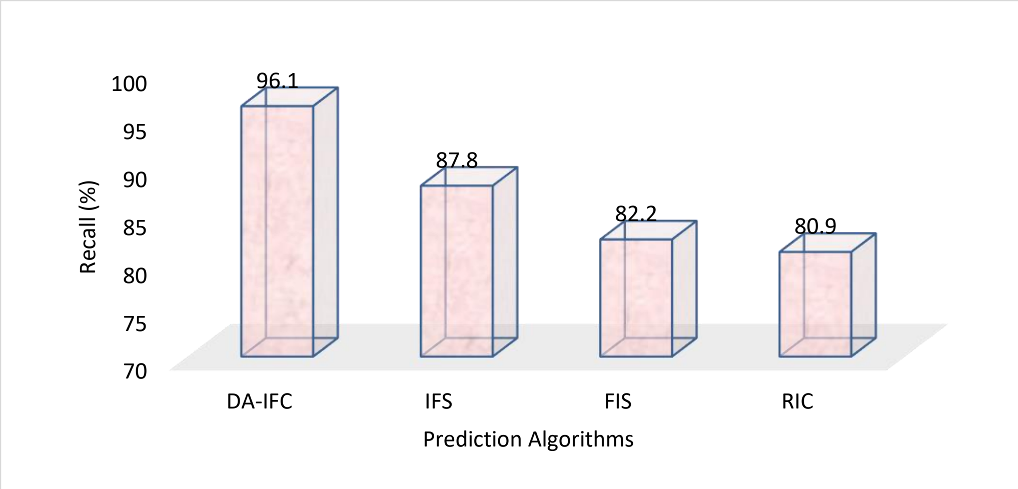

Figure 6: Comparative Analysis based on Recall

The figure displays the recall values obtained by four distinct models used in dyslexia prediction. The classification of indeterministic or vague pattern of instances in dyslexia dataset which neither or nor exhibits symptoms related to dyslexic is a challenging task in prediction system. The two-stage investigation and revealing the pattern of instances using DA-IFC improves the detection rate of dyslexia. Hence, recall value of DA-IFC is high compared to the existing conventional models.

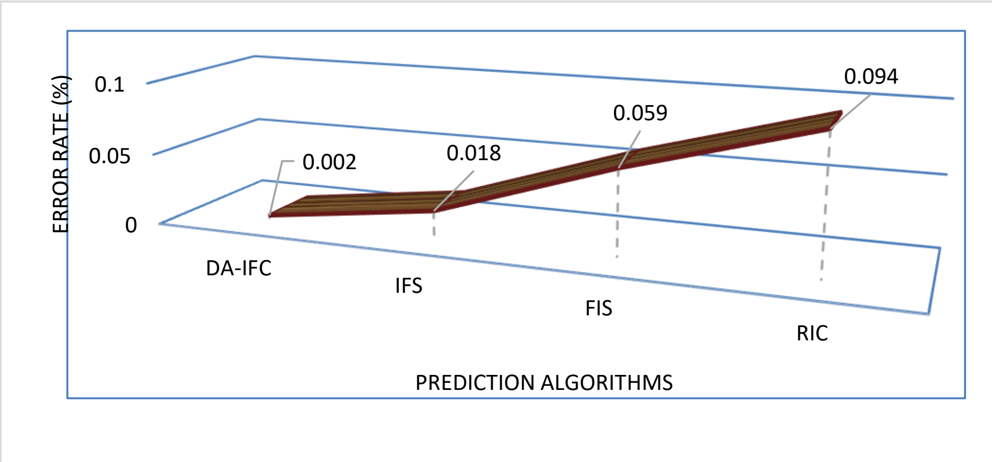

Figure 7: Comparative Analysis based on Error Rate

The error rate of the proposed DA-IFC is significantly lower compared to existing algorithms in the prediction of dyslexia, as depicted in the figure. The input received by the deep adaptive neural network is already clustered using the previous work []. In this proposed work, the discrimination and classification of non-dyslexic from other learning disability is the major focus and it is accomplished by empowering the knowledge base of the intuitionistic inference system. The conventional intuitionistic, fuzzy and rule induction needs the expert’s input, whereas in the proposed DA-IFC the deep knowledge is acquired during the training phase of deep neural network which yielded more precise outcomes. Thus, the error rate of DA-IFC is reduced much compared to other state of art algorithms.

V. CONCLUSION

This paper contributes a two-stage process algorithm to improve the accuracy rate of dyslexia prediction. The dyslexia dataset contains a vague information which is very tough to analyse precisely and discriminate dyslexia child from others. The fruit fly optimization algorithm is used to improve the DNN's training phase. The optimal values for assigning the hyperparameter values involved in the DNN training process are found by analyzing the behavior of fruit flies. The information derived from DNN is used to boost the knowledge of classification ability of Intuitionistic Fuzzy classifier. The inconsistent pattern of instances is clearly delineated through the application of intuitionistic fuzzification and the rules derived from an intuitionistic fuzzy inference system. This system demonstrates a higher level of accuracy compared to the conventional intuitionistic fuzzy system, fuzzy inference system, and support vector machine.

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