Hybrid Intuitionistic Fuzzy Fused Quantum Particle Swarm Intelligence for the Prediction of Dyslexia

J.Loveline Zeema, D.Francis Xavier Christopher

Abstract**:** ***Discovering the presence of dyslexia among the children needs proper analysis in earlier childhood days. The method used for diagnosing such disability is often done by making children to solve non-writing based graphical test. Depending on their performance specialist score these test, and identify whether the children suffer from dyslexia or not. Controversy in an assignment of scoring by experts exploits uncertainty in the dyslexic dataset, which has been recently accredited as a new challenge in the field of cognitive computing. The uncertainty in the diagnosis of dyslexia is intensified due to certain symptoms that are well-matched with multiple disorders. In this paper to overwhelm the vagueness, uncertainty, impreciseness in datasets, an intelligent intuitionistic fuzzy with quantum particle swarm optimization is fused in the artificial neural network is developed. This model tackles the issue of uncertainty by introducing the degree of hesitation which well defines the instances with multiple class labels. The quantum mechanism of particle swarm optimization makes the ANN in an intelligent manner by inferring the knowledge about the weight assigned among hidden nodes in a parallel manner. The simulation results prove the performance of this proposed QPSO-IFANN model which greatly assists the parents to discover the symptoms of dyslexia and recommend them to take their children to a psychologist for an individual checkup.***

Keywords**:** ***Dyslexia, uncertainty, vagueness, artificial neural network, intuitionistic fuzzy, quantum particle swarm optimization and indeterminacy***

I. INTRODUCTION

Dyslexia is a kind of neurological condition which is characterized by complications that primarily affect a person or child to write, read and spell. As this is recognized as a learning disability it generally exhibits as an issue in thinking, listening, speaking, writing or spelling or ability to do math. Dyslexia is not a sign of intelligence because many children who suffer from dyslexia are of above average intelligence. But with the limited ability to read fluently due to some problem in the area of language development and memory, which makes a dyslexic child learn diverse, this is defined according to Dyslexia Association of India [4].

In India, roughly 10% of children are estimated to be dyslexic, this is analogous to the world average but there are no official figures on the subject. The public consciousness and acceptance have been dolefully low. In India, academic and education performance is an important issue for families. If dyslexia goes unnoticed, it is stressful for the child. People often think that the child is not trying hard enough [3].

Many Indian Education Institutions do not have programs to help children with learning disabilities, and faculties are not generally trained to deal with such children, if not completely ignorant of it. Few private education institutions offer special education often charge extortionate prices which aren't accessible to common persons. Investigating these issues this research work interested in the early diagnosis ages between 6 and 8 of school children. An early detection of dyslexia can alleviate the treatment. This research work is the first stage of design and development of prediction of dyslexia with improving results which can help in detection of those symptoms which recommend taking their children to an expert for an individual inspection. With the advent of cognitive computing in the medical field, it enables researchers to uncover new insights in relationships among phenotypes, pathways, proteins, and diseases.

II. RATIONALE OF USING INTUITIONISTIC FUZZY SET

This research work uses low-quality data of dyslexia dataset which in real time consist of imprecise, vagueness and uncertainty. There are many previous works done using fuzzy methods which are used to learn medical diagnosis approaches specifically in [3, 9 and 1] used fuzzy techniques in the diagnosis of disabilities in language. However, the fuzzy system only works on the grade of membership which often arises problem when it mixes together the evidence and evidence against an object. Thus this research work uses the generalization of fuzzy logic which is known as intuitionistic fuzzy which represents each object in terms of two different grade membership and non-membership (hesitation).

The vagueness and imprecise knowledge of the dyslexic dataset are well handled using intuitionistic fuzzy linguistic representation than crisp values or fuzzy values. This work uses an artificial neural network as a prediction model and its performance is enriched by introducing quantum particle swarm optimization which works in parallel for optimizing the assignment of nodes among hidden nodes. Because the accuracy outcome of neural network primarily depends on the assignment of weights between input nodes and hidden node and to the hidden nodes to output nodes.

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III. RELATED LITERATURE

This section discusses some of the existing work in the detection of dyslexia using various procedures, material, and approaches.

Hoeft et al. [5] in their work developed a multivariate pattern study of brain activity during a reading task over the entire brain. They used the linear support vector machine and performed cross-validation for training and testing. The reading observation greatly influences the factor for predicting dyslexia with more classification accuracy. Tanaka et al [17] demonstrated that by collecting dataset of normal and poor reading children, they used leave-one-out linear SVM for analysis of brain activation during phonological processing and they classified the dyslexia students. Pernet et al [14] developed a classification model by analyzing right cerebellar declive and the right lentiform nucleus to classify dyslexic readers. Their work aims to investigate whether young adults with and without dyslexia can consistently be categorized based on anatomical variances.

Tamboer et al [16], five behavioral factors accompanying dyslexia were determined using exploratory and confirmatory factor for analyzing the severity of dyslexia using the regression model. They used z-score normalization on five different factors namely spelling, phonology, short-term memory, visual/attention confusion, and whole-word reading. Maitrei Kohli&Prasad [12], introduced a systematic approach for discovery of dyslexia using an artificial neural network in order to analyze significant cases more accurately. But still, there is a lack in identifying potential features to achieve sufficient accuracy. Luz Rello &Miguel Ballesteros [11], in their work they adapted the statistical model to predict readers with or without dyslexia by measuring eye tracking of each person under consideration. This model uses support vector with binary classification. It is trained and tested with cross-validation of dataset composed of 1,135 readings of people.

The aforementioned works don't have proper proof on handling low-quality dyslexia dataset which consist of imprecise and uncertain knowledge. Thus the aim of this research paper is to develop an enriched approach for detection of dyslexia in earlier stages by handling uncertainty, indeterminacy and vagueness exists in the dataset, with knowledge of intuitionistic fuzzy fused with behavioral inspiration based artificial neural network.

IV. PRINCIPLE PARTICLE SWARM OPTIMIZATION AND INTUITIONISTIC FUZZY LOGIC

This section discusses basic terminologies of intuitionistic fuzzy logic and about particle swarm optimization which is a need in the sequel.

A. Intuitionistic Fuzzy Logic

K. T. Atanassov [7, 8] presented the concept of an Intuitionistic Fuzzy Set (IFS) as a generalization of a Fuzzy Set (FS). Here each element or instance of the universe is represented by means of two degrees, they are a degree of membership to a vague subset and other is a degree of non-membership to that specified subset

Definition 1: Let Y be the universe. In Intuitionistic fuzzy set let D is assumed to be a triplet denoted as $\{< y, \mu D(y), \nu D(y) > | y \in Y\}$, where $\mu D(y)$ is the membership degree of element y to D and $\nu D(y)$ is the non-membership degree of element y to D, both the elements μ, ν: Y—> [0,1] and also satisfies the condition $0 \leq \mu D(y) + \nu D(y) \leq 1$for every $y \in Y$ in D.

Definition 2: In each Intuitionistic fuzzy set of y in D it is also defined as $\Pi D(y) = 1 - (\mu D(y) - \nu D(y))$, where $\Pi D(y)$ is another new degree used in uncertainty handling which is known as the degree of uncertainty or hesitancy or indeterminacy of an element y in D where for each $y \in Y$ in D, $0 \leq \pi D(y) \leq 1$. Evidently, it s takes a lack of knowledge of whether $y \in D$ or not.

Definition 3: Intuitionistic fuzzy becomes fuzzy logic when $\mu D(y)+\nu D(y) =1$ and which it means there is no degree of hesitation.

B. Particle Swarm Optimization

Based on the behavioral inspiration from fish schooling, bird flocking Kennedy and Eberhart [6] developed particle swarm optimization for searching optimal solutions in a given problem space. It starts with the initialization of the particle's population and their position and velocities on search space are assigned randomly during the initial period. During the iteration of the process starts, the velocity and the position of particles are updated. And a fitness function is applied to each particle to determine its fitness value in every iteration. In this process, two significant positions which greatly influence the complete process is involved they are a global best position (gb) and personal best position (pb). The particles so far visited the best position is denoted as pbest and the best position among swarm visited since first time is denoted as gbest. Particles velocity and position are updated a follows:

$$\mathrm{Velc}(t+1) = \mathrm{wt}.\mathrm{v}(t) + \mathrm{cn}_1\mathrm{rn}_1\big(\mathrm{pb}(t) - \mathrm{pos}(t)\big) + \mathrm{cn}_2\mathrm{rn}_2\big(\mathrm{gb}(t) - \mathrm{pos}(t)\big) \quad t = 2,3,..p \quad \ldots\ldots(1)$$

$$\mathrm{pos}(t+1) = \mathrm{pos}\big(t0 + \mathrm{Velc}(t+1)\big) \quad \ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

Where, pos and Velc are position and velocity of the particle, respectively. wt is inertia weight, cn1 and cn2 are positive constants, called acceleration coefficients which control the influence of pb and gb on the search process, p is the number of iterative generation, rn1 and rn2 are random values in the range [0, 1].

Global Best PSO

Among entire swarm, the particle whose position is significantly influenced best is measured as global best PSO (gb). All the information of each particle from entire swarm is collected using star based social network topology. In this approach, every single particle has a current position in space of search, a current velocity and personal best position in space of search. The personal best position of each particle is associated with the smallest value acquired using an objective function to the position in space of search which takes into account the problem of minimization. The position yielding lowest value among all the personal best of particles in a swarm is denoted as gbest

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Local Best PSO

The lbest PSO or local best PSO approach allows each particle to be influenced by the best-fit particle selected from its neighbor and it replicates a social topology of a ring. To represent the local knowledge of the atmosphere the information is exchanged within the nearby particles [13, 6].

V. METHODOLOGY OF QPSO-IFANN

In this proposed work Quantum Particle Swarm Optimization (QPSO) is used in Intuitionistic Fuzzy Artificial Neural Network (IFANN) to enrich the detection of dyslexia by handling uncertainty, vagueness, and indeterminacy. To perform this process the dataset is collected from Knowledge Extraction based on Evolutionary Learning (KEEL) dataset [15] termed as dyslexic- 12_4 dataset. The dataset values are in various ranges and they are normalized to a same range of value between [0-1]. The dataset is fed as input to the IFANN which consist of several layers and each layer performs a unique process to produce output to determine the presence of dyslexia or not. The IFANN is fine-tuned by applying QPSO to update and assign optimal weights and bias on hidden nodes so that it guarantees to handle the indeterminacy, uncertainty, and vagueness presented in the input dataset more positively to increase the accuracy at a higher rate.

VI. QUANTUM PARTICLE SWARM OPTIMIZATION

Instead of using standard PSO this research work adapted Quantum Particle Swarm Optimization (QPSO), which is developed based on basic principles of PSO and quantum mechanism [2]. The distinctive feature of QPSO is its fast convergence and good searching aptitude. QPSO diverges from traditional PSO due to its uncertainty principle; PSO doesn't have the ability to govern both position and velocity of a particle simultaneously [10]. In this approach, among M particles, the position of the kth particle(Ptk) in D-dimensional space at (t+1) iteration is updated as follows :

$$\text{meanbest} = \frac{1}{M}\sum_{k=1}^{M} Pt_k \qquad \ldots\ldots\ldots.(3)$$

$$Ptk = (Cn1Ptpb + Cn2Ptgb)/ (Cn1 + Cn2) \qquad \ldots\ldots\ldots.(4)$$

If random() > 0.5, then

$$pos_{id}(t+1) = Pt_{kd} + \sigma|\text{meanbest}-pos(t)|\ln\frac{1}{v}$$

else

$$posid(t+1) = Ptid - \sigma|\text{meanbest}-pos(t)|\ln\frac{1}{V}$$

Where, meanbest denotes mean the best position, which is the mean value of the personal best position (pb) of entire particles in the solution space. The contraction expansion coefficient is denoted as σ and v are two random number all these values lies between [0, 1]. Pb is the personal best position of each particle and gb is the global best position of the entire swarm.

Algorithm of QPSO

The functionality of QPSO is discussed here. This algorithm involves few variables like N is the total number of particles in the swarm and each particle personal position is signified as posi in a given search space. Each particle has the ability to travel with the velocity of Velci. During each iteration, particles are progressed arbitrarily to take their new position and they have their own best position negotiated so far and it is deposited and signified using pbi. The whole best known position from the whole swarm is signified as gbi. rnp and rng are consistently disseminated arbitrary numbers in the range [0,1] and n is the amount of dimensions.

Procedure for Quantum Particle Swarm Optimization Steps

1. Initialize the swarm particles with uniformly distributed random numbers
2. Compute meanbest using the formula
   $$\text{meanbest} = \frac{1}{M}\sum_{k=1}^{M} Pt_k$$
3. Update particle's velocity using the formula
   If random() > 0.5, then
   $$pos_{id}(t+1) = Pt_{kd} + \sigma|\text{meanbest}-pos(t)|\ln\frac{1}{v}$$
   else
   $$pos_{id}(t+1) = Pt_{id} - \sigma|\text{meanbest}-pos(t)|\ln\frac{1}{V}$$
4. Update particle personal best position and global best position using fitness function
   $$\text{Fitness}(pt) = \sum_{i=1}^{s} pt_i^2 - 10\cos(2\pi pt_i) + 10)$$
5. If (fitness(xposi) < fitness(pbest,i)) do:
   - Update the particle's best known position: pb ← pos
   - If (fitness(Ptpb)< fitness(Ptgb)) update the swarm's best known position: Ptgb ←Ptpb
   - Now gb holds the best found solution.

There are three main aspects which make the QPSO superior to traditional PSO:

1. It is an ***uncertain scheme*** and additional diverse state of particles and larger search space can be produced in this approach. So that it can able to generate better offspring.
2. In conventional PSO, convergence occurs faster and leads to local optima very easily in very few iterations. Once an approach falls to local optima very quickly means it fails to obtain the best solution. But in QPSO, hosting μbest (mean best) improves the average error rate of converging as the particles cannot converge very fast without considering their neighbor particles, thus it avoids falling into local optima more frequently and less compared to conventional PSO.
3. Finally, Parameters involved in process of QPSO is very fewer than the conventional PSO. Thus it makes the process to execute easier and thus the performance of QPSO is significantly improved.

VII. INTUITIONISTIC FUZZY NEURAL NETWORK FOR DYSLEXIA DETECTION

In this section working principle of the intuitionistic fuzzy artificial neural network is explained in detail for the detection of dyslexia. This model comprised of four different layers to accomplish its function. Fig:1 depicts the architecture of the IFANN.

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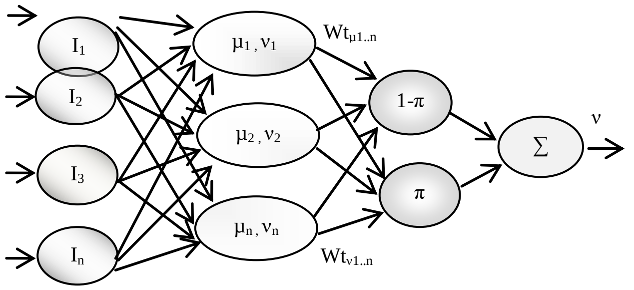

Fig1: Architecture of Intuitionistic fuzzy artificial neural network

The IFANN consist of four different layers. The first layer is the input layer which receives the input of dyslexia dataset. In the second layer, the crisp values are converted into intuitionistic fuzzy value by representing them in terms of degree of membership and non-membership values as follows:

$$\mu_D(y) = \begin{cases} 0; & y \le e \\ \left(\frac{y-e}{f-e}\right) & e < y \le f \\ \left(\frac{g-e}{g-f}\right) & f \le y < g \\ 0; & y \ge g \end{cases} \quad \ldots\ldots\ldots(5)$$

$$\nu_D(y) = \begin{cases} 1-\in; & y \le e \\ 1-\left(\frac{y-e}{f-e}\right) & e < y \le f \\ 1-\left(\frac{g-e}{g-f}\right) & f \le y < g \\ 1-\in; & y \ge g \end{cases} \quad \ldots\ldots\ldots(6)$$

In third layer for a single neuron with input i of IFANN it is represented in intervals [0,1]. The weight wt assigned to the link between the previous layer node and the current layer node is multiplied with the input i using the following formula:

$$wt_i \equiv \langle \mu_i, \nu_i \rangle = \langle \max(\mu_w, \mu_i), \min(\nu_w, \nu_i) \rangle; \quad \ldots\ldots\ldots(7)$$

The fourth layer is a summation Σ. The other element that is passed to the summation, is $\mu_b + \nu_b \le 1$. To optimize the Intuitionistic fuzzy Neural Network the PSO algorithm is used to initialize weight assignment between the network layers and initializing thresholds between neural nodes to perform a global search within the solution space and to determine optimal initial weights and threshold at a fast convergence rate. The NPSO can utilize these initial weights and thresholds for both training and testing samples. Fig 2 describes the triangular function of intuitionistic fuzzy. e, f and g are triangular coordinates

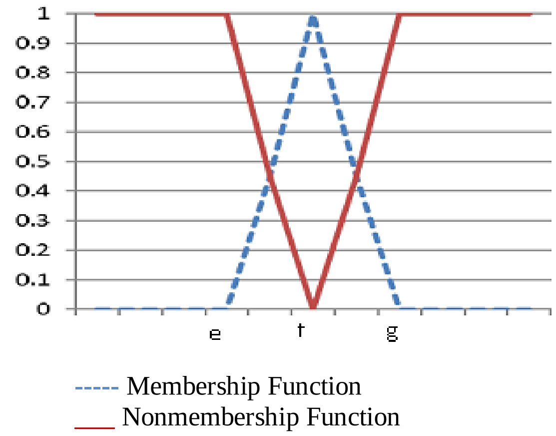

Fig2: Triangular function of intuitionistic fuzzy

The procedure of the Neuro-PSO can be described as follows:

1. Initialize QPSO parameters based on population size
2. Define the topology of the Intuitionistic neural network
    - The first layer is input layer receives dataset of dyslexia
    - The second layer performs conversion of input values to intuitionistic fuzzy value
    - The third layer does the process of intuitionistic fuzzy inference
3. Each particle corresponds to a neural network connection weight or threshold.
4. Evaluate each new particle's fitness value using the mean best value. If the ith particle's new position is better than P_{best}. P_{best} is selected as the new position of the ith particle. If the best position of all new particles is better than g_{best}, then g_{best} is updated.
5. If the maximal iteration times or the fitness values are met, stop the iteration, and the positions of particles represented by g_{best} are the optimal best solution. Otherwise, the process is repeated from step3.
6. Allocation the weights and threshold values which is optimized by Quantum PSO as the initial parameters, the intuitionistic fuzzy neural network performs autonomous learning

The learning phases of the QPSO-IFANN are as follows:

7. Input the training dataset and compute the observed output of the network layer.
8. Calculate the learning error of the network by finding the difference among observed and expected values.
9. Evaluate whether the error fulfills the belief and whether the maximum limit of iteration has reached. If whichever condition is met, then the training ends. Else, the learning process on model continues.

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VIII. EXPERIMENTAL RESULTS

The model QPSO-IFANN is simulated using MATLAB software. The dataset is collected from dyslexic_12_4 dataset available in KEEL repository [15]. This dataset is a combination of crisp and vague values. Each attribute can be either continuous or discrete so that it can be converted to either crisp or intuitionistic fuzzy value. The dataset consists of 65 instances with 12 attributes. The vagueness data is available both in input and output and it consists of missing value also. The instances are classified using four different class labels such as No dyslexic, control and revision, dyslexic & inattention, hyperactivity or other problems. In this work, the missing values are handled by applying KNN based imputation method to produce the complete dataset. The missing values of a particular instance are selected and their remaining attributes are compared with other complete set instances. After determining k-nearest neighbors, the missing value is filled by their obtained mean value of those neighbors's corresponding attribute value. The input dataset consist of interval value is transformed into midpoints and then they are converted into intuitionistic fuzzy domain representation. The imprecision of output are handled by duplicating so many times as different alternatives exist as mentioned in [13].

A. Performance Evaluation

To measure the performance of a model this work used three different metrics:

- *Magnitude of Relative Error (MRE)*: Finding the difference among the expected value and observed value. Its absolute value is known as MRE. The formula is :

$$\text{MRE} = \frac{|Expectedvalue - Observedvalue|}{Expectedvalue}$$

- *Mean Magnitude of Relative Error (MMRE)*: By taking the mean of the magnitude of relative error the mean magnitude of relative error is obtained. The formula is:

$$\text{MMRE} = \sum_{I=1}^{N} MRE_I$$

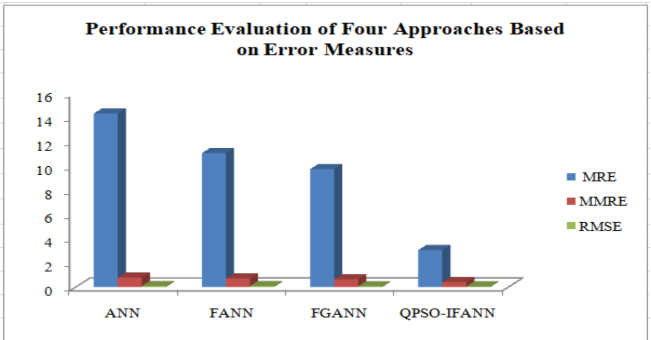
- *Root Mean Square Error (RMSE):* The root mean square error is defined as a frequently used measure of the variances among values predicted by a model or an estimator and the values observed.

$$\text{RMSE} = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

- *Predict:* It is a metric which defined observed values whose MRE is less than or equal to a specified value. The formula is shown below, where M is the number of observed values which are lesser than or equal to the specified value, r is the specified value and N is the total number of instances.

$$\text{Pred(r)} = \frac{M}{N}$$

Fig:3 shows the performance evaluation of four different approaches namely artificial neural network (ANN), fuzzy artificial neural network (FANN), Fuzzy artificial neural network with genetic algorithm (FGANN) & Quantum Particle Swarm Optimization based Intuitionistic fuzzy artificial neural network (QPSO-IFANN). The results show that the error rates of QPSO-IFANN is considerably very less while comparing the other models. The reason is the vagueness in both input and output of the dyslexia dataset is well-handled by introducing intuitionistic fuzzy in the artificial neural network to define each instance in terms of grade of membership and non-membership. The weights assigned to the hidden nodes are fine-tuned using the knowledge inferred from particle swarm optimization, along with a quantum mechanism which speeds up the process in parallel and increases the accuracy by its intelligence approach and the optimal weights are assigned depends on its fitness value.



Approaches	MRE	MMRE	RMSE
ANN	14.327	0.786	0.082
FANN	11.064	0.702	0.078
FGANN	9.739	0.641	0.065
QPSO-IFANN	3.0531	0.411	0.048

Fig.3: Performance Evaluation of Four different Approaches based on Error Measures

Fig: 4 shows the simulation analysis based on the accuracy obtained during training, testing and prediction of Pred(1) control and revision and discovery of Pred(0) no-dyslexia. From the result, it is observed that the fuzzy-based neural network fails to achieve the better results because of the lack of knowledge in handling uncertainty and indeterminacy in the input dataset. The reason is that they consider only the grade of membership which is not suited for the instances which have multiple labels. The FGANN which uses genetic algorithm for assignment of weights on hidden nodes doesn't produce better results than QPSO-IFANN due to earlier convergence and often it satisfies the local optima. The training performance of the QPSO-IFANN is higher by gaining the interaction among the preceding and succeeding nodes importance and assigning the weights accordingly. The prediction of control and revision is quite complex because it lies between no-dyslexic and dyslexic which is well handled by using a grade of membership, non-membership which reveals the degree of indeterminacy of these kinds of instances. Thus the proposed QPSO-IFANN helps to predict more accurately the presence of dyslexic in earlier stages itself.

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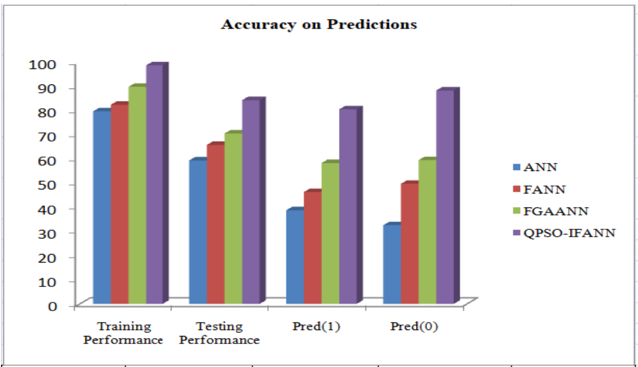

Models	Training Performance	Testing Performance	Pred(1)	Pred(0)
ANN	79.6	59.3	38.7	32.5
FANN	82.3	65.7	46.2	49.6
FGAANN	89.7	70.4	58.2	59.4
QPSO-IFANN	98.6	84.2	80.4	88.2

Fig.4: Simulation analysis based on the accuracy

IX. CONCLUSION

The main motivation of this work is to enhance the screening process to discover the presence of suspicious symptoms among children in their earlier stages and suggesting them to consult expert psychologists. With the significance of using intuitionistic fuzzy in the low-quality dataset the imprecision prevails among dataset is improved by converting them into intuitionistic fuzzy domain representation. The uncertainty in diagnosis process is well-handled by introducing the quantum particle swarm optimization which involves in the assignment of weights to those instances with multi-class labels, more precisely. In this work, the standard artificial neural network is transformed to an intelligent model by integrating both intuitionistic fuzzy and QPSO for dealing vagueness in the detection of a dyslexic student by producing better results with less computation complexity.

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