Empowered Deep Belief Network Learning fused with Shuffled Frog Leaping Algorithm for Autism Spectrum Disorder Prediction among Children at its Early Stage

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Abstract: Despite the ongoing rise in the frequency of autism spectrum disorder (ASD), prompt intervention and improved results depend on efficient early screening.For prompt treatments to enhance outcomes and help children reach their full potential, preliminary identification of Autism is essential.The main problem statement of this paper is to expedite Autism diagnoses by providing a machine learning system that uses different machine learning algorithms that lead to the make Autism predictive model with most possible accuracy. There are many machine learning models are developed by researchers to detect the autism at its early stage, but the problem of class imbalance greatly affects the performance and challenging issue. After the emergence of deep learning methods, the voluminous dataset is handled very effectively by this large network with depth layers. Still, the problem of overfitting due to class imbalance affects the accuracy rate in autism detection. Hence, this paper highlights the issue of overfitting while using deep learning algorithm which occurs mainly due to inappropriate assigned of hyperparameter values. The proposed model overcomes this issue, by adopting Shuffled Frog Leaping Algorithm (SFLA) to assign the optimized values to the hyperparameters of Deep Belief Network based Learning Model (DL). The fitness value evaluation of SFLA is used for learning rate and weight parameter assigned in DBN, while the conventional DBN follows it in a random approach. The UCI ML repository and Kaggle provide the data used to apply the approaches.The simulation results proved that the proposed EDL-SFLA produced the highest accuracy rate of 98.2% in prediction of autism among children compared with other conventional models.

Keywords: Autism Spectrum Disorder, machine learning, early prediction, shuffled frog leaping algorithm, deep belief network, Hyperparameter.

1. Introduction

A disorder that impacts a child's nervous system, growth, and development is known as autism spectrum disorder (ASD) [1].Children with Autism may not be able to learn social skills. This is partially due to the possibility that an ASD child will be unable to read other people's emotions or facial expressions. An autistic child may:

- Reluctance to be handled
- Desire to play alone
- Resistance to routine changes

Additionally, autism child may mimic actions. They could be rocking or fluttering their hands. Further they could develop strange attachments to things. However, a child diagnosed with autism may also excel at specific mental skills [2].As of right now, there isn't a specific ASD treatment plan. Nonetheless, experts have thoroughly investigated a number of intervention strategies to reduce symptoms, boost mental function, and enhance everyday living abilities. Implementing different intervention modalities successfully requires early and accurate identification of Autism.The aim to incorporate artificial intelligence into this sophisticated medical diagnosis system stems from recent advancements in the field [3]. By giving medical professionals useful data and insights to help them make better decisions, artificial intelligence (AI) can increase the precision and effectiveness of medical diagnosis.

One of the most significant technologies of the modern era is machine learning. Machine learning has been a major development in many areas of research, particularly data analytics. Because there is so much data being collected and analysed, one area where machine learning has advanced significantly is healthcare.Recent studies in the literature have shown that deep learning-based techniques can be quite helpful in the diagnosis of ASD [4].

Many layers of hidden neurons are learned in all the variants of deep learning models, for example, using a Restricted Boltzmann Machine (RBM) in conjunction with Backpropagation and error gradients from the Stochastic Gradient Descent. This is a common feature of all these models. But handling the hyperparameters like learning rate, weight and bias parameter involved in analysing the incoming patterns of data to classify them is very crucial. The efficiency of the deep learning models depends on the hyperparameter values which influence the accuracy of the model. Most of the conventional deep learning networks assigns the values in a random manner, which results in overfitting problem and affects the proficiency of the accuracy rate in detection of autism presence.

Hence, in this research work an empowered model of deep belief network with the stack of RBM, improves the accuracy rate of autism prediction by adopting the memetic knowledge of shuffled frog leaping algorithm is developed and implemented. The detailed working principle of the proposed empowered deep belief network learning with shuffled frog leaping algorithm (EDL-SFLA) to predict autism among children at its early stage is discussed.

Related Work

Et al [5] in their work used the machine learning approaches to diagnose the presence of ASD among children. The importance of screening, monitoring regularly and assign helps for early detection of autistic child is strongly discussed in this work.

Et al [6] deployed a recommender model to predict the presence of autism among children. They used multi-classifiers to improve the detection rate. The random forest and decision tree is suggested by the authors for better accuracy in prediction of autism.

Using the sMRI as their feature selection approach, the authors in [7] created a pipeline-based classifier. The biomarkers are employed to draw attention to the existence of autism. The topic of small datasets used to diagnose autism is also covered, and the importance of robust methods and large datasets is highlighted.

According to the theoretical underpinnings of the research conducted in papers [8,9,10], motor anomalies may serve as a distinguishing feature of ASD, and machine learning may be the best approach for analysing them. In this work, the latent distribution description of motion features identified by a tablet-based psychometric scale is analysed using a variational autoencoder, a specific kind of Artificial Neural Network, to enhance ASD detection.

Vijayalakshmi et al [11] devised regression mechanism as a hybrid recommender to enhance the prediction accuracy for autism patients. Three different classifiers were used in their work by utilising the voting based multi-classifier. The behavioural and demographic attributes are used in the dataset to predict the autism.

2. Methodology

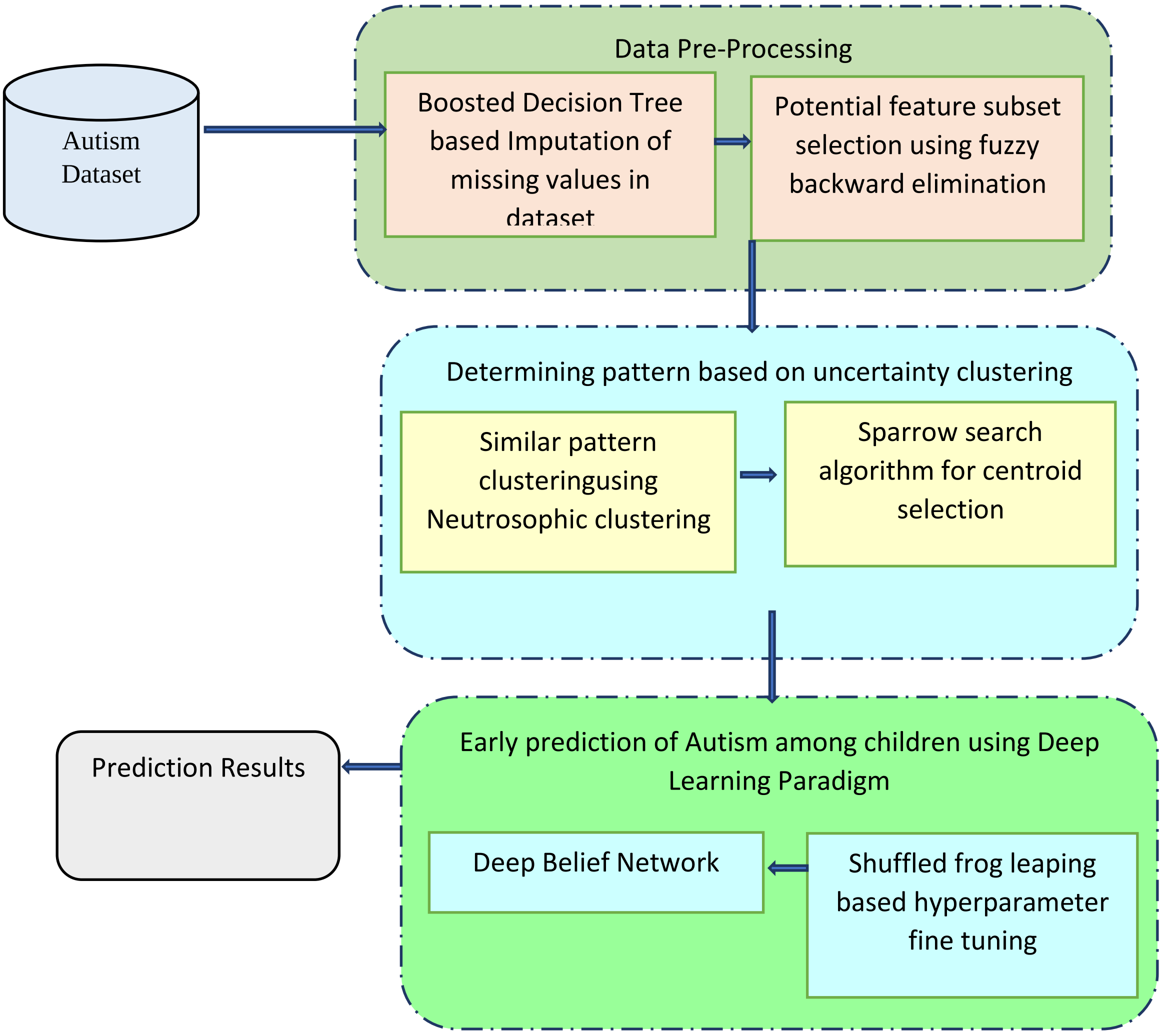


Figure Overall Work flow of Empowered Deep Belief Learner with Shuffled Frog Leaping Algorithm for Autism Prediction

The dataset for autism in toddlers was gathered from the repository maintained by Kaggle [14] and included 1054 instances with 18 variables in addition to a class variable.In our previous work, the raw dataset of autism detection is pre-processed with the two different methods boosted decision tree and fuzzy backward elimination for missing value imputation and feature selection respectively. In this research work, the detection of autism among children is done by developing an Empowered Deep belief network with its hyperparameters are scrutinized using memetic based algorithm known as shuffled frog leap algorithm(SFLA). The fitness value evaluation of the SFLA is used to assign values to the parameters of DBN such as learning rate, weight and bias instead of random values. The experimental results also produced clinically acceptable results in detection of ASD among children at its early stage more prominently compared with the existing state of arts classification methods.

Autism Dataset Pre-processing

Boosted Decision Tree based Imputation and fuzzy backward elimination feature subset selection in Autism Dataset

In our previous work [12] we have deployed a boosted imputation model which uses decision tree as the base learner. To improve the model's accuracy, the regression model makes use of a large number of decision trees. It builds the tree using a different method; to create a new tree, an arbitrary portion of all the data is chosen. It determines the weight of the next tree using the boosting approach, and then builds a new tree based on the tree with the highest chance of subset. Thus, the raw autism dataset is converted to complete dataset for further processing.

Fuzzy Backward Feature Elimination (FBFE) is a potential feature that can be used to remove unnecessary and redundant attributes from the Autism dataset [14]. In order to more effectively distinguish between the distribution of patterns, it computes the features independence measure using the fuzzy entropy measure. An attribute is said to have a stronger discriminating capability if its fuzzy entropy value is lower. Up until the endpoint condition is met, the backward elimination process starts with the entire feature set and eliminates features based on the calculated fuzzy entropy value.

Determining the pattern of autism using Neutrosophic Clustering with sparrow search optimization Algorithm

An uncertainty unsupervised neutrosophic clustering is developed in this work to distinguish between the pattern of autism and healthy toddlers. By choosing the best features for clustering, a new type of metaheuristic algorithm called the sparrow search optimisation method is employed. To improve the pattern discovery in children with or without autism, we have created in our earlier work [13] the neutrosophical representation and the method of detecting the unknown pattern of the autism dataset by neutrosophical clustering. The triplet factors, which were independent of one another and all belong to the degree of membership, are used to represent the neutrosophic logic.

Deep Belief Network for prediction of autism among children at its early stage

After performing the neutrosophic clustering of autism dataset, they are fed as input to the Deep Belief nets which is a type of stochastic model with concealed variables and several stochastic layers [15]. Latent variables, also referred to as feature detectors, are hidden units with binary values. Associative memory is performed by the top two levels of the deep belief network, which are symmetric, unstructured connections among themselves. The architecture of the human brain served as the model for DBN hierarchical learning. Logistic regression method can be applied to each layer of the deep network.The DBN model's input data consists of the two-dimensional (2D) matrix that was acquired through pre-processing.In pretraining, each RBM layer was trained independently. The hidden variable from the preceding layer was a duplicate of the visible variable that followed. Layer by layer, the parameters were transferred, and the characteristics were acquired from the layer before. The uppermost layer's LR underwent fine-tuning, wherein the cost parameter was updated through back propagation.

- ❖ After the predictive algorithm has finished learning, a single bottom-up run that starts with witnessed information from the bottom level and uses generating weights in reverse is used to obtain the latent variable values for each layer.

In this method, information is learned about and each layer's latent variable values are handled one at a time in order to train and comprehend the data in order to train the subsequent layer. Greedy learning can be used alone or in conjunction with different learning models. By fine-tuning all of the network's weights, this method of learning enhances discriminatory performance and streamlines the network's operation. Hence, shuffled frog leaping algorithm is used for fine tuning the hyperparameters of the DBN to improve the accuracy rate in detection of autism among children at their early stages.

Fine tuning parameters of DBN using Shuffled Frog Leaping Algorithm

The Shuffled Frog Leaping Algorithm (SFLA), which was created based on the way frogs leap to find food, is one of the creative memetic metaheuristic models [16]. This algorithm, which solves important optimisation problems, is a type of population-based algorithm. In this work, the aquatic effectiveness of the prospective search amplification process is improved by selecting important features in the AD Dataset by inheriting the structure of a genetic algorithm. The SFLA integrates the particle group optimisation and memetic process for conducting local search among subgroups. Because of its ease of use and quick convergence, the SFLA is becoming a more well-liked and effective global. The frog population as a whole is divided into smaller subgroups, each of which represents a variation type of frog dispersed over the solution space, encompassing all of the properties of the AD dataset in this work. Assuming that arbitrary problem size is Q and that the number of frogs is F, the location of the kth frog can be expressed mathematically as $Y_k= (y_{k1}, y_{k2}, \ldots, y_{kQ})$. (1)

The F frogs are divided into p memeplexes, which are groups of frogs with similar structures but varying levels of adaptation. They are placed in descending order based on the calculation of each frog's fitness value. Until there are no more frogs to assign, the first frog on the first list belongs to the first memeplex, the second frog goes to the second memeplex, and so on. Note that at the end, the first memeplex receives the p+1th, and this process is repeated until all of the frogs receive subsidies. In Figure 2, it is depicted.

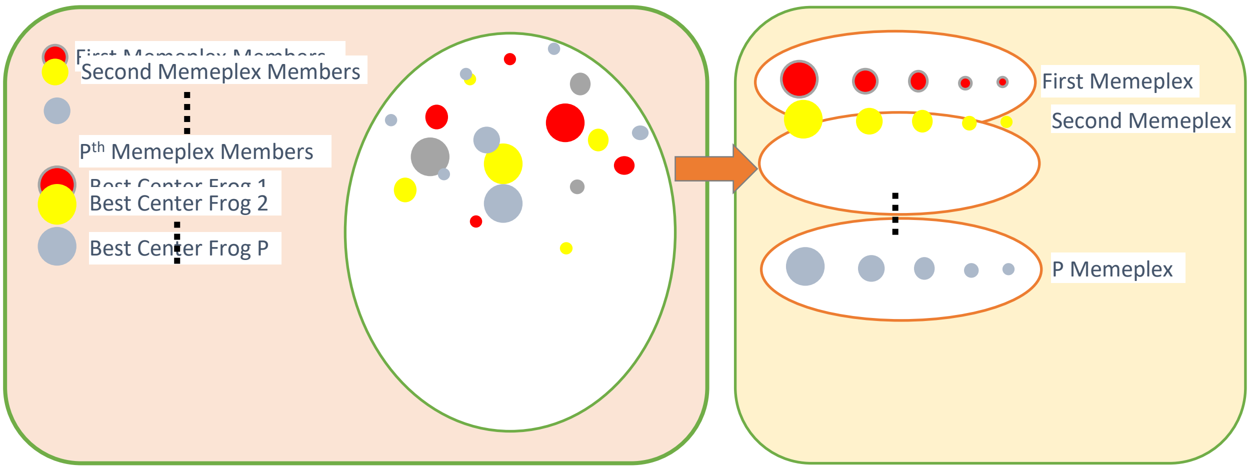


Figure Shuffling Frog Leaping Algorithm Behaviour

The SLFA approach uses each person's fitness value to assign them to various groups during each iteration (r), with the worst frog (F^{r}_{wf}) going to each group firsthas learned from the best individual (F^{r}_{bf})in a subgroup. It learns from the world's greatest individuals (F^{r}_{gb}) if its learning behaviour towards locating the ideal answer remains stagnant. Though, the it doesn't progress its position then (F^{r}_{wf}) will be substituted by an arbitrary frog from the population. Figure 3 shows the individuals grouped together.

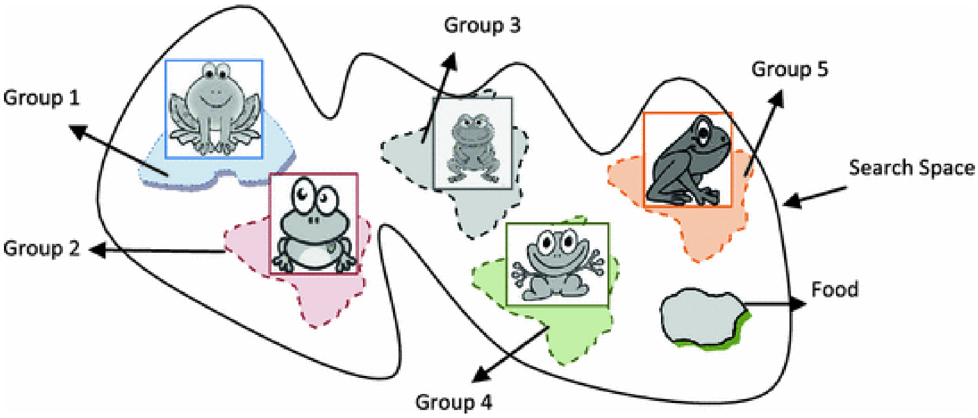
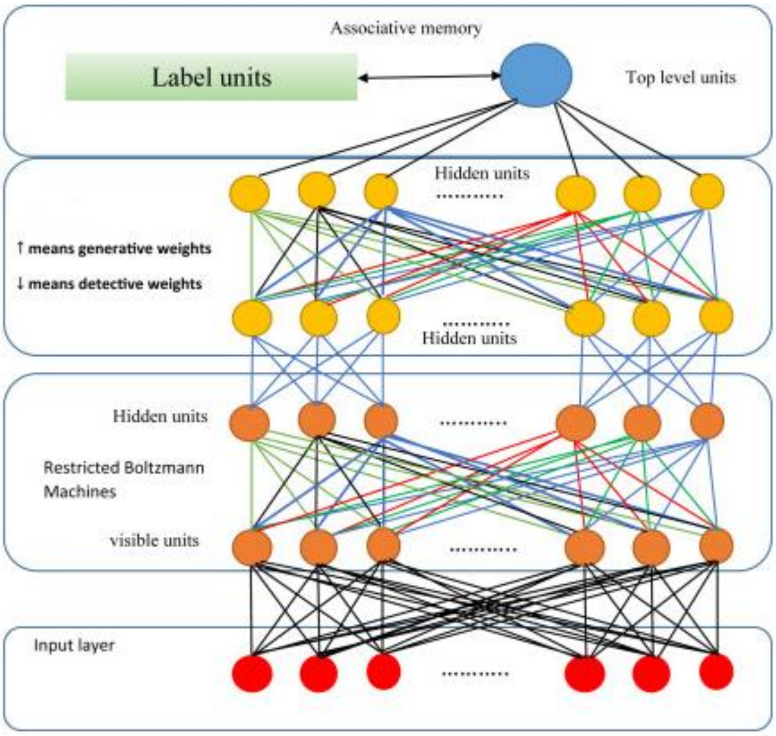


Figure Virtual Frogs Searching behaviour

$$D^r = M\ X\ (F^r_{bf} - F^r_{wf})\ \text{eq (1)}$$

$$F^{r+1}_{wf} = F^r_{wf} + D^r(D_p \geq D \geq -D_p)\text{eq (2)}$$

The new individuals $F^{r+1}_{wf}, F^{r+1}_{wf1}, F^{r+1}_{wf2} .. F^{r+1}_{wfp}$ generated by the updated process is mathematically expressed in equation. Where the moving distance of each frog is represented by D^r, M refers to the random variable whose value lies among [0..1]. The distance of leaping is among $[-D_p, Dt_p]$. After evalation of the fitness of the newly selected frog F^{t+1}_w, and if it is getter than the previous individual F^r_{wf} then the old one is repelaced by the newly seelcted individual. Other wise, F^r_{bf} will be replaced by F^r_{gb}. Still there is no progress then F^r_{wf} will be replaced in an arbitrarily by new individual. Iteratively, this is done until the desired number of subgroups is reached. Following the completion of the subgroup processing, each subgroup will be randomly sorted and then broken up again into new subgroups until the predefined termination is reached.



Architecture of DBN

In a traditional DBN, the last layer is used for variable fine-tuning to produce the desired output and erroneous derivatives from back propagations. Back propagation functions better in networks with a higher number of concealed layers for handling large amounts of incoming data. This is made possible by the existence of feature detectors in hidden layers, which are initiated by the deep belief net that creates the input data structure.

Deep belief nets can be characterized as composition of simple learning phases each of which is constrained (Restricted) Boltzmann Machine (RBM). RBM comprised of a layer with visible units and hidden units which represents data and information about features which gain high correlation in data respectively. The symmetric weights (W) is assigned to the connections among two layers using matrix formation. But there is no connection with in layer and activities of vector (v) of the visible and hidden unites are conditionally independent, so that it is very easy to sample the vector (h) from the factorial posterior distribution on hidden vectors $fpd(h|vc,Wt)$.

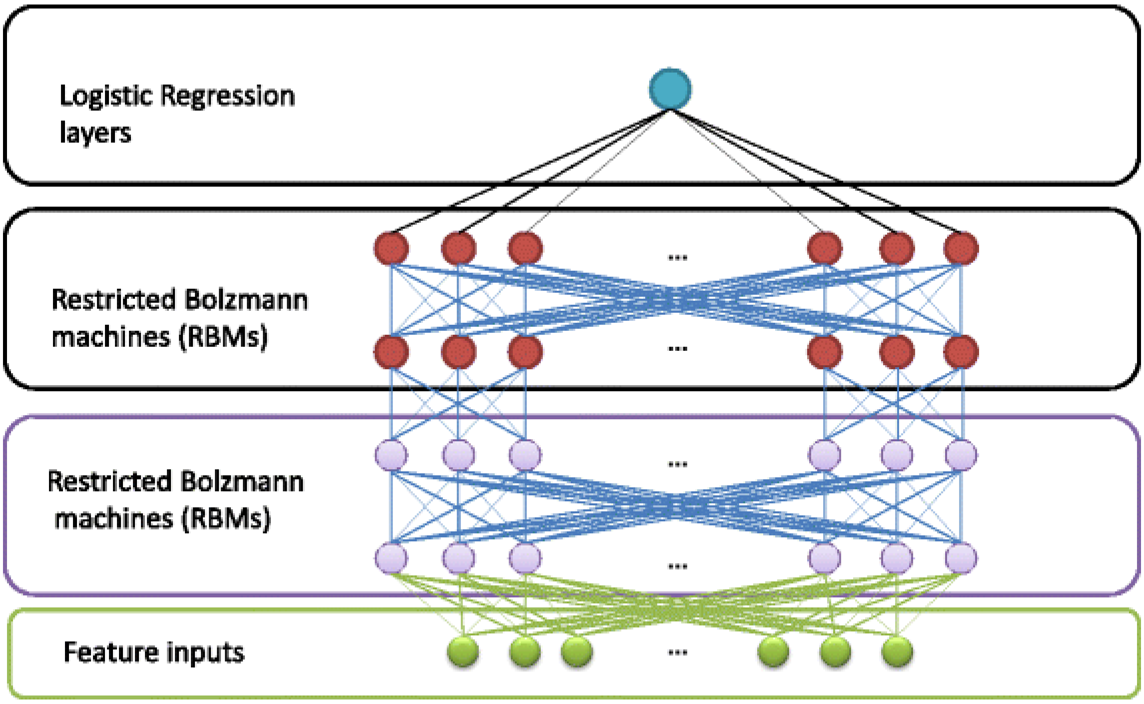


Figure Architecture of Deep belief Network with logistic regression as the topmost layer

The major concept in deep belief net is using Restricted Boltzmann machine to understand the weights that has to be assigned to the visible vectors for computation $\rho(\mathrm{v}|H, W)$ and prior distribution over hidden vectors $\rho(H|W)$. The probability of visible vectors is denoted as

$$\rho(\mathrm{v}) = \sum_{H} \rho\,(H|W)\,\rho(\mathrm{v}|H, \square)$$

The weight and the learning parameter values are evaluated using shuffled frog leaping based fitness value evaluation and the best values are assigned to them instead of performing random assignments. Hence, the problem of overfitting due to the class imbalance which affect the training phase of the deep belief network is improved by adopting the SFLA.

Experimental Results and Discussions

The evaluation of the proposed model Empowered Deep Belief Network fused with Shuffled Frog Leaping Optimization (EDBN-SFLO) is discussed in this section for predicting the autism at its early stage. The proposed work EDL-SFLO is deployed using python software. The autism dataset is collected from Kaggle repository. The performance of the proposed EDL-SFLO is compared with Artificial Neural Network (ANN), Multilayer Perceptron (MLP) and Deep Neural Network (DNN).

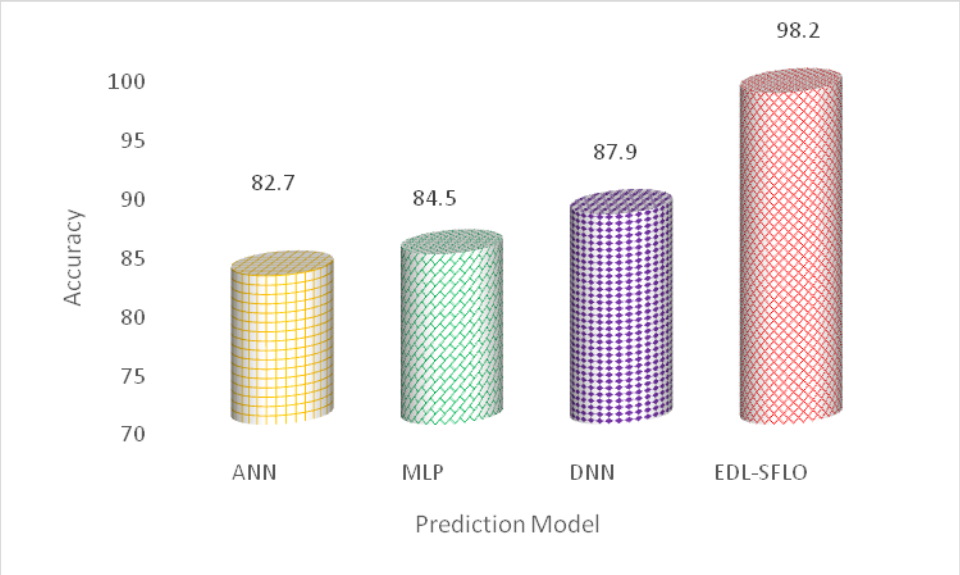


Figure: Evaluation based on Accuracy

The accuracy in prediction of autism among toddlers accomplished using four different classification models is depicted in figure.The outcome of the result revels that the proposed empowered deep learning integrated shuffled frog leap optimization (EDL-SFLO) produced highest accuracy rate of 98.2%. The other existing models produced less accuracy rate because the issue of class imbalance and overfitting problem affect their prediction accuracy, so that ANN produced 82.7%, MLP generates 84.5% and DNN achieves 87.9%.

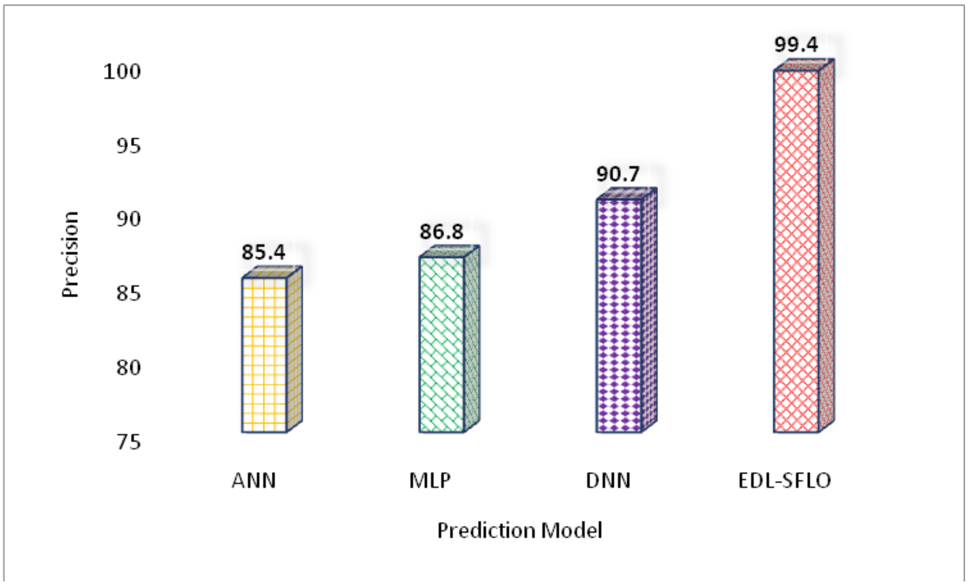


Figure: Evaluation based on Precision

The figure displays the precision rate of ANN, MLP,DNN and proposed EDL-SFLO for discovering autism children at its early stage. The EDL-SFLO understands the pattern of autism disease more precisely by finetuning hyper parameters involved in prediction process. The learning rate and weight parameter of deep neural network is updated with memetic based algorithm known as shuffled frog leap algorithm. The fitness value of SFLO is used for assigning optimal values to the hyper parameters. Hence the proposed EDL-SFLO produced highest precision rate of 99.4%, while ANN, MLP and DNNproduced 85.4%, 86.8% and 90.7% respectively.

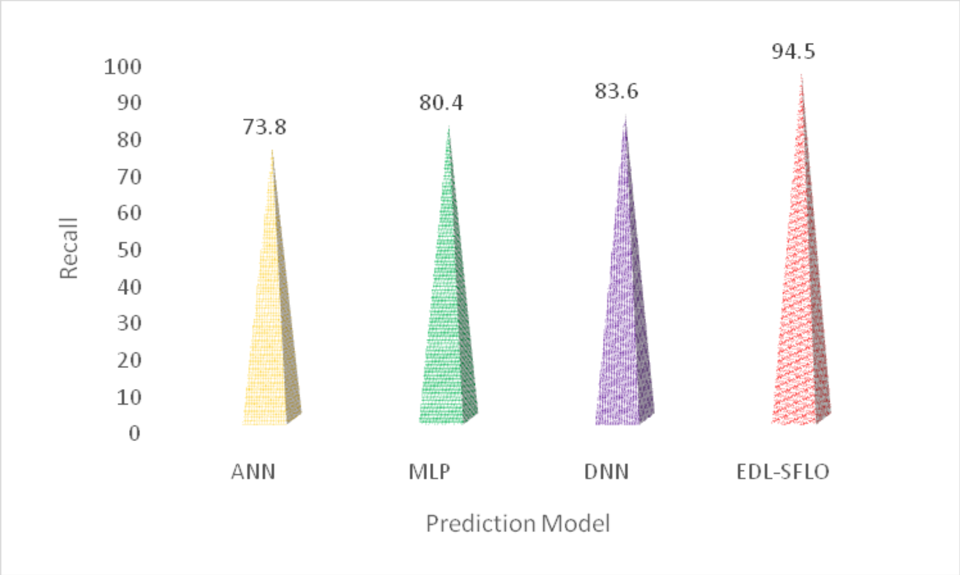


Figure:Evaluation based on Recall

The proposed EDL-SFLO with the ability of handling class imbalance during the training phase improves the recall rate in detection of autism disease. The conventional algorithms ANN, MLP and DNN assigns the values to the learning rate and the other hyperparameters like weight and bias based on gradient descent method and with trail and error. When the class distribution is not even, then during testing phase the prediction process fails to achieve their optimal level. Thus EDL-SFLO produced 94.5% as highest recall rate, the conventional ANN, MLP and DNN produced 75.8%, 80.4% and 83.6 respectively.

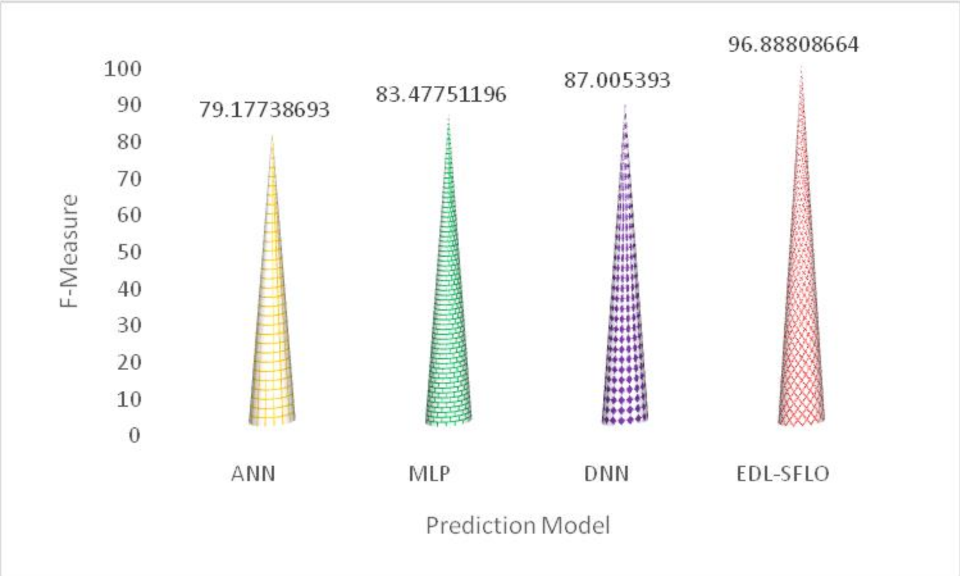


Figure:Evaluation based on F-Measure

The F-Measure shown in the figure, reflects the outcome of both precision and recall values of the four prediction models. The result provides the evidence of that proposed EDL-SFLO achieves highest f-measure rate of 96.88% , while ANN, MLP and DNN produced 79.17%, 83.47% and 87.005 respectively . The EDL-SFLO uses the knowledge of optimization problem in assigning the hyperparameter values by the memetic algorithm shuffled frog leaping optimization. The problem of overfitting and class imbalance in prediction of autism children is done effectively by the newly constructed EDL-SFLO.

3. Conclusion

The main objective of this paper, is to handle the class imbalance which causes overfitting problem in deep learning model is handed to enhance the prediction accuracy of autism among children

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