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Autism Spectrum Prognosis using Worm Optimized Extreme Learning Machine (WOEM) Technique

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***ABSTRACT* - Nowadays, exponentially increasing psychological disorder is Autism Spectrum Disorder (ASD). ASD is caused due to the improper functioning of the brain and even in the change of gene hereditary. This kind of disorder affects the interaction, communication, and learning capabilities of persons. Moreover, it was observed that ASD has a significant impact on the children than the adults. At present, this sort of autism spectrum syndrome is detected a great deal later than is conceivable. Hence early detection of Autism Spectrum Disorders is needed, which grows the overall mental health of persons. In this article, we present the new idea Worm Optimized Extreme Learning Machines (ELM) for early diagnosis of Autism Disorders. The proposed algorithm is intelligent learning algorithm that completely works on the hybrid integration of glowworm optimization and Single feed-forward extreme learning machines. The WOEM algorithm provides stable and accurate decisions in predicting autism disorders. Also, these algorithms are tested with Kaggle ASD datasets and compared with the other machine learning algorithms in which the proposed algorithm outperforms in terms of specificity, Sensitivity as well as accuracy.**

Keywords: Autism Spectrum Disorder, Worm optimized Extreme Learning Machines (WOEM), gene hereditary, Kaggle ASD.

I. INTRODUCTION

These days, babies are most usually influenced by ASD because of hereditary changes and ecological factors. ASD is described by a blend of prohibitive and monotonous practices and deficiencies in correspondence and social abilities [1]. The mental imbalance prevails in numerous forms which begin from the gentle structure to extreme structure, which relies upon the seriousness of manifestations. It is seen that mental imbalance range issue has been expanding day by day, from around 8 to 10k and 6 to 1k kids [1, 2]. Johnson et al. [3] likewise focused on the way that early identification programs are valuable for the general prosperity of a kid. As expressed previously, doctors can utilize explicit dependable and smart proper screening instruments to build the accuracy of forecast in regard to the formative status of kids. However, it may be, the use of such instruments is done by just a minority of physicians [4]. One approach to improve the exactness would be standard formative screenings for all kids [5], which may prompt exorbitant as far as accuracy and time complexity.

Hence on the other side, the intelligent expert system needs to be developed, which can be used by physicians to detect and predict children at the early stage of disorders. Hence machine learning algorithms play an essential role in designing intelligent expert systems for better accuracy, detection, and less time complexity. In this paper, we have focused on designing and implementing the hybrid integration of the Worm algorithms in ELM.

The traditional ELM is the class of NN - ("Neural Networks") which is characterized by the auto-tuning of hidden neurons. The auto-tuning property leads to the instability of the network, which results in inaccurate predictions and increases in time complexity. Hence the paper proposes the new implementation of the WORM algorithm to optimize the hidden neurons/bias weights of ELM, which then leads to stable networks with high accuracy of prediction. The WOEM works on the principle of optimizing the hidden layers and bias weights in Extreme learning machines using GLOW WORM algorithm, which in turn gives the higher order of accuracy in prediction and detection. Papers sections are arranged as follows,

Section-I details about the literature survey proposed by other authors. The preliminary view about the Extreme learning algorithms and Glowworm optimization algorithms were discussed in the Section-II. The proposed architecture has been presented in the Section-III. The dataset descriptions with result analysis were discussed in Section-IV. This framework Conclusion and future research work is given in Section V.

A. RELATED WORKS:

N.V Ganapathi Raju has suggested the application of supervised machine learning algorithms to Autism Spectrum disorder datasets. The methodology involves the reduction of the datasets by removing the outliner values. Also, the author has implemented the XGBoost classifier and Gradient Boosting Classifiers to test the datasets in which 97.1 % accuracy has been obtained as the result. Furthermore, the author has concluded the addition of a greater number of balanced datasets may increase accuracy of the classifier in predicting and classifying the above-mentioned disorders. [6].

The authors et all [7] has developed a successful autism forecast model by consolidating Random Forest Iterative Dichotomies 3 as well as Random Forest Classification & Regression Trees. This work utilized dataset which is called AQ-10 having 250 data sets taken in real time. It is gathered from lot of people without and with authentic qualities. In this methodology, prediction accuracy, reduced false rates were achieved when compared with the traditional machine learning algorithms.

Kayleigh K. Hyde gives an extensive survey of 45 papers in ASD by utilizing regulated AI. This work analyzed classification methodologies as well as text analysis methodologies. Main aim of this framework is to recognize and portray the ASD issues with the help of ML techniques. So, this will help researchers to collect the data computationally, clinically, and also from data mining techniques. [8].

Fadi Thabtah concentrated on machine learning techniques to handle ASD issues. Besides, this work demonstrated the significant advances required to guarantee the improvement of insightful diagnostic approaches dependent on AI instead of handmade principles inside ASD screening instruments with prescient model. Ultimately, the proposed work featured the earnestness of refreshing ASD screening devices to reflect changes proposed in DSM-5 manual. The scattering of the "DSM-5" requested an adjustment in manner that indicative calculation coded inside the apparatus of ASD screening acts during time spent arranging cases. Generally, there is a need to reconsider questions or highlights inside the ASD demonstrative instruments to satisfy new criteria of "DSM-5". This requires mapping new ASD criteria to the properties utilized in clinical conclusion instrument, just assessing how analytic calculation works [9].

Bram van cave Bekerom use AI to decide many conditions of ASD. The proposed method is an extraordinary for physicians to identify disease at a lot prior to the stage. This will be done through writing surveys, information investigation, and assessment. Anticipating if a youngster has autism spectrum disorder demonstrated conceivable by utilizing formative deferral, learning inability and discourse, or other language issues as properties and incorporate physical movement, birth weight as well as untimely birth in order to improve percentage of accuracy. 1 away technique also utilized for predicting ASD which gives improved accuracy of 54.1% to 90.2%. The seriousness is dependent on the caretakers of the kids, prompts the requirement for issues in future research [10].

II. PRELIMINARY VIEW

A. *EXTREME LEARNING MACHINES: AN OVERVIEW*

G.B.Huang[11] proposed the new type of learning called extreme learning machines technique, which is based on network utilization and preparing velocity, great speculation/exactness, with universal approximate capabilities, SHL – ("Single Hidden Layer")[12,13].

This network also having hidden layers, with 'L' neurons & differentiable activation function (Ex. Sigmoid Function). Hence output of ELM is straight. There is no necessary to tune HL – ("Hidden Layers") mandatorily. But these layers not to be tuned compulsorily.

Nodes of HL are arbitrarily appointed & it is not irrelevant. These nodes are not to be tuned in ELM technique and the ELM parameters haphazardly delivered in prior which means earlier to data set utilized for training.

Mathematical Model of ELM

ELM framework SHL output is as follows (equation 1)

$$Y_K(x) = \sum_{i=1}^{K} \gamma_i c_i(x) = c(x)\gamma \qquad (1)$$

Where x → input

γ → Output weight vector

$$\gamma = [\gamma_1, \gamma_2, \dots \dots \dots \dots . \gamma_K]^T \qquad (2)$$

C(x) → HL output

$$c(x) = [c_1(x), c_2(x), \dots \dots \dots \dots . . c_K(x) \qquad (3)$$

O → target vector of HL and HL is given as follows (equation 4)

$$C = \begin{bmatrix} c(x_1) \\ c(x_2) \\ \vdots \\ c(x_N) \end{bmatrix} \qquad (4)$$

ELM methodology utilized ("Minimum non-linear square") which is given as follows (equation 5).

$$\gamma' = C^* O = C^T (CC^T)^{-1} O \qquad (5)$$

Where C∗ → Moore−Penrose generalized inverse (just as inverse of C)

γ' *determined as follows*

$$\gamma' = C^T (\tfrac{1}{e} CC^T)^{-1} O \qquad (6)$$

The objective function of ELM is given below

$$\mathrm{Y}(x) = c(x)\gamma = c(x)\, C^T (\tfrac{1}{e} CC^T)^{-1} O \qquad (7)$$

FLOW-CHART of ELM:

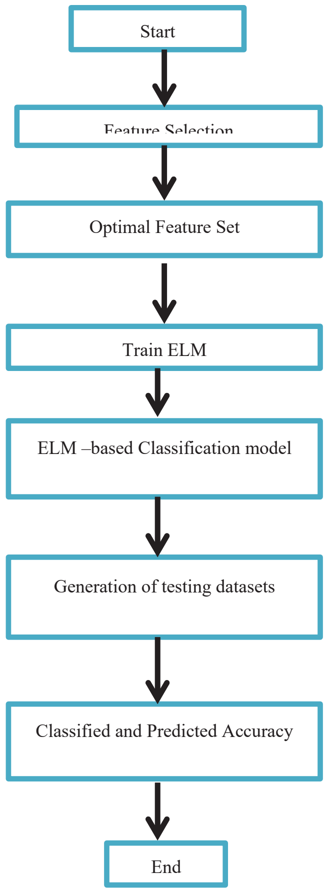


Fig.1. ELM Flow-Chart

B. *DRAWBACKS OF ELM*

Even though the Extreme learning machines prove to be efficient in both training and testing, the major disadvantage is the non-optimal tuning of input weights and biases. Also, to adjust the optimal weights, ELM uses multiple hidden layers when compared with the other conventional learning algorithms, which may affect the accuracy of detection.

In overcome the above drawback, a new Glow Worm Optimizer algorithm is used to optimize the input weights and bias factors to produce the high accuracy of classification. The significant advantages of Glow Worm Optimization algorithms are as follows as

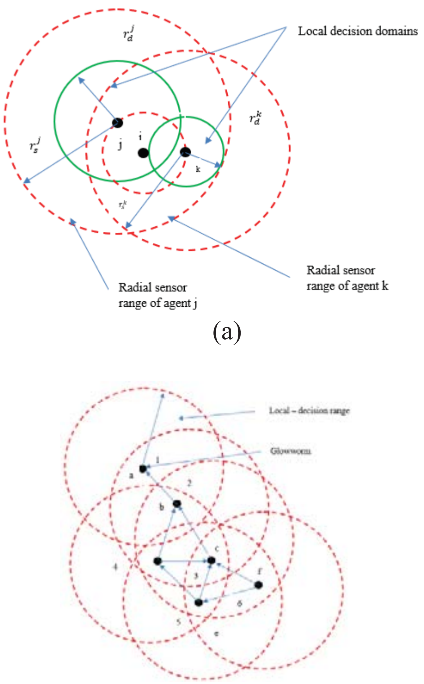
1. High Efficiency than PSO, GA and other heuristic algorithms
2. Faster and versatile search space.

The working mechanism of the Glow Worm Optimization algorithm is explained in the preceding section.

C. *GLOW WORM OPTIMIZATION ALGORITHMS*

In the glow-worm calculation, physical substances (operators) are viewed as that are arbitrarily appropriated in workspace. The operators in glow-worm calculation convey a radiance amount called Luciferin alongside them. Specialists are thought of as glow-worms that transmit a light whose force is corresponding to related Luciferin & have a variable choice ranger I, limited by a round sensor run rs (0 < ri ™ ri). Every Glow worm is pulled in by the more splendid shine of other neighbouring glow-worms. This algorithm recognizes another neighbour when it is situated inside its present nearby choice area. Operators in glow-worm calculation depend just on data accessible in neighbourhood choice range to settle on their choices (Fig. 1(a)). The subsequent calculation is profoundly de-brought together and takes into account the necessities of group mechanical frameworks. Three phases of glow-worm optimization algorithm is given below:

In this phase, glow-worms are placed randomly in the workspace and the Luciferin present equally in all glow-worms. The placement of glow-worms with equal Luciferin is shown in figure 1.



(a)

(b)

Fig.2. a) r_d^k< d(i, k) = d(i, j) <r_d^j < r_s^s < r_s^j where i → sensor range of i & j (Equidistant). b)direct graph relies on every agent Luciferin level, local information availability.

1) Updating phase

As the glowworms starts moving in the workspace, values of Luciferin are changed from its initial state. These values will change in accordance to the final positions of glowworms and as mathematically calculated as equation 3.

The Luciferin update is given as follows.

$$X_j(T+1) = (1-\tau)X_j(T) + \beta J_j(T+1) \quad (8)$$

Where

Jj(T) → objective function of agent j's location during time t.

β → Luciferin augmentation constant

τ → Luciferin decay constant (0 < τ < 1)

2) Movement-phase

In this phase, a probabilistic mechanism has been implemented for glowworm's movement so that Luciferin values updated and remains greater than the previous state value.

For most of the glowworm i, probability moves towards neighbor j and it is represented as follows

$$p_K(s) = \frac{l_j(s)-l_i(s)}{\sum_{k\in W_i(s)} l_k(s)-l_i(s)} \quad (9)$$

where, k ∈ wi(s),wi(s) = {K : di,j (s) < r_d^i(s); li(s) < lj(s)},

s → time index or step index,

di,j(s) →Euclidian distance of glowworm between i & j at time s

lj(s) → Luciferin level of glowworm j at time t,

r_d^i (s) → Variable local-decision range

rs → Luciferin sensor radial range.

Glowworm movement's discrete-time model is given as follows

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t)-x_i(t)}{\|x_j(t)-x_i(t)\|}\right) \quad (10)$$

3) Update rule for local-decision range

The local information is required to decide their movements then numbers of peaks are captured as the function of radial sensor range. Previous decision rule which used in [16] results in oscillator behavior. Hence the decision rule has been proposed and the supporting mathematical engineering has been formulated. Where β is a constant parameter.

$$Z_d^i(s+1) = \min\{Z_{s,}\max\{0, r_d^i(s) + \beta(n_t - |w_i(s)|\}\} \quad (11)$$

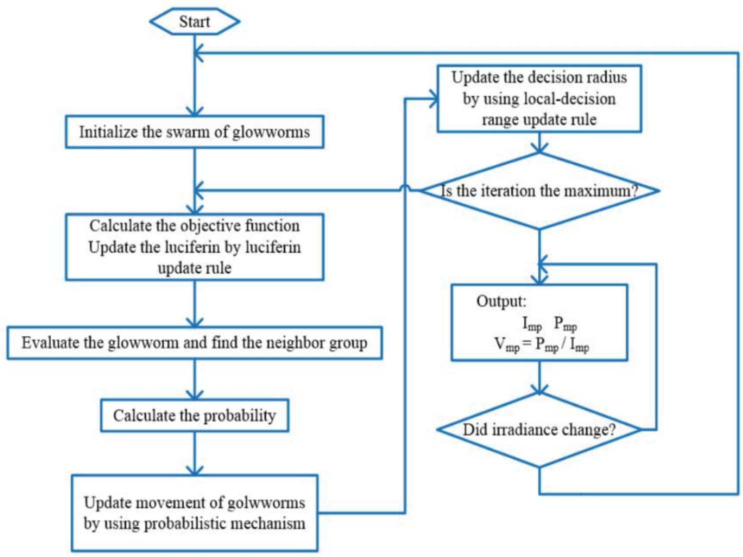


Fig.3. Flowchart of Glow-worm

III. PROPOSED ALGORITHM:

The working principle of ELM and Glowworm algorithms are discussed in the previous section. The major drawback of the ELM is the non-optimum selection of hidden neurons, which may affect the accuracy of detection. To fix this problem, we have integrated the optimization algorithm in Extreme learning Machines. The Glowworm has reduced time complexity when compared with other heuristic algorithms such as PSO, GA, and even BAT algorithms.

The proposed WOEM algorithms take the no of neurons as the initial populations, obtained lucifer function in terms of the accuracy to be obtained from the extreme learning machines. Each time, some neurons are iterated until it gives the maximum accuracy. The proposed algorithm pseudo-code is given below

Pseudo Code

/*Initialization*/

Let Pj = Glow Worm individuals , d= decision variables n-Population size(No of neurons), s-Step size

N_max= No of maximum Iteration, l0= No of lucifer (Accuracy), R0= No of radial distance

Set a,b,c and n values for optimization

Set t=0

/*Updation and Decision*/

While True :

For i=1 to n

do

loop :Randomly generate the initialize Pj, ,l0 =l0(t), R0 =R(t)

Calculate the objective function Fij

For i=1 to iter_max do

Lucifier Update phase

For each step, calculate the glow worm and glow worm neighborhood until

l0(t)= At // At = Accuracy threshold

if l0(t) < At then

go to loop

then

end

end

IV. DATASET DESCRIPTION

The proposed algorithm has been tested with the datasets which are downloaded from the kaggle websites. These datasets consist of 20 features that are more useful for the determination of important autistic traits. In order to establish better classification accuracy AQ-10adult data base has chosen and it has 10 behavioural features & individual characteristics. This dataset is proved that it suits for all ASD cases in behavioural science. The different attributes which are used in the datasets are tabulated in Table I

TABLE I. DATASET DESCRIPTION

Variable in Dataset	Description of Features
A1	Represents the Child's Attentive ness
A2	Represents Child's eye contact
A3	Denotes Child's Speech Interest about the things
A4	Denotes Child's Interest
A5	Denotes the Child's Face reaction towards the other things
A6	Denotes the Child's reaction towards Family members.
A7	Does your child show signs of to comfort them (e.g., hugging them, stroking hair)? If you or someone else in family is visibly upset?
A8	Description of Child's First word
A9	Denotes the Child's gestures

A10	Denotes the anxiety of children without any reasons.

V. RESULTS AND DISCUSSION

The proposed algorithm is implemented in the python 3.6 with Anaconda 3.vb distribution with Sci-kit machine learning packages. Also, the proposed algorithm is compared with other supervised machine learnings by measuring the following evaluation parameters

$$\text{Accuracy} = \frac{\text{DR}}{\text{TNI}}\ \text{x}100 \quad (11)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+TN}}\ \text{x}100 \quad (12)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TP+TN}}\text{x}100 \quad (13)$$

Where TP → "True Positive"

TN → "True Negative"

DR → "Detected Results"

TNI → "Total number of Iterations"

The performance of the proposed WOEM algorithms has been evaluated by different cases, which are as follows.

A. *ACCURACY EVALUATION:*

The accuracy of prediction has been evaluated based on the different neurons used for the training, which are then optimized by a glow worm algorithm. Table II shows the accuracy obtained for the different neurons for the proposed algorithms

TABLE II. ACCURACY DETERMINATION

SL.NO	No of Neurons	Accuracy of detection (%)
01	20	93.5%
02	40	94.0%
03	60	93.0%
04	80	92.0%
05	100	91.0%
06	120	94.0%
07	140	96.0%
08	160	98.0%
09	200	98.5%
10	220	99.0%
11	240	99.0%
12	260	99.0%
13	280	99.0%
14	300	99.0%

From the above table II, it is clear that Glowworm optimizes at 220 neurons for getting the highest accuracy of 99%. The proposed WOEM has also been tested with the different activation function which is tabulated in Table III

TABLE III. PROPOSED WOEM TESTING WITH DIFFERENT ACTIVATION FUNCTION AND ACCURACIES

Sl.no	No of the Neurons(optimized)	Activation Functions	Accuracy Obtained
01	220	Sigmoid	99.0%
02		Sine	96.5%
03		Tan	95.5%
04		RBF	97.5%

Table III shows the different accuracies obtained for the proposed algorithm using different activation functions in which the sigmoid function maintains the 99% for the optimized neurons by the glowworm algorithms. Besides, the accuracy of the proposed algorithm has compared with the other ML algorithms such as Single feedforward networks, SVM – ("Support vector machines"), Artificial neural networks (ANN), and KNN algorithms, and comparative analysis are shown in fig.

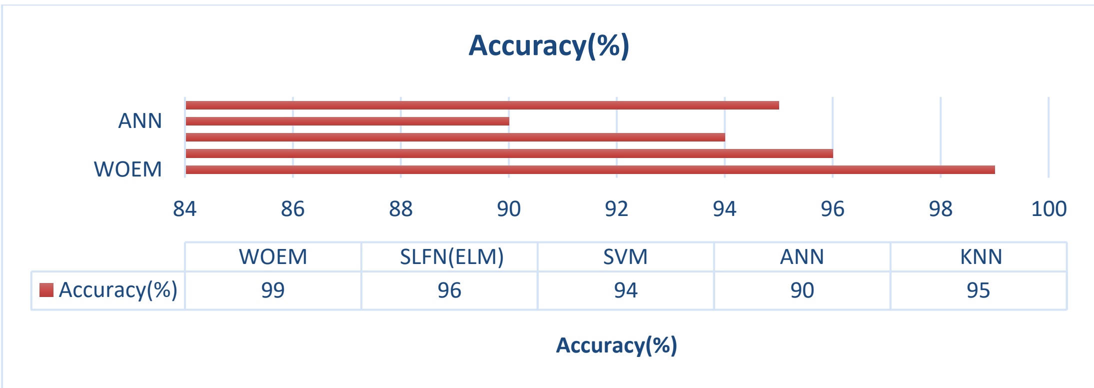


Fig.4. Prediction accuracy - WOEM algorithm Vs existing algorithms.

Fig shows the accuracy of detection for the proposed WOEM algorithm is 99% whereas the ELM without the optimizer has 96%, SVM has 94% KNN has 95%, and ANN has 90%. Moreover, Sensitivity and specificity have also been calculated by using the above equations for the proposed algorithm and other ML algorithms. Fig shows the comparison between proposed and existing algorithms.

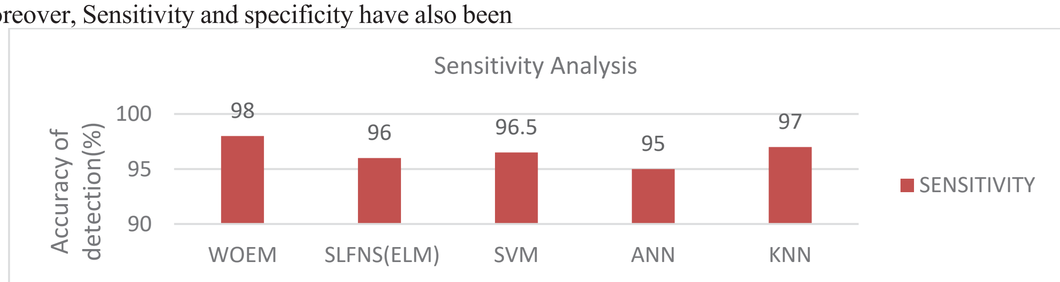


Fig.5. Sensitivity Analysis between the proposed WOEM algorithm with existing learning algorithms.

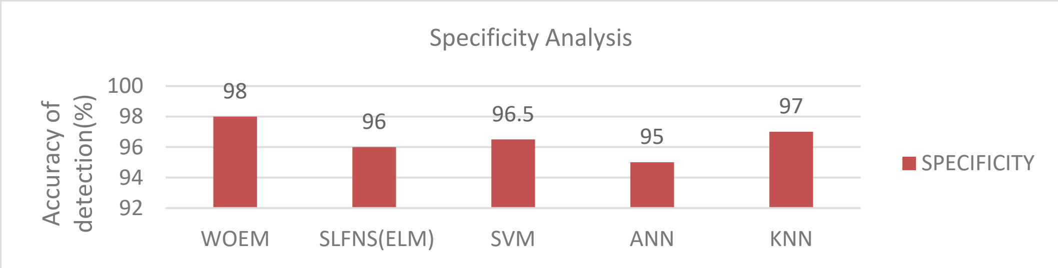


Fig.6. Specificity Analysis between the proposed WOEM algorithms with existing learning algorithms.

Fig.4 shows WOEM better accuracy of prediction, Sensitivity & specificity when compared with other ML algorithms. Also, the training and testing time has been calculated for the proposed WOEM algorithm. Fig 5 gives different training & testing time for WOEM algorithm and existing ML algorithm.

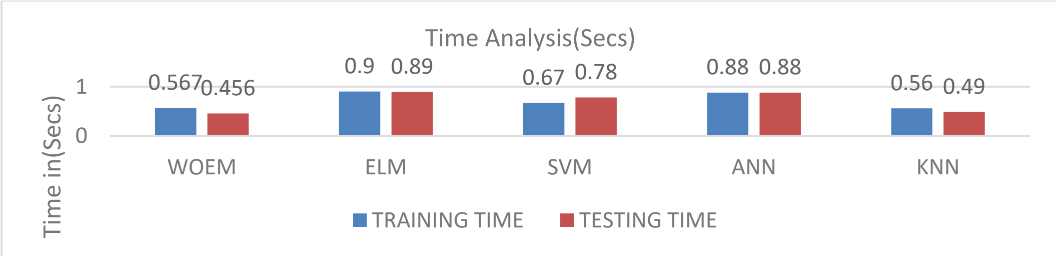


Fig.7. Time Analysis between the Proposed WOEM algorithms with other existing learning algorithms.

From the above Fig.5, the proposed algorithm and KNN has less training time and testing time, but the WOEM algorithm has outperformed KNN by 20% of total time consumption. Hence optimized WOEM has even reduced the time complexity in the prediction and detection of Autism Spectrum Disorder (ASD).

VI. CONCLUSION:

The proposed WOEM algorithm has proved to be more efficient when compared to the other existing machine learning algorithms. The proposed algorithms integrated with the glowworm optimizer has optimized the neurons for getting the better accuracy of detection /prediction when compared with the other ML algorithms. The proposed WOEM algorithm has highest accuracy of 99% when compared with the other algorithms; even the time complexity is also reduced for the glow worm optimized ELM, which is suitable for early diagnosis and treatment.

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