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Student Academic Performance Evaluation Using Efficient Spiking Neural Network

S. Muruganandam[1] , Dr. Aruchamy Rajini[2]

[1]Department of Computer Science, Hindustan College of Arts and Science, Coimbatore, Tamil Nadu, India.
[2]Department of Computer Science, Nallamuthu Gounder Mahalingam College, Pollachi, Tamil Nadu, India.

Abstract: *Education data mining allows educational organizations to operate efficiently and effectively by using information related to all its stakeholders. The study assists to build recommendation engine and alert the students in different stages. In the study, are developing a Efficient Spiking Neural Network for determining student performance. Initially, the database is obtained from the open-source system. The proposed approach is acting in systemic steps for determining the academic performance of the students while considering both classification and clustering students' data. The data is gathered based on their behaviours, academic features and demographics characteristics. Once the dataset is collected, so that initial pre-processing technique is performed, this involves the data cleansing, data reduction, data transformation and feature selection. The cleaning data is sent to the clustering method for unifying data. In the pre-processed data, game based k-means is applied. Lastly, the proposed classifier ESNN is applied for classifying the student performance. The proposed approach consists of Spiking Neural Network and Ebola Optimization Algorithm. The proposed approach is implemented in MATLAB and evaluation is done in terms of performance matrices such as accuracy, precision, recall, sensitivity, and F_Measure. The proposed approach is compared to conventional approaches such as Deep Neural Network, Adaptive Neuro Fuzzy Interference System, and Artificial Neural Network.*

Keywords: *spiking neural network, automatic student recommendation system, Ebola optimization algorithm, game-based k means clustering and demographic features.*

1. INTRODUCTION

Due to the rapid growth of the internet, online education has become one of the most favoured and widely adopted models of teaching and learning. Many universities, such as the Open University, emphasize the provision of quality online undergraduate and postgraduate courses, spanning a range of disciplines, including biology and computer-science. They also facilitate the flexible learning environment and provide resources to assist with planning and evaluating courses. The materials and technologies were used to capture and analyse student's learning activities and test performance automatically. Many applications of learning analytics could then be developed, for example, to predict students' future performance, to identify students who are likely to fail or drop out very early, and various other activities with respect to behaviour patterns. To be more precise, learning analytics is developed for validating the student performance.

One such example is student evaluation or exam score prediction which is used to predict a student's performance in a later assessment or examination [5]. This application is the most common and popular of all the applications of learning analytics [6]. The term educational data mining can be defined as the process of discovering knowledge from data focussing on large data sets, and the collective application of multiple theoretical and technological disciplines [7]. Many governments are now recommending the practice and use of EDM as well. Student modelling is the main goal of EDM, and SM focuses on uncovering the learning characteristics of students, such as support structures, behaviours, learning styles, dropout, effort level, cognitive level, and learning ability, using student models [8]. SM has become more popular due to its significance for improving teacher's teaching practice.

There are a variety of data mining approaches including K-nearest Neighbour, Naive Bayes classifier, support vector machine, decision tree and neural networks that can be used for educational data mining. Although they are all different, they can mostly be categorized as fitting either classification or clustering. While some algorithms utilize the classification approach to promote success in predicting the academic performance of students [9], whilst many other forecasting methods can produce the similar outcome via applying the clustering methodology. The current research offers a hybrid algorithm involving both classification algorithm and clustering algorithm, to for improved identification accuracy compared to the classic approaches [10]. There are classification approaches that are impacted by the training process that is improved using optimization methods. Researchers have developed optimization methods such as Genetic Algorithm and Particle Swarm Optimization, Whale Optimization Algorithm and Grey Wolf Optimization. The new optimization approaches are paired with the classification algorithm to foster student academic performance.

The key contribution of this paper will be made known as follows:

- ❖ Develop an ESNN in this paper for identifying student performance. The databases are collected from an open-source system. The proposed method is established by going through several phases to predict academic performance of the students considering the classification and clustering of student data.
- ❖ The data is collected based on their behavioural, academic and demographic features. After gathering the dataset, the processing method is used which works on data cleaning, data reduction, data transformation and data feature selection processing. The cleaning data is put to the clustering method for gathering data.
- ❖ GBK-means is used in the processed data. The proposed classifier ESNN is ultimately used for identifying student performance.
- ❖ The proposed method is an integration of EOA and SNN.

The rest of this paper will be organized in the following way, section 2 presents the related works of the research study on student performance evaluation. The proposed method defined in section 3. The results of the system for student performance in section 4. Article conclusion will be discussed in section 5.

2. LITERATURE REVIEW

Authors implement various approaches to determine student performance. A small number of works are discussed in this section. Shah Hussain et al., [11] have given a machine learning method for data mining to determine the student academic performance at an intermediate and secondary level. This study was aimed toward marks prediction and recognizing student grade using supervised machine learning methods. The validation of the mechanism was done by the board of intermediate and secondary education Peshawar, Khyber Pakhtunkhwa. This research study was intended to validate the education quality that was closely assisting to the sustainability. This system was produced so much data and needs to be validated so that a correct dataset can become apparent for educational development and planning senior management.

Xiangyu Song et al., [12] have released a sequential engagement approach for identifying predictive model. The process consists of two primary tools, the engagement detector and the sequential predictor. The sequential predictor utilizes the Long Short-Term Memory design and trains the connection from the demographic features and engagement feature spaces. The engagement detector draws on the strength of the Convolutional Neural Network to identify students' engagement patterns based on student daily behaviours. Through their integration of Deep Learning with traditional cognitive diagnostic approaches, Lina Gao et al., [13] developed a framework for deep cognitive diagnosis to determine students' mastery for gained abilities; and the problems that arose for students. Initial modelling entered the simulation of student skill competency and the responses to objective and subjective tasks aligned. Second, relevant and interacting skills considered in modelling the student's mastery of problems using Neural Networks and Attention Mechanism. Predicting student performance uses the offered model and includes the consideration that students may randomly select or throw a number, as students do.

A behaviour classification-based e-learning performance identification design offered by Feiyue Qiu et al., created the characteristics of e-learning characteristics, and combined this with characteristics data based on the behaviour classification definition to derive the class feature parameters for each kind of characteristics, followed by developing a machine-learning model for predicting learning performance. We have proposed the process-behaviour classification model for online behaviour classification because traditional e-learning characteristics classification models fails to address the learning process.

An e-Learning performance prediction through a Multi-criteria Machine Learning based Model to Predict Students Academic Performance, Myla M. Arcinas et al., EDM models are important because you are trying to predict future student performance from the behaviours of students in the past. The Educational institutes provide a variety of ways to measure the characteristics of students while they are learning via a number of ways of getting involved, to help both students and teachers improve performance, the task is to create a machine learning based approach to predict student performance. The three machine learning techniques used in the modes were Regression Analysis, ID3 and support vector machine. The experimental results have shown that the students' performance affects SVM performance.

3. PROPOSED SYSTEM MODEL

In this section, we present the proposed methodology, which incorporates the stages involved in detection of theoretical student presentation taking into consideration clustering and classification data. The overall process of the proposed method is shown in figure 1. The data is collected based on their demographic features and academic features as well as their behaviour features. After data are collected, we utilize the preprocessing technique which facilitates data transformation, data reduction, feature selection and data cleaning. After the data is cleaned, it is inputted into the clustering technique to cluster the data. The GBK-means implements on the preprocessed data.

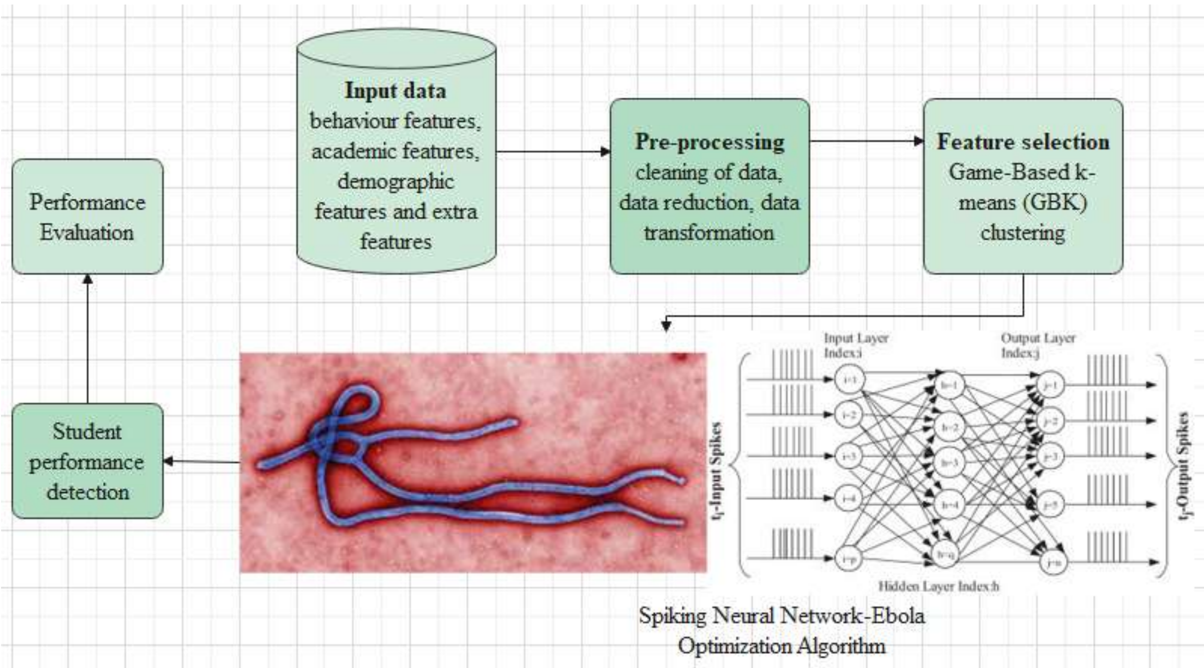

Figure 1: Proposed Architecture

Lastly, the proposed classifier ESNN is used to identify the student performance. The proposed method is an amalgamation of SNN and EOA. The details of the proposed method will be explained in the following sections.

3.1: Stage 1: Attribute data collection

The architecture of identification the student attributes with their explanation is developed. The data is collected which is related regarding the behaviour attributes and academic attributes and demographic attributes and additional attributes. The information about the attributes is shown in table 1.

Features Set	Explanation	Features
Behavioural features	Based on learning of education with the student behaviour	Discussion
		Announcement view
		Visited resources
		Raised hands
Academic features	Semester of school year	Semester
	Topic of the course	Topic
	Classroom section which the student related to	Section ID
	Grade stage of students	Grade ID
	Education phase of students	Stage ID
Demographic features	Relation	Relation who is related to students
	Place of birth	Student place of birth
	Nationality	Students' nationality
	Gender	Student gender

3.2. Stage 2: Pre-processing

In order to enhance the quality of the data set, the various pre-processing techniques are considered and implemented on the dataset collected. Data processing is presented as a necessary step in the processes of knowledge discovery which involve data transformation, data reduction, feature selection and data cleaning. The pre-processing data is referred to the clustering method for feature selection.

3.3. Stage 3: Feature selection

Clustering is an unsupervised data mining method that divides the objects into homogenous clusters regarding the similarity operation defined. In addition, the two main challenges in clustering are to determine the number of clusters and to detect complete clusters of data. In the present method, the best features are selected using GBK means clustering as a methodology. The dataset from an attribute X_I, I=1, 2,...,N is defined as features f_j,j=1, 2,..f including K clusters. Each cluster consists of a defined centre via a centroid function C_K,K=1, 2,...,K is defined as the centre of each cluster [16]. The purpose of k-means is to minimize the total of sum of squares deviations between each object and the corresponding cluster centre. Relating to this, the mathematical formulation framework is defined in the following transformation,

$$MIN \sum_{K=1}^{K} \sum_{I=1}^{N} Y_{IK}\, d(X_I, C_K) \qquad (1)$$

$$C_K\big(d(X_I, C_K)\big) = \sum_{P=1}^{P} (X_{IP} - C_{KP})^2 \qquad (2)$$

Here, $d(X_I, C_K)$ is defined as the distance function among X_I and C_K, $Y_{IK} \epsilon \{0,1\}$ is defined as the variable that is allocated 1 if entity i related to cluster K. The aim of the bargaining game is presented as follows,

$$MAX(U - U_0)(V - V_0) \qquad (3)$$

Here, it is required to describe V and U. If C_1 and C_2 can be the centres of the clusters and d_1 and d_2 can be set of distances among the centres and the associated cluster variables. $\overrightarrow{d_1}$and $\overrightarrow{d_2}$ are presented as follows,

$$\overrightarrow{d_1} = \alpha_1 MAX(d_1) + (1 - \alpha_1) mean\,(d_1) \qquad (4)$$

$$\overrightarrow{d_2} = \alpha_2 MAX(d_2) + (1 - \alpha_2) mean\,(d_2) \qquad (5)$$

$$d_1 = MIN(d_1) \qquad (6)$$

$$d_2 = MIN(d_2) \qquad (7)$$

$$U_0 = \beta_1 mean\left(\frac{1}{d_1}, \frac{1}{d_2}\right) \qquad (8)$$

$$V_0 = \beta_2 mean\left(\frac{1}{d_1}, \frac{1}{d_2}\right) \qquad (9)$$

Here, every player in its group related to manage at least $\%\beta_2$ and $\%\beta_1$of the mean inverse parameters of $d_1$and d_2, U_0 and V_0 is selected with related to $\frac{1}{d_1}, \frac{1}{d_2}$ or inverse distance managed in every player in its group as utility breakdown points. Here, V and U that can be utility operations of the initial and second players should be described on the foundation of k-means formulation. The main function of k-means is to reduce the sum of distances so the bartering utility function might be described.

$$MAX\left(\frac{1}{\overrightarrow{d_1}} - U_0\right)\left(\frac{1}{\overrightarrow{d_2}} - V_0\right) \qquad (10)$$

The rewritten target operation of the bargaining game related on k-means implies which the players with the function $\frac{1}{\overrightarrow{d_2}}$ and $\frac{1}{\overrightarrow{d_1}}$ are trying to achieve the highest number of members in their group by moving the centre of the groups.

$$MAX\left(\frac{1}{\overrightarrow{d_1}} - U_0\right)\left(\frac{1}{\overrightarrow{d_2}} - V_0\right) \qquad (11)$$

$$\frac{1}{\overrightarrow{d_1}} \geq U_0 = \beta_1 mean\left(\frac{1}{d_1}, \frac{1}{d_2}\right) \qquad (12)$$

$$\frac{1}{\overrightarrow{d_2}} \geq U_0 = \beta_2 mean\left(\frac{1}{d_1}, \frac{1}{d_2}\right) \qquad (13)$$

Hence, the normal form of the game related to the k-means fitness function is presented as follows,

$$MAX\sum_{I=1}^{N}\prod_{k=1}^{K} Y_{IK}\left(\frac{1}{\overrightarrow{d_k}} - U_{0k}\right) \qquad (14)$$

$$\frac{1}{\overrightarrow{d_k}} \geq U_{0k} = \beta_k mean\left(\frac{1}{d_1}, \dots, \frac{1}{d_k}\right) \qquad (15)$$

Here, $\overrightarrow{d_k} = \alpha\, max(d_k) + (1-\alpha)mean(d_k)$

The essential features are identified based on the clustering technique. The identified features are used to predict student performance using the database.

3.4: Stage 4: Classification of ESNN for student performance

In this stage, the ESNN is used to classify the student performance. The identified features are forwarded to the classifier to classify the student academic performance. The proposed classifier is the most widely used for classifying the academic performance of students based on their features. The proposed classifier is the merger of EOA and SNN. In the SNN, the EOA is used to determine to updating of the weighting parameter in SNN. The detail information of both SNN and EOA is demonstrated in the following section.

3.4.1. Spiking Neural Network

SNN is being used identify assessment prediction based on the features. For that particular SNN classifier, those features are sent as input signal. SNN classifier is operating in two process which are training related to a target and testing. Those selected features are trained to distinguish academic presentation of student. We take 80 % from the databases for training and 20% for testing.

In this chapter a general background of SNN is provided. A SNN design [17] contains a feedforward architecture of spiking neurons with varying delayed synaptic terminals. This neuron is specified about a single unit of a SNN and typical configurations of spiking neurons are spike response model, Hodgkin Huxley model and leaky integrate and fire model. This article utilizes the classical three-layer feedforward SNN as defined on original SRM. The connection among neuron in the proposed first and second-layer neuron and a random spiking neuron which is represented in figure 2.

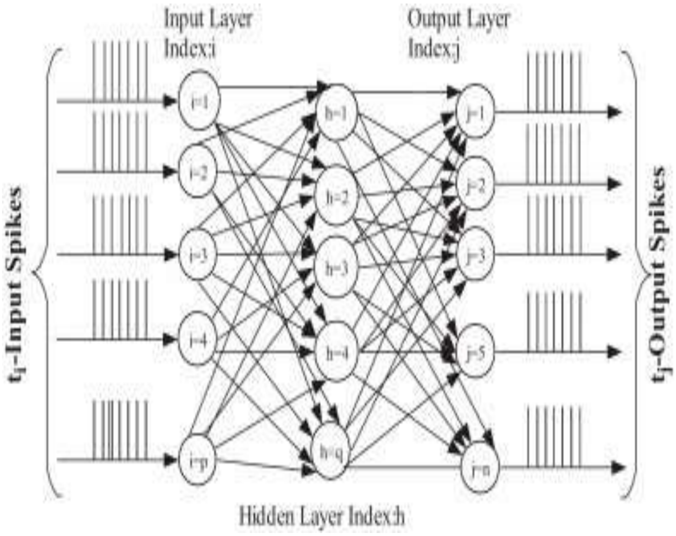

Figure 2: Connection among neuron in the successive layer and random spiking neuron

Based on the above figure, SNNs vary from traditional back propagation (BP) neural networks in that a given topology consists of a fixed number of M synaptic terminals. Each terminal acts as a sub assembly associated with a weight W_HI^K and delay function D^K. The immediate active working representation of continuous time resources in SNNs includes the temporal encoding schemes that represent the firing duration of a spiking neuron output signal in relation to the input signal instantaneously. The modalities of the many synaptic terminals, combined with the dynamic time encoding scheme, provided SNNs not only functionality and effective computing ability but also time series control in particular.

Each neuron is designed to produce at most a single spike at the representation cycle, and generally only spikes when the internal state parameter, also known as the membrane potential, exceeds the known reference θ for neuronal excitability. Regardless of representing the spike, the neuron by creating the spike produces an output signal called the post synaptic potential (PSP), which we describe with the spike response function.

$$\varepsilon(T) = \begin{cases} \frac{T}{\tau_s} e^{1-\frac{T}{\tau_s}} & T > 0 \\ 0 & T \leq 0 \end{cases} \qquad (16)$$

Where, neuron h achieves a series of spikes, τ_s is defined as membrane potential decay time constant which computes the decay time and rise period of the PSP and its firing time T_H. Hence, the normal firing time T_I^a of neuron I can be computed as follows,

$$y_H^K(T) = \varepsilon(T - T_H - D^K) \qquad (17)$$

$$X_I(T) = \sum_H \sum_{K=1}^{M} W_{HI}^K \, y_H^K(T) \qquad (18)$$

$$T_I^a : X_I(T_I^a) = \theta \; and \; \frac{dX_I(T)}{dt}\bigg|_{T=T_I^a} > 0 \qquad (19)$$

Where, W_{HI}^{K} is defined as the weight related with kth synaptic terminal, D^{K} is defined as delay related with kth synaptic terminal, $X_{I}(T)$ is defined as MP of neuron and $y_{H}^{K}(T)$ is defined as unweight influence of a single synaptic terminal to MP.

The learning algorithm executed aimed at the SNN is spike propagation that is supervised learning technique. In the SNN, the weight of the structure is attuned to reduce the learning error E for the complete network till it is within a recognized lenience. The weight adjustment is achieved with the assistance of the EOA. The three-layer feed forward SNN is computed as shadows,

1. Compute E aimed at the complete network related towards the variation among the desired firing period $\left(T_{J}^{a}\right)$ and normal spike firing period $\left(T_{J}^{d}\right)$ of complete neurons in output layer J.

$$E=\frac{1}{2}\sum_{J\epsilon j}\left(T_{J}^{a}-T_{J}^{d}\right)^{2} \qquad (20)$$

2. Compute δ_{J} for complete neurons J in output layer j.

$$\delta_{J}=\frac{\left(T_{J}^{a}-T_{J}^{d}\right)}{\sum_{I\epsilon\Gamma_{J}}\sum_{k}W_{IJ}^{K}\frac{\partial\gamma_{I}^{K}\left(T_{J}^{a}\right)}{\partial T_{J}^{a}}} \qquad (21)$$

3. Compute δ_{J} for complete neurons I in hidden layer i.

$$\delta_{I}=\frac{\sum_{I\epsilon\Gamma_{J}}\delta_{J}\left(\sum_{k}W_{IJ}^{K}\frac{\partial\gamma_{I}^{K}\left(T_{J}^{a}\right)}{\partial T_{J}^{a}}\right)}{\sum_{h\epsilon\Gamma_{I}}\sum_{k}W_{hI}^{K}\frac{\partial\gamma_{I}^{K}\left(T_{I}^{a}\right)}{\partial T_{I}^{a}}} \qquad (22)$$

Here, Γ_{I} and Γ^{I} can be set of complete presynaptic neurons and postsynaptic neurons for neuron I [18].

4. Manage the weights ΔW_{hI}^{K} and ΔW_{IJ}^{K} for hidden layer and output layer related to the network learning rate η is presented as shadows,

$$\Delta W_{IJ}^{K}=-\eta\delta_{J}\gamma_{I}^{K}\left(T_{J}^{a}\right) \qquad (23)$$

$$\Delta W_{hI}^{K}=-\eta\delta_{I}\gamma_{H}^{K}\left(T_{J}^{a}\right) \qquad (24)$$

The weight of the SNN is optimally chosen by EOA algorithm.

3.4.2. Ebola Optimization Algorithm (EOA)

In the SNN, weighting parameter is chosen with the help of EOA. The initial population of SNN is a random weighting parameter. Based on the fitness function, the optimal weighting parameter is selected which sent to the SNN for identifying the student performance from the collected database. The detail explanation of the EOA is presented in the section. This EOA is developed based on the SEIR-HDVQ (susceptible), Exposed (E), Infected (I), Recovery (R)-Hospitalized (H), Death (D), and Vaccinated (V) and Quarantine (Q) model. The formulation of the EOA is attained with below process such as initialize complete vector and scalar quantities that are parameters are individuals of SEIR-HDVQ. After that create the index instance from susceptible individuals [19]. Fix the index situation of the current optimal and global optimal and calculate the fitness parameters of the index state. The count of iterations is not achieved and here presents at least and infected separate then. This condition is managed by below formulations,

- ❖ Every susceptible individual creates and apprises their location related on their movement. Additionally, it is infected instance is displaced and high number of impurities. Hence, short displacement defined exploration or exploitation.
- ❖ Create newly infected individuals.
- ❖ Addition of newly created cases.
- ❖ Calculated the count of individuals to be added Q, V, B, R, D and H utilizing theire representative rates related on the size of I.
- ❖ Update I and S related on NI.
- ❖ Choose the present best from I and contrast it with the global best.
- ❖ The termination condition is checked.

To upgrade the positions of every exposed separate is obtainable as follows,

$$Mi_I^{T+1} = Mi_I^T + \rho m(i) \qquad (25)$$

Here, $m(i)$ is defined as the movement rate finished through individuals, Mi_I^T is distinct as original positions, Mi_I^{T+1} is defined as updated positions, ρ is described as the scale factor of displacement of a separate. The movement rate of the EOA is presented as follows,

$$m(i) = SRATE * RAND(0,1) + m(IND_{best}) \qquad (26)$$

$$m(i) = IRATE * RAND(0,1) + m(IND_{best}) \qquad (27)$$

The exploitation phase is developed related on the supposition which infected individual also presents within a distance of zero otherwise expatriate within a limit not exceptional$STATE$, here it is described as short distance movement. The exploration phase is calculated on the fact that the infected separate moves beyond the average neighbourhood time $IRATE$. In this process, the high count of individuals in S are developed to infection. The above equations are considered as the infection condition. The $IRATE$ and $SRATE$ can be managed with the consideration of neighbourhood parameter which is neighbourhood is $>= 0.5$, a specific individual is moved high the neighbourhood increasing to the high infection, otherwise it manages within the neighbourhood that curbs infection [20].

Initialization Process

Initially, the initial population is formed through random count distribution whose initial sites are measured as zero. The initial population is formed with random weighting parameter. The random weighting parameter is initialized. The individual is created based on the below equation,

$$Individual_I = l_I + RAND(0,1) * (u_I + l_I) \qquad (28)$$

Where, l_I is described as lower bounds and u_I is described as upper bounds $(I = 1,2,3,..N)$ in the population size.

Fitness evaluation

In this proposed approach, the MSE is considered a fitness function. Based on the fitness function, the weighting parameter is selected with the help of EOA.

$$FF = min(MSE) \qquad (29)$$

$$MSE = Traning\ error \qquad (30)$$

The current best is selected based on the computation of infected persons in period T which presented in below equation,

$$BestS = \begin{cases} GBest & fitness(CBest) < Fitness(GBest) \\ CBest & fitness(CBest) \geq Fitness(GBest) \end{cases} \qquad (31)$$

Here, $fitness$ is defined as objective function of MSE, $CBest$ is defined as current best solution, $GBest$ is defined as global best solution and $BestS$ is defined as best solution.

Algorithm 1: Pseudocode of EOA

Output: Optimal weighting parameter
Input: Objective function, lb, ub, epoch, population size, evdincub
$S, E, I, H, R, V, Q, Sols \leftarrow \emptyset$
$S \leftarrow Createsusceptibleindud(psize, S)$
$icase \leftarrow generatedIndexCase(S)$;
$GBEST, CBEST \leftarrow icase$
$While\ e \geq epoch\ \wedge Len(I) > 0\ do$
$Q \leftarrow RAND(0, Eq\ 38 \times i)$;
$fraci = i - q$;
For $i \leftarrow 1$ to $Len(fraci) do$
$POS_i \leftarrow movrate()$
$d_i \leftarrow RAND()$;
$Newi \leftarrow \emptyset$;
If $d_i > evdincub$ then
$neighborhood \leftarrow prob(POS_i)$;
If $neighborhood < 0.5$ then
$tmp \leftarrow RAND(0, eq\ 33 \times i \times SRATE)$
End
Else
$tmp \leftarrow RAND(0, eq\ 33 \times i \times IRATE)$
End
$Newi + \leftarrow tmp$;
End
$i + \leftarrow newi$
End
$H \leftarrow RAND(0, eq\ 34 \times i), h + \leftarrow H$;
$R \leftarrow RAND(0, eq\ 35 \times i), r + \leftarrow R$;
$V \leftarrow RAND(0, eq\ 36 \times i), v + \leftarrow V$;
$D \leftarrow RAND(0, eq\ 37 \times i), d + \leftarrow D$;
$I + \leftarrow i - Add(R, D)$;
$S + \leftarrow R$;
$S + \leftarrow D$;
$CBest = Fitness(objfunction, i)$;
$if\ GBest > GBest$ then
$GBest = CBest$;
$Sols \leftarrow GBest$;
End
End
Save the optimal weighting parameter

Updating process

Here difference $CBest$ and $GBest$ is an infected persons which are spreader and super spreader of the ebola virus. Updating process of Quarantine (Q), Funeral (F), Recovered (R), Vaccinated (V), Exposed (E), Hospitalized (H), Infected (I) and susceptible (S) is achieved based on below equations.

$$\frac{\partial S(T)}{\partial T} = \pi - \big(\beta_1 i + \beta_3 d + \beta_4 r + \beta_2 (PE)\big)S - (\tau S + \Gamma i) \tag{32}$$

$$\frac{\partial i(T)}{\partial T} = \pi - (\beta_1 i + \beta_3 d + \beta_4 r + \beta_2 (PE)\lambda)S - (\Gamma + \gamma)ii - (\tau)S \tag{33}$$

$$\frac{\partial h(T)}{\partial T} = \alpha i - (\gamma + \varpi)h \tag{34}$$

$$\frac{\partial r(T)}{\partial T} = \gamma i - \Gamma r \tag{35}$$

$$\frac{\partial v(T)}{\partial T} = \gamma i - (\mu + v)V \tag{36}$$

$$\frac{\partial d(T)}{\partial T} = (\tau S + \Gamma i) - \delta d \tag{37}$$

$$\frac{\partial q(T)}{\partial T} = \big(\pi i - (\gamma r + td)\big) - \xi q \tag{38}$$

In this study, the above equations are considered as scalar function and very contain parameter that is signified as a float. This is not far detached from few shared scalar differential equations and related F roles like exponential development of populations or money managed by scalar differential equations.

Here, calculated the rate of change of the population susceptible persons afterwards apply it to the current size of susceptible vector to achieve the count of susceptible persons at period T. This similar procedure is applied towards compute the pair of individuals in vectors Q, D, V, R, H and I. This study assumes with some initial conditions. With the assistance of the EOA, the optimal weighting parameter is selected. After that, it is sent to the SNN for identification of student academic performance. The proposed approach is utilized to identify the student performance from the collected data.

4. OUTCOME EVALUATION

The performance of the proposed approach is analysed and validated in this section. To justify the presentation of the projected technique, it is contrasted with the conventional techniques such as DNN, ANN and ANFIS. The proposed method is executed in MATLAB and evaluate the performance. The statistical measurements are utilized to analysis the proposed method such as F-measure, recall, sensitivity, specificity, precision, accuracy, NPV, FPR and ROC. To validate the presentation of the proposed apporach, the student academic data is collected from the open-source system [21]. This dataset is an educational data set that is gathered from learning management system (LMS) named as kalboard 360. The dataset contains of 175 females and 305 males. The students come from various origins like as one student from Venezuela, 4 students from Morocco, 6 students from USA, Iran and Libya, 7 students from Syria, 9 students from Egypt, 11 students from Saudi Arabia, 12 students from Tunis, 17 students from Lebanon, 22 students are from Iraq, 28 students from Palestine, 172 students are from Jordan and 179 students from Kuwait. This dataset contains a new category of features, this feature is parent parturition in the educational procedure. The implementation parameter is presented in table 1.

Table 1: Implementation parameters

S. No	Method	Description	Parameters
1	Proposed method	Learning time	5000s
2		Learning rate	10^-7
3		Contribution of the input spikes	-1.05
4		Synaptic delay	10ms
5		Upper bound for weights	-0.2
6		Lower bound for weights	0.2

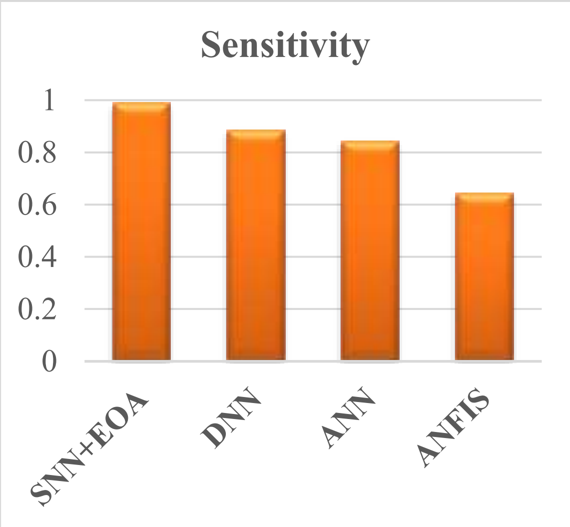

Figure 3: Sensitivity

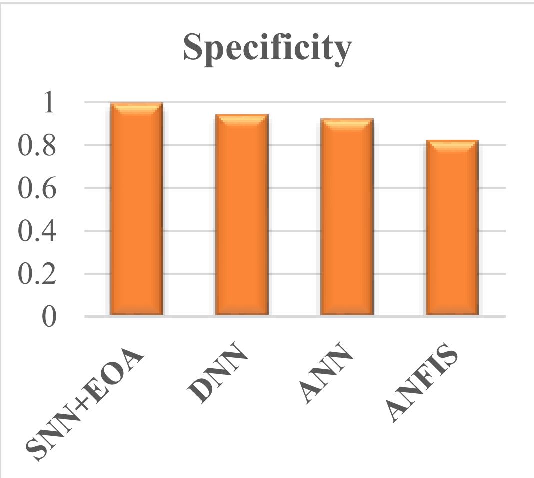

Figure 4: Specificity

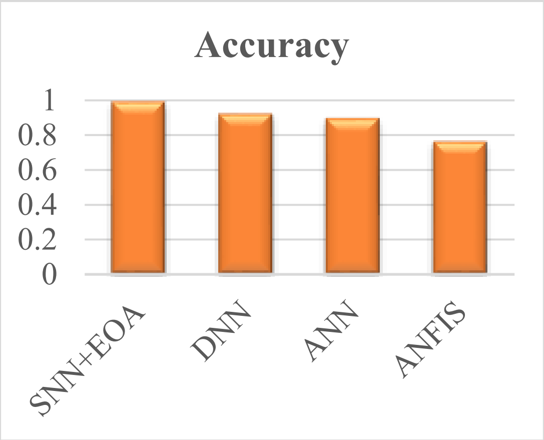

Figure 5: Accuracy

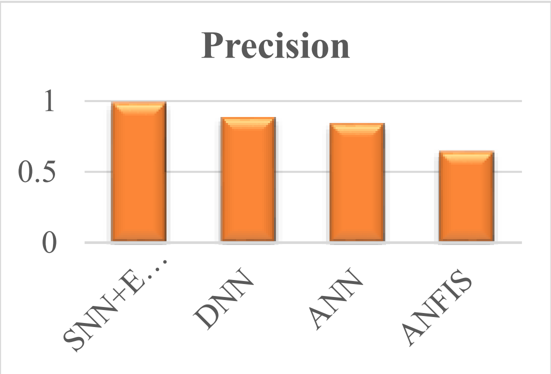

Figure 6: Precision

The proposed method is assessed in the sensitivity measure which presented in the figure 3. The proposed method is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.98 sensitivity in the student academic performance. Similarly, the traditional approaches of DNN, ANN and ANFIS are attained 0.88, 0.842 and 0.642.

Related with the validation, the projected approach is achieved the optimal parameter in terms of sensitivity. The proposed method is assessed in the specificity measure which presented in the figure 4. The proposed method is contrasted with the traditional methods like DNN, ANN and ANFIS. The proposed method is achieved the 0.994 specificity in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.94, 0.92 and 0.82. Related with the validation, the projected technique is achieved the best parameter in measure of specificity. The proposed approach is assessed in the accuracy measure which presented in the figure 5. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.99 accuracy in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.92, 0.89 and 0.76. Related with the validation, the proposed method is achieved the best parameter in terms of accuracy. The proposed method is assessed in the precision measure which presented in the figure 6. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.98 precision in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.88, 0.84 and 0.64. Related with the validation, the proposed method is achieved the best parameter in terms of precision.

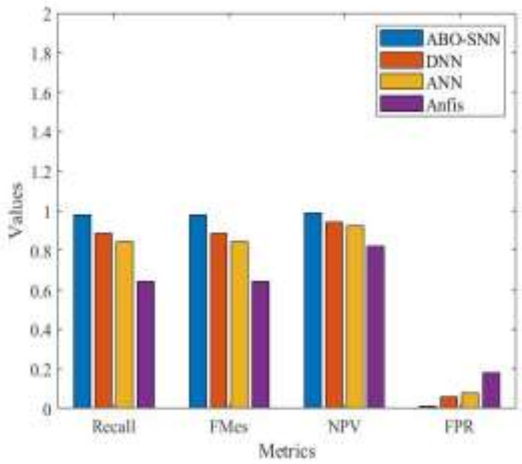

Figure 7: Recall, F-measure, NPV and FPR

The projected technique is evaluated in the recall measure which presented in the figure 7. The proposed technique is compared with the conventional techniques such as DNN, ANN and ANFIS. The proposed method is achieved the 0.98 recall in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.88, 0.84 and 0.64. Related with the validation, the proposed method is achieved the best parameter in terms of recall. The proposed method is assessed in the F-measure which presented in the figure 7. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.98 F-measure in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.88, 0.84 and 0.64. Related with the validation, the proposed method is achieved the best parameter in terms of F-measure. The proposed method is assessed in the NPV measure which presented in the figure 7. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.99 NPV in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.94, 0.92 and 0.82. Related with the validation, the proposed method is achieved the best parameter in terms of NPV. The proposed method is assessed in the FPR measure which presented in the figure 7. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.005 FPR in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.057, 0.078 and 0.178. Related with the validation, the proposed method is achieved the best parameter in terms of FPR.

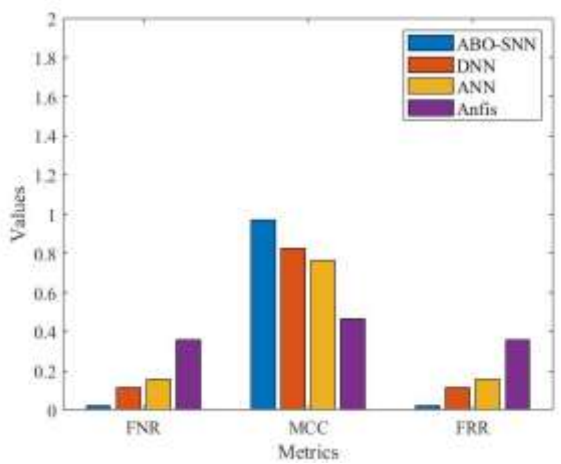

Figure 8: Analysis of FNR, MCC and FRR

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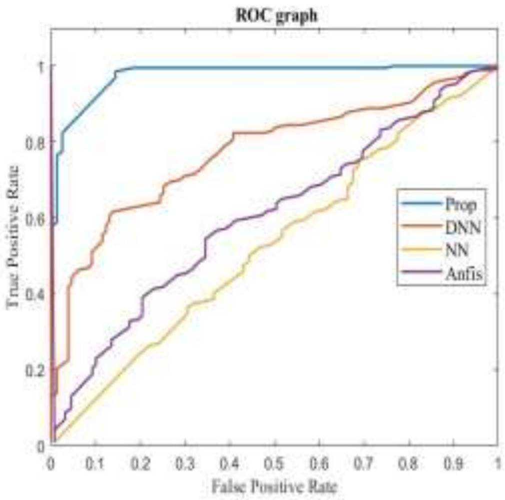

Figure 9: ROC

Table 2: Comparison Analysis

S. No	**Method**	**Accuracy**	**Precision**	**F_Measure**
1	Machine Learning [11]	**96.5**	**92.51**	**90.25**
2	Sequential Engagement [12]	91.52	91.01	88.52
3	Deep Cognitive Diagnosis [13]	90.58	95.12	86.01
4	Classification-based E-learning [14]	95.1	90.36	91.21
5	A Machine Learning Based Model [15]	97.3	89.62	95.12

The proposed method is assessed in the FNR measure which presented in the figure 8. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.010 FNR in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.115, 0.157 and 0.357. Related with the validation, the proposed method is achieved the best parameter in terms of FNR. The proposed method is assessed in the MCC measure which presented in the figure 8. The proposed technique is compared with the conventional techniques such as DNN, ANN and ANFIS. The proposed method is achieved the 0.9842 FNR in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.826, 0.763 and 0.463. Related with the validation, the proposed method is achieved the best parameter in terms of MCC. The proposed method is assessed in the FRR measure which presented in the figure 8. The proposed approach is contrasted with the traditional approaches like DNN, ANN and ANFIS. The proposed method is achieved the 0.010 FRR in the student academic performance. Similarly, the traditional methods of DNN, ANN and ANFIS are attained 0.115, 0.157 and 0.357. Related with the validation, the proposed method is achieved the best parameter in terms of FNR. The ROC characteristics of the proposed method is presented in the figure 9. The comparison analysis of the proposed method is presented in the table 2.

5. CONCLUSION

The research has been designed an ESNN for detection of student performance. Initially, the databases have been collected from the open-source system. The proposed technique has been happening with different phases for the identification of academic performance of the students with the consideration of classification and clustering student data. The data has been collected based on their behaviour features, academic features and demographic features. After collecting the dataset, the pre-processing technique has been utilized which operates the cleaning of data, data reduction, data transformation and feature selection. The cleaning data is sent to the clustering approach for gathering data. In the pre-processed data, GBK-means has been utilized. Finally, the proposed classifier ESNN has been utilized to identify the student performance. The projected approach has been a combination of SNN and EOA. The proposed methodology is executed in MATLAB and presentation is assessed with the basis of performance matrices such as accuracy, precision, recall, sensitivity and F_Measure. The projected approach is contrasted with the traditional approaches such as DNN, ANFIS and ANN. Based on the validation, the proposed method is achieved optimal outcomes in terms of statistical measurements.

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