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NEURAL NETWORK MODEL FOR DETECTION OF RESULT ANOMALIES IN HIGHER EDUCATION

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ABSTRACT

The performance of students in tertiary institutions within and outside Nigeria is based entirely on end of academic-session examination. The processes involved in carrying out semester examinations are complex and crucial in tertiary institutions and confidentiality must be ensured. Anomaly detection in result computation is an academic problem that has been well-studied within diverse research areas and application domains. The admission of students into different departments of tertiary institutions in Nigeria is increasing at a very high rate and has now reached a position where it is becoming difficult for the available manpower and the existing system to cope with the magnitude of Continue Assessments (CA) and exam irregularities in result computation. This leads to delay in approving students' semester results for decision making. In this paper, an efficient neural network model is developed to systematically detect anomalies in students' results as an effective measure which can enhance the efficiency and accuracy of student results. The designs of the was carried out using the Object Oriented and Design Methodology (OODM), simulated using MATLAB in the design, training and testing in order to detect result anomalies from the dataset. The model was successfully trained and tested with 96% level of accuracy with the proposed system dataset.

Keywords: Neural network, anomaly detection, academic results, object-oriented design, simulation

INTRODUCTION

Machine learning is a subset of artificial intelligence that uses statistical methods to help machines learn through experience by (Aderemi, & Andronicus, 2017) and (Talwar, & Kumar, 2013), where the experience gained is used to help computers perform specific tasks intelligently. Learning systems can carry out complex processes by learning from data patterns rather than following pre-programmed rules. Within the field of machine learning there have been algorithmic advancements, which provides a better machine learning power. In recent years the concept of machine learning techniques have been used in many applications domain and is a core concept for intelligent systems by (Singh, & Kaur, 2014) and (Vrat, Aggarwal, & Venkatesan. 2015). *A*s the field of computing progresses, machine learning has supported potentially transformative advances in different study areas or fields, and the social and economic opportunities that follow are very significant.

Within the Nigerian institutions, processing of students' results across tertiary institutions are largely manual in nature. These results have some form of anomalies in respect to the discrepancy that occurs between students continuous assessment (CA) and exam scores. The negative side of this is that it causes delay in computations and result approval by dedicated authorities: It is also prone to some human errors.

Examinations are one of the most important activities that take place in institutions of learning. In many tertiary institutions of higher learning series of meetings are held at the departmental, faculty and senate levels to manually examine and approve computed student examination results which comprises of assignment, course work, test or quiz score as CA and exam scores. At such board meetings, student results are checked, scrutinized, and then reasonable explanations provided for any anomaly that is detected prior to approval by (Alireza, et al. 2008) & (Aneetha, 2012). This paper intends to develop a neural network model that can detect students' result anomalies to increase the integrity of the process.

The paper is divided into sections as followings: Section II presents a brief review of some of the previous approaches to the study area and the gap in exploring the proposed model; Section III, introduces the materials and methods which the different methods adopted and materials used for developing the model; Section IV, focuses on the results and detailed discussion of results; Section V presents the conclusion.

Related Works

Despite the substantial advances made in the study of artificial neural network models in many machine learning problems, there is a relative scarcity of neural network learning approach for exam anomaly detection Hamza, et al. (2016). However, there are some research works that have direct bearing on the work presented in this paper.

Alireza, et al. (2018), carried out a study on the overview of different supervised and unsupervised anomaly detection algorithm in the detection of intruders to improve the intrusion detection system(IDS). The results of the experiment reveals that supervised learning methods were significantly better than the unsupervised if the test data contains no unknown attacks and developed a decision tree model with labeled leaf nodes containing 42 instances using the Waikato Environment for Knowledge Analysis (WEKA) as a pre-processing tool by Fujimaki, et al. (2005) and Mohammed, et al. (2019). Some important parameters of the j48 and C4.5 decision tree algorithms were changed for comparison after repeatedly running few initial experiments. The confidence level for pruning was set to 0.25 and the minimum number of instances per leaf node was fixed at 2. The dataset was randomly divided into 405 or 60% for training and 266 or 40% for testing. The challenge of this process is the use of decision tree for detecting borderline failure anomalies. It has not been able to identify any of the two anomalous cases during training which results in sensitivity value of zero. Moreover, at testing stage, sensitivity could not be computed because of biasness (systematic error) meaning that the test data was not part of their training dataset. This results to a sensitivity value of zero and there has been poor performance due to instances of borderline failure cases in the training dataset.

A futuristic approach of combining K-means and decision tree was developed by John, et al.(2017). They chose K-means clustering thereby accelerating the convergence of clusters on large datasets. The first stage of K-means clustering was performed on training instances to obtain k disjoint clusters based approach by Andrew, et al.(2011). Each k-means cluster represented a region of similar instances or data points in terms of Euclidean distances between the instances and their cluster centroids and the second stage of combining K-means and the decision tree was cascaded with the decision tree learning by building an iterative dichotomiser 3 decision tree using the instances in each input data to K-means cluster to analyze, grouped data into clusters. It has different number of clusters K_1, K_2… K_n and each cluster is having its own rules for an unknown data by which default is considered to be N (representing the number of clusters) and depends on the criteria given.

A model was developed to compared the efficiency of artificial neural networks(ANNs) and support vector machine(SVM), with the hope of providing an efficient and more accurate detection system by Jamal, et al.(2017). The mean value of their proposed model was computed from the training cycle. This produced higher performance rate with intrusion detection benchmark dataset for detecting user-to-root(U2R) and remote-to-local(R2L) attacks that affects a larger number of computers in the world Shekhar, et al. (2013). (a). User-to-root attack (U2R): the intruder have access to the target system using normal user account or valid user authentication and attempt to abuse or take advantage of the vulnerabilities of the user system in order to gain access to supper privileges Singh, et al. (2014). Attacks belong to the U2R are as follows: buffer overflow attack, load-module and rootkit etc (b). Remote-to-local(R2L) attack: The Attacker in this scenario uses existing machine vulnerabilities to access target account in which the intruder does not own the target system but access it locally by Adetunmbi, et al.(2008). Examples of R2L attacks are as followed: multi-hope, guess and password etc

Finally the result of the k-means and ID3 tree was classified as data into anomaly. The limitations in this work is that; their proposed systems cannot work well with large volume of data and any little variation in data set give rise to a different result. Ruggieri developed and presented the results of the running time behavour of the E4.5 and C4.5 decision tree models using three different strategies for detecting anomalies which highlighted some efficiency and improvements by Ruggieri, (2002). The dataset was subdivided into four categories: x_train, y_train, x_test and y_test and applied a function to perform training with entropy that fit into the decision tree to determine the accuracy level of both models. He concluded that the C4.5 tree performed better with small test and training dataset than the E4.5. A simple multi-layer neural network model comprises of two(2) inputs, eight(8) hidden, and 2 output layers was developed but unable to detect specific attacks types centred on computer networks for denial of network services by Hawkins, (2001). However, the efficiency and the accuracy of their proposed model controlled by the adjustable epochs, hidden-layers and desired error parameters.

A novel hybrid-based radial basis function (RBF) in neural network and quantum-behaved particle swarms optimization(QPSO) was proposed for network anomaly detection by Ruhui, et al.(2008). The results of QPSO produced high detection rate while maintaining a low false positive rate with some adjusted parameters compared to the RBF with lower detection and maintained false positive rate respectively. The quantum-behaved particle swarm optimization (QPSO) algorithm, which performed better than the RBF in neural network and converges faster.

The hybrid algorithm in training RBF neural network was further improved with new evolutionary algorithm, carried out based on the hybrid of quantum-behaved particle swarm optimization (QPSO) by the addition of gradient descent algorithm (GDA), employed to train the radial basis function(RBF) in neural network which increased the intelligency of the RBF model in detecting more attacks by Fujimaki, Yairi, and Machida (2005). The added GDA helped the RBF to produce a higher detection rate and maintained a low false positive rate compared to their existing model.

MATERIALS AND METHODS

In the architecture of the existing systems we were able to identify and narrow our study to CA and Exam type of anomalies in student results with a well define anomalous data boundaries after training the machine using the proposed neural network model. The experimental dataset we intend using in designing the model are promising in terms of accuracy, precision, and time complexity.

Dataset: The data used by this model is sourced from an experimental dataset generated randomly using MATLAB randomized function consist of instances that gives detailed information about student's CA and Exam scores.

In order to know the efficiency of the neural network model over the exact system solution, we intend to develop a model and compare the results with the proposed system as an approximated solution to produce better and more accurate result in avoiding truncated errors for handling problems relating to floating point values recorded as grade point(GP) in detecting result anomalies.

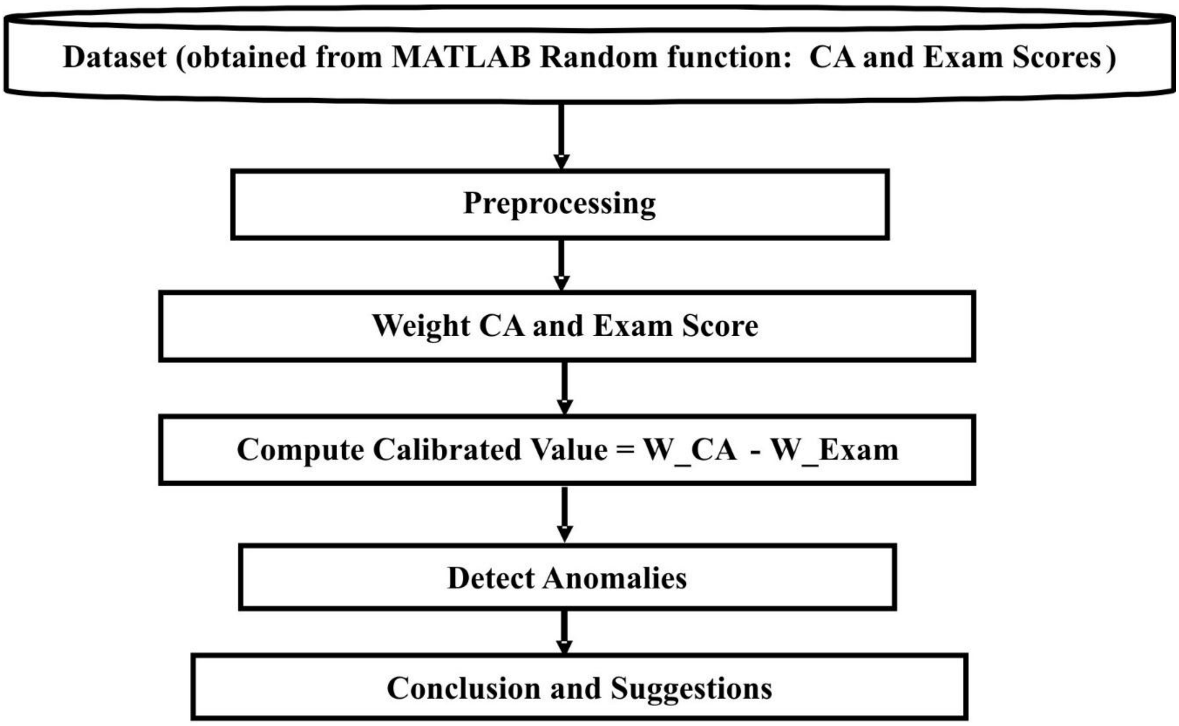

Dataset (obtained from MATLAB Random function: CA and Exam Scores)
Preprocessing
Weight CA and Exam Score
Compute Calibrated Value = W_CA - W_Exam
Detect Anomalies
Conclusion and Suggestions

Figure 1: The Architecture of the old system.

The proposed system is based on the feed-forward artificial neural network (ANN) algorithm for result anomaly detection with a weighted student's CA (WCA) as added advantage to the proposed system for detecting CA and Exam Anomalies. The neural network model is trained with a dataset for prediction using MATLAB while a database is designed for the application where the details of student's such as name, registration number, and courses offered, course codes, course titles, CA's and exam scores are stored and implemented with VB.NET for deployment. Access to the system is through user authentication, where each user is prompted to supply his/her username and password to gain access if it matches in the database to show student's CA and exam scores with the detected anomalies. Otherwise, access will be denied. The score sheets are presented and stored using a data grid view control in the form of Microsoft excels spreadsheet. The user is prompted to enter Student CA's and exam scores into the application through the result icon that pops down first and second semester score sheets. The floating point computations are done by the application from which anomalies will be detected as if found using the CA's and exam scores. The proposed system is developed to meet up with the functional (core) system requirements in order to detect irregularities imbedded in student results and non-functional requirements using machine learning technique or paradigm (neural network)

The proposed model is developed in a modular fashion with each module performing a specific task.

Algorithm of the Proposed (neural network) Model[15]

Step 1: Initialization of synaptic weights.

1.1 Pre-processing of input block with weighted CA before passing into the ANN

Step 2: Two input block pass through ANN and real output block (**O_r**) is compared to expected output block (**O_e**).

(a): If there is a total match, pattern will be successfully recognized and there is no need to change synaptic weights. If pair is the last one from the training set, then process may eventually end here.

(b): If any mismatch is discovered, Then ANN would need to be trained by learning Mechanism

(c): Define anomaly sensibility – defines the boundaries for data points

Step 3: Specific output parts which are anti-coincident define the required changes to synaptic weights according to δ rule. Weights are adjusted gradually from the output layer to the input layer. This process is entitled as a backpropagation. Algorithm continues with the step 2 until the training set is empty.

Step 4: Record the training set for patterns similar but not exactly that of the training set.

Step 5: If training process is complete; then evaluate the overall faultiness of ANN.

According to evaluation results it is determined whether the network is sufficiently trained or the whole process must be repeated in the new iteration.

a. Design of the proposed system

The design examined the architecture, synthesizes system components, modules, interfaces, and data for the system to satisfy core requirements. It is done in such a way that the system becomes interactive to the user. System design lay emphases on data structure, software architecture, procedural details (algorithms etc) and interface between the modules.

b. Methodology used in the proposed model

In this study, we adopted the Object Oriented Analysis and Design Methodology (OOADM). The object-oriented approach combines data and processes known as methods into single entities called objects. The stages for object–oriented design can be identified as: (a). Definition of the context of the system which could either be static or dynamic. (b). Designing system architecture by partitioning the system into layers and each layer is decomposed to form the subsystems.

(c). Identification of the objects in the system. The objects identified are grouped into classes. (d). Building of design models. (e).Design of object interfaces. The methodology breaks down the components of the proposed system based on the objects that surround the system and using the object components to build the new system around the identified objects. The new system will have relationships, activities and even dependences around the identified objects. Messages for the performances of any identified activity will be delivered to objects which will interact with the corresponding method to make sure that the activities are carried out within the system. When there are existing components outside of the system message can also be delivered to it to perform certain actions and return corresponding result back to the calling methods or classes. In other to achieve a well-organized system, section of activities will be categorized into classes in a way that will make each group of activities and the processes easier to implement by aneetha, et al.(2012).

c. Neural Network Model

The neural network evolves in time and operates with each of its input units in parallel, and each unit presented mathematically. A collection of interconnected units changing in time and yet operating in parallel can be referred to as an Artificial Neural Network(ANN) by Alireza, et al.(2008); Axons and Dendrites are represented by the units while a weight μ_{ij} that moderates the influence of unit j on unit i are assigned to each connection (j,i). We can now say that the ANN is a weight-directed graph where each node i is linked with a threshold value of s_i along with a transfer function f_i, in such a way that unit i will deliver an output y_i of the form by (Salima, et al.(2013).:

$y_i = f_i(u_{ij}x_j - s_i)$ ....equation(1)

Where the jth input of this unit is x_j and the sum of all its weighted CA inputs is μ_{ij} x_j. For producing the output y_i unit i is activated only if this sum is greater than the threshold s_i, if not, then unit i is considered to be in an inactive state. To produce some desired behaviour on the neural network, the parameters μ_{ij} and s_i can be adequately adjusted. To alter the expected results to meet the new requirements made to the weighted CA's and bias parameters in order to train the neural network can be trained by adjusting the weighted CA by adding input bias and output bias.

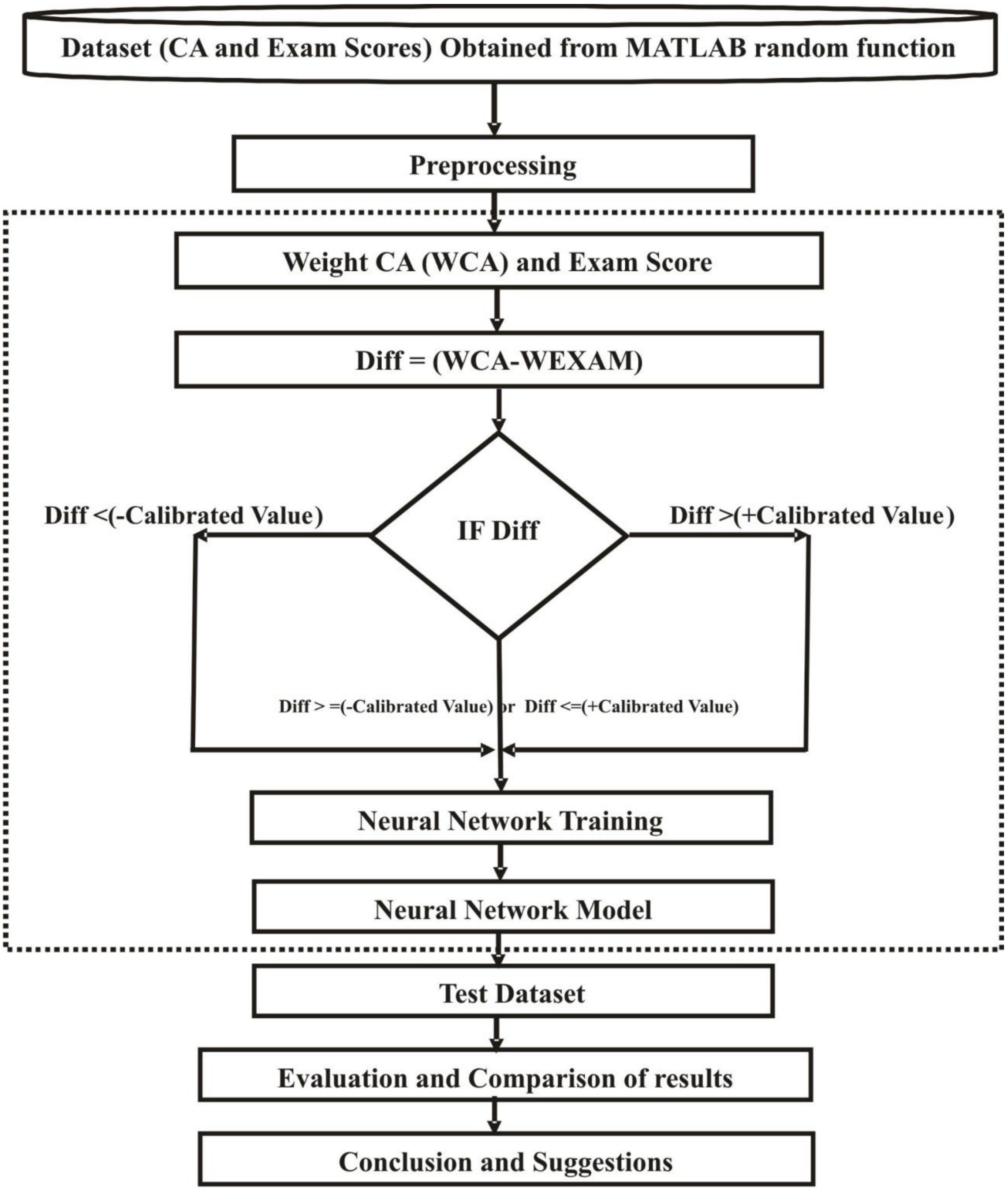

Dataset (CA and Exam Scores) Obtained from MATLAB random function
Preprocessing
Weight CA (WCA) and Exam Score
Diff = (WCA-WEXAM)
IF Diff
Diff <(-Calibrated Value)
Diff >(+Calibrated Value)
Diff > =(-Calibrated Value) or Diff <=(+Calibrated Value)
Neural Network Training
Neural Network Model
Test Dataset
Evaluation and Comparison of results
Conclusion and Suggestions

Figure 2: The Architecture of the proposed System.

d. Artificial Neural Network model for the proposed system

The neural network architecture of the proposed system is made up of two input variables(CA and exam scores), a hidden layer and the two(2) output layers(CA and exam anomalies) with a weighted CA(WCA) value to standardize abnormal data points that falls within the rejected region and normal data points that falls within the accepted region by a calibrated value which is the accepted level of anomaly been computed. The design and architecture of ANN selected for the result of anomaly detection system is based on the feed - forward neural network shown in figure 2 below as sample of neural network architecture.

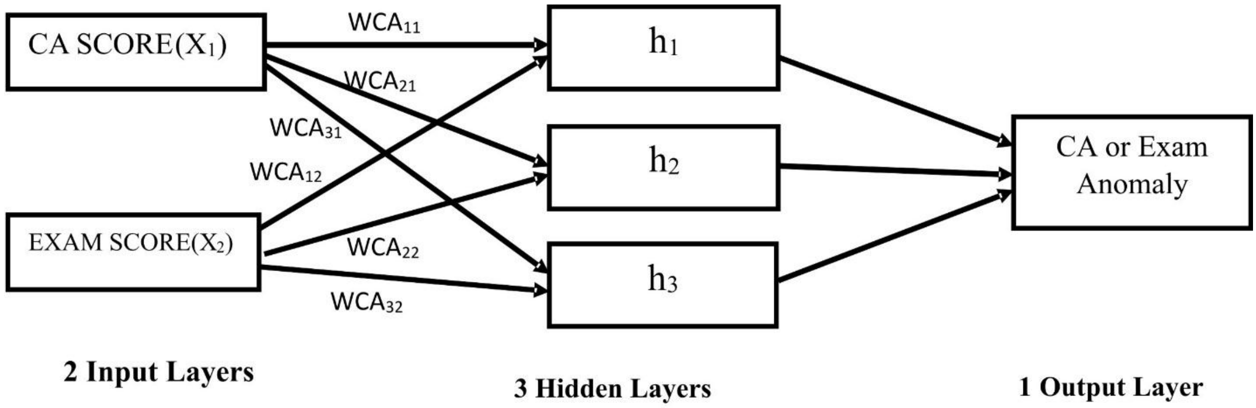


Figure 3:Neural Network representation of selected result anomalies by Alireza, et al.(2008)

The pieces that remain in between the input and the output layer of the neural network model are the hidden layers in neural network by Salima, et al. (2013). The increase in hidden layer does not affect the accuracy and efficiency of the model however depends on the complexity of the problem and its tolerant level but decreases neural network training time by Vrat, et al.(2015) and Adetunmbi, et al. (2008). The output of the input will be stored in the hidden layer and that becomes the input of the hidden layer. The output of the hidden layer becomes the input of the output layer as shown in Figure 2. The weighted matrix of the feed-forward neural network model shown in the above Figure 2 becomes.

$$\begin{bmatrix} WCA_{11} & WCA_{12} \\ WCA_{21} & WCA_{22} \\ WCA_{31} & WCA_{32} \end{bmatrix} \text{--} \qquad \text{(2) by Padhy, et al.(2012)}$$

$$h_i = WCA_{ij} I_i \text{--(3)}$$

$$\begin{array}{l} h_1 \;\; \text{-----}\!\!\rightarrow \\ h_2 \;\; \text{-----}\!\!\rightarrow \\ h_3 \;\; \text{-----}\!\!\rightarrow \end{array} \begin{bmatrix} WCA_{11} & WCA_{12} \\ WCA_{21} & WCA_{22} \\ WCA_{31} & WCA_{32} \end{bmatrix} \text{X} \begin{bmatrix} X_1 \\ \\ X_2 \end{bmatrix} \text{------------------------------------ (4)}$$

The matrix product of the weighted sum becomes

$$\begin{array}{l} h_1 \;\; \text{-----}\!\!\rightarrow \\ h_2 \;\; \text{-----}\!\!\rightarrow \\ h_3 \;\; \text{-----}\!\!\rightarrow \end{array} \begin{bmatrix} WCA_{11}X_1 & WCA_{12}X_2 \\ WCA_{21}X_1 & WCA_{22}X_2 \\ WCA_{31}X_1 & WCA_{32}X_2 \end{bmatrix} \text{---(5)}$$

The matrix product is the product of the weighted matrix and the column of the two input(CA(X_1) and Exam Score(X_2) where $h_1, h_2,$ and h_3 are the hidden layers that stores the results of the first phase $X_1$and X_2 are the input variables as a single column.

$$h_i = WCA_{ij} B_i \text{--- (6)}$$

Where B_i is the bias added to the result of the hidden layer by Peddabachigari, (2007)

$$\begin{bmatrix} WCA_{11}X_1 & WCA_{12}X_2 \\ WCA_{21}X_1 & WCA_{22}X_2 \\ WCA_{31}X_1 & WCA_{32}X_2 \end{bmatrix} + \begin{bmatrix} b_1 \\ \\ b_2 \end{bmatrix} \text{--(7)}$$

$h_i = \sigma\ (WCA_{ij}I_i + B_i)$ --- (8)

Where σ is the sigmoid function

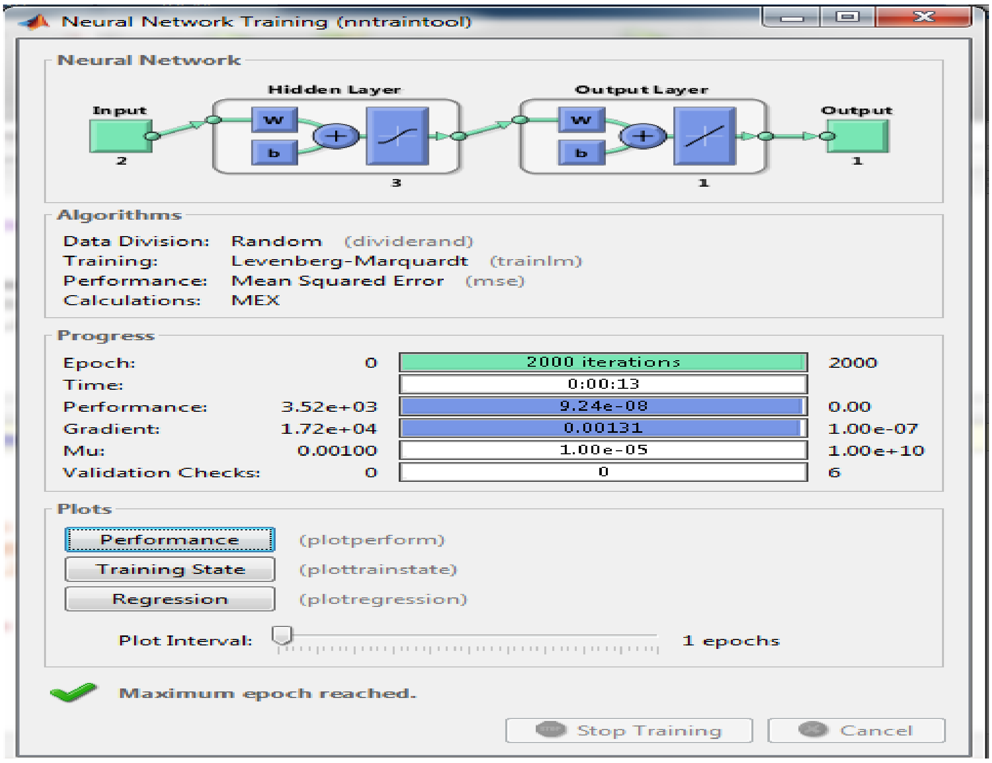
$\text{Output}(O) = \sigma\ \left(WCA_{ij}I_i + B^0\right)$------------------------------------ (9) by Ruhui, (2008)

RESULTS AND DISCUSSION

The discussion about the methods adopted and the results obtained are here presented.

a. The dataset

The data used in the model is sourced from an experimental dataset generated randomly in MATLAB using the randomized function consist of instances that gives detailed information of student's weighted CA and Exam scores, and every data that flow through the input layers of the neural network model has different weighted CA and Exam scores up to 1300.



Algorithms

Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MEX

Progress

```
Epoch:                 0      2000 iterations    2000
Time:                            0:00:13
Performance:    3.52e+03        9.24e-08         0.00
Gradient:       1.72e+04        0.00131          1.00e-07
Mu:              0.00100        1.00e-05         1.00e+10
Validation Checks:     0           0             6
```

Plots

Performance (plotperform)
Training State (plottrainstate)
Regression (plotregression)

Plot Interval: 1 epochs

✓ Maximum epoch reached.

Figure 4: The MATLAB IDE showing Graphic user interface

Figure 4 shows the MATLAB graphic user interface of the neural network with two(2) input layer that accepts weighted CA and exam scores, three hidden layers, one output layer with a progressive bar indicating the number of iterations (Epoch) that runs from 0 to 2000 iterations, time, performance, Gradient, Mu and validation check respectively at the time of training the network model.

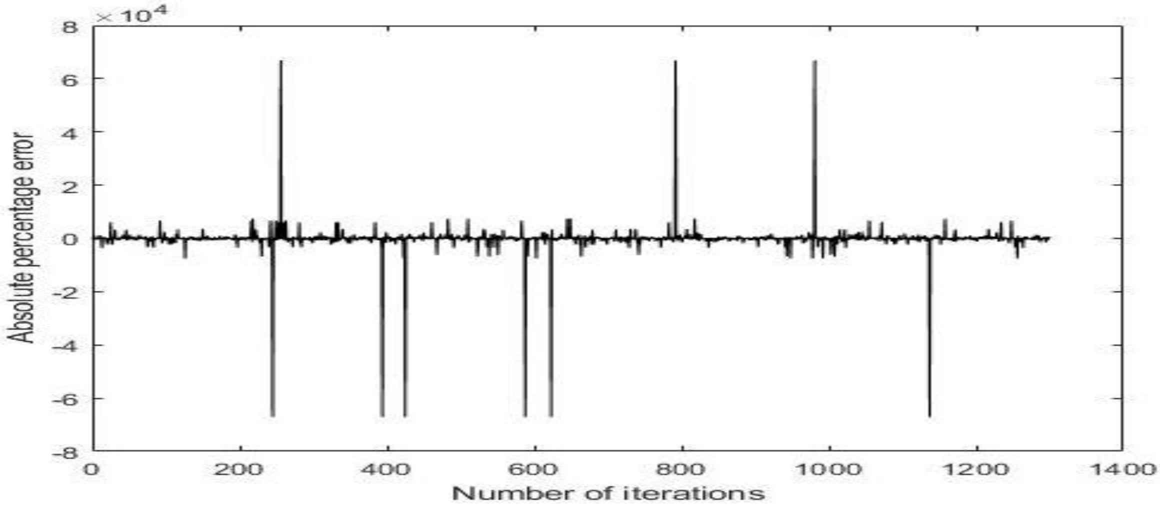


Figure 5: Graph of absolute Percentage error

Figure 5 shows the graph of vertical axis (absolute percentage error) against the horizontal axis (number of iterations) from the figure 4 displaying the convergences of different data points; just few points falls far and out from the points of convergences(zero point or plane) during training stage shown in the above chart.

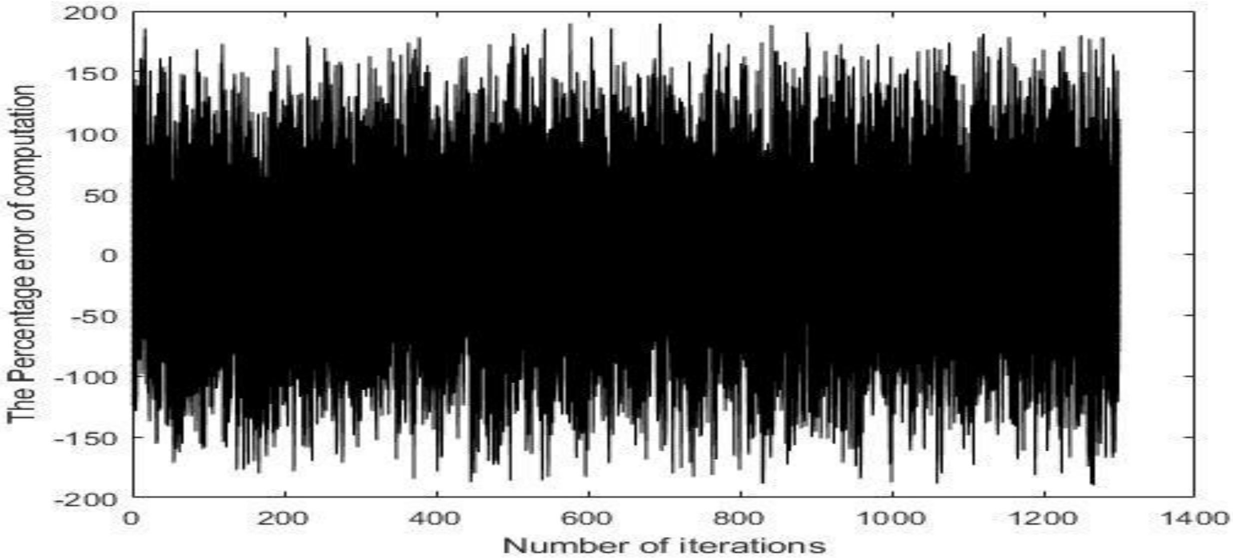


Figure 6: The graph of percentage error in computation

Figure 6 shows the neural network graph of percentage error of computation represented at the vertical axis against the number of iterations represented at the horizontal axis. The density of converging points ranges fall within 100, 50, 0, -50 and -100 at the vertical axis(the percentage error of computation) while the horizontal axis representing the number of epochs or iterations ranges from 0 to 1,400 but the density of points clusters within 0 to 1,300 with some few point falling outside the required margin (accuracy level) of computation greater than +100, 150 and 200 or less than -100, -150 to -200 at the horizontal axis.

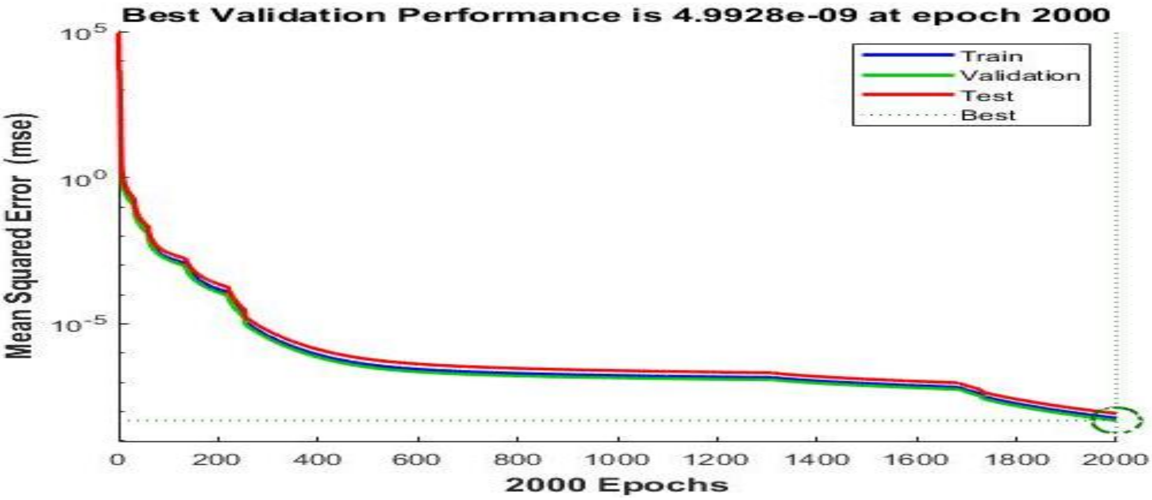


Figure 7: Neural Network Training Performance plot

Figure 7 shows the performance from a confusion matrix demonstrating the decreases in errors of training, validation, testing stages and terminates at its tolerance level within the iterations to match the best possible solution in terms of accuracy for the final trained neural network model for detection of CA and exam anomalies which demonstrates the training, validation and testing errors all decreases until iteration 2000 to match the best solution. From the test it does not appear that any over-fitting and under-fitting has occurred, since testing, validation and training errors decreases before iteration 2000 and produced the target exactly at 2000 epochs respectively. The test coincide with the best solution at exactly 2000 epochs or iterations been circled with green colored circle in the legend which falls within its tolerance level as valid test shown in figure 6 above. The machine was able to learn and produced the exact solution with high accuracy level at 2 place of decimal with best validation performance value of 4.9928e-09 at epoch 2000.

Table 1: The Processed Data

S/N	WCA	CA	WEXAM	EX	ADFF	MDFF	ANOMALY
1	3	1	31	22	28	28.428	CA_anomaly
2	27	8	19	13	8	8.4284	Exam_anomaly
3	57	17	7	5	50	49.857	Exam_anomaly
4	30	9	61	43	31	31.428	CA_anomaly
5	67	20	100	70	33	33	CA_anomaly
...	....	...	...	...	...	...	...
2299	13	4	31	22	18	18.429	CA_anomaly
2300	70	21	86	60	16	15.714	CA_anomaly

By comparing what the machine leant and produced as the difference gotten from the weighted CA(W_CA) and the exam(W_Exam) scores as the predicted difference (PDFF) and the exact or actual difference(ADIFF or Exact difference) between the existing and new system revealed that; the proposed model produced the same result as the exact solution in two places of decimal(2pd) in terms of accuracy and precision. In the first row of the of figure 5 displayed 28 as the exact value gotten from the difference between the weighted CA and exam and 28.428 as the neural network predicted value with an error value of 0.428, row two 8 as the exact difference and 8.4284 as the predicted value with an error value 0.4284 to produce the exact value at two place of decimal, third row 50 as the exact value and 49.857 as the predicted neural network value etc.

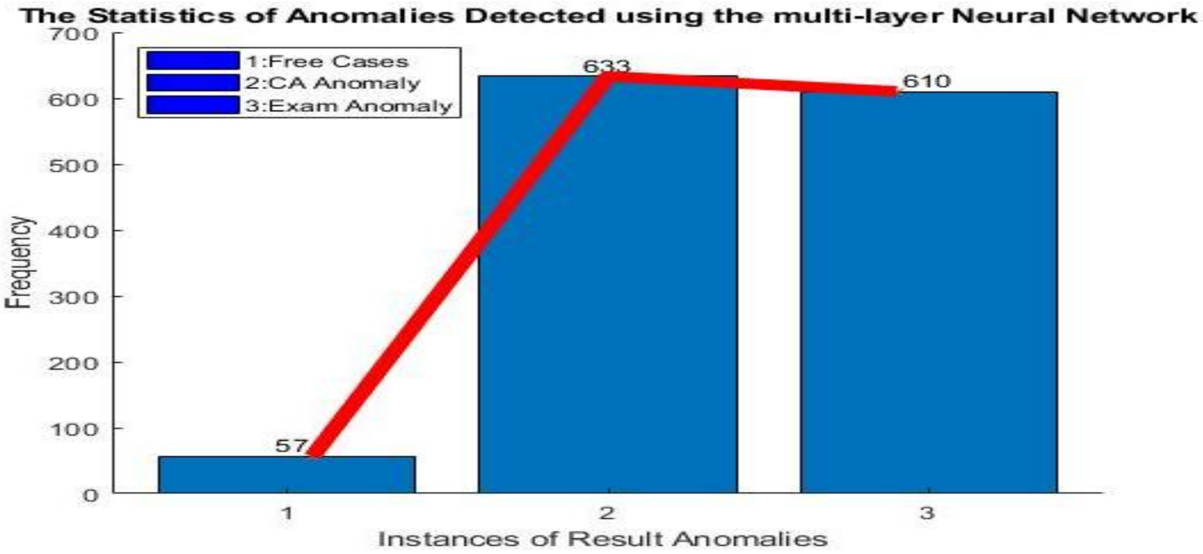


Figure 7: The Statistics of anomaly detected by the proposed model(Neural network model)

In testing the neural network for detection of result anomalies (NNMDRA) system; using one thousand three hundred different dataset contain weighted CA and exam scores generated from MATLAB random function and the results paired suitable with the expected anomalies of the NNMDRA detected CA and exam anomalies as recorded and free cases of irregularities recorded in situations where there are no CA or exam anomalies.

The accuracy of the proposed model refers to the proportion of correct classifications (True positives and negatives) from the overall number of cases using MATLAB function given below in the equation as:

$$\text{Accuracy}=\frac{\text{total number of correct classification}}{\text{total number of cases}}=\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad \text{------------------------(10)}$$

Where TN represents true negative=633, FP is false positive=76, TP is True positive=610, FN is false negative=19 cases and produced 96% level of accuracy.

CONCLUSION

The existing method of operation in most organization has proved to be highly ineffective in organizations that deal with result anomaly detection system and maintained fast, effective, reliable and accurate result with the proposed method. Most of the shortcomings of the existing system are corrected by the new system. From the above analysis, we conclude that the proposed system with the aid of neural network feed-forward machine learning algorithm is much better than the existing method (system).

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