SE-Net based DBN Network model using AHP Method for Analysis of Student Performance of Outcome Based Education

Dr. R. Hemalatha [1] , M.V.Sethuramalingam[2]

[1]Associate Professor and Head, PG & Research Department of Computer Science, Tiruppur Kumaran College for Women, Tirupur 1

[2]Research Scholar, PG & Research Department of Computer Science, Tiruppur, Kumaran College for Women

Abstract

Automatic Student performance prediction is a very decisive and imperative work since we have to handle large volume of data in educational databases. This job is being addressed by educational data mining (EDM). EDM enlarges the scheme of determining of the data that is obtained from educational environment. The educational institutions are often curious that how many students will be pass/fail for necessary arrangements. In review of literature, it has been observed that many researchers have intension on the selection of appropriate algorithm for just classification and ignores the solutions of the problems which comes during data mining phases such as data high dimensionality, class imbalance and classification error etc. Such types of problems reduced the accuracy of the model. Several well-known classification algorithms are applied in this domain but this proposed work, a student performance prediction model based on SE-Net based DBN Neural network model using AHP Method of Deep learning model using OBE framework. In addition, Deep learning based neural method is applied to improve the performance of the classifier. This study proves the significance of data preprocessing that leads to crack the data quality issues. In the era of educational evolution, traditional education system is mislaying its applicability. In modern world, everything changes very rapidly and continuously. More skills are required for Quality of Education with very fast developing technology. The educational institutions should produce graduates to cope with technological development. To face the future challenges, it is mandatory to shift from traditional education system to Outcome Based Education (OBE), which includes Program Educational Objectives (PEO), OBE based curriculum development, teaching learning process assessment. The major buzzwords of OBE are PEO, PO, PSO and CO. This study result shows the need of OBE in modern education system to achieve the expected outcomes. The main objective of the paper is to analyze the students' performance based on the Outcome Based Education with respective program educational objectives and outcomes.

I. INTRODUCTION

OBE is the education theory that bases each part of an educational system around outcome. Each student should have achieved the outcome by the end of the educational experience. In context to teaching learning process the objectives describe what is expected of the teacher who delivers the course within a time frame and available resources. Objectives state the purposes of the course and focus on content and skills important within the classroom or program. The objectives are generally specified on the basis of the topics that are being covered in the course. These can be thought of the expected results after an activity is performed in the class. Outcomes are the measurable evidence of achievements of the objectives. For example, an objective may be "to make students competent to solve the complex problems". But the outcome of the objective is "students are able to solve complex problem". We can measure this outcome using any suitable assessment method; may it be examination, some project, case study etc. The evaluation may result in the level of attainment of the outcome. Medium level attainment may reflect the student may be able to apply the knowledge to solve some average level of problems not the complex problems.

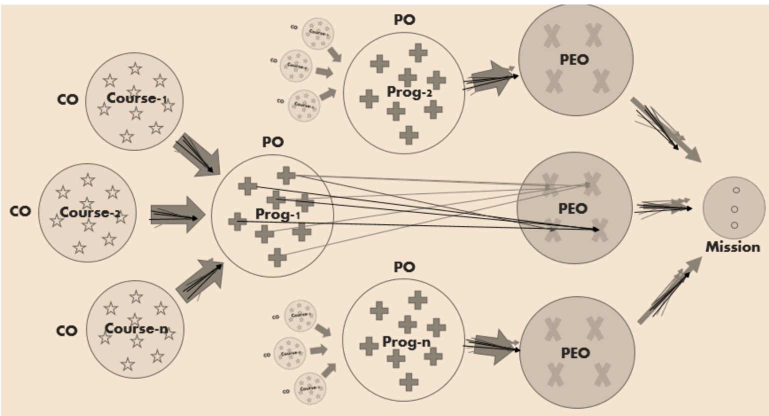

Figure -1 Frame work for OBE Attainment

Performance Indicators (PIs) are to be designed as the explicit statements of expectations of the student learning so that these can be used to measure the extent of attainment of outcomes. The figure 2 describe how the OBE attainment is processed.

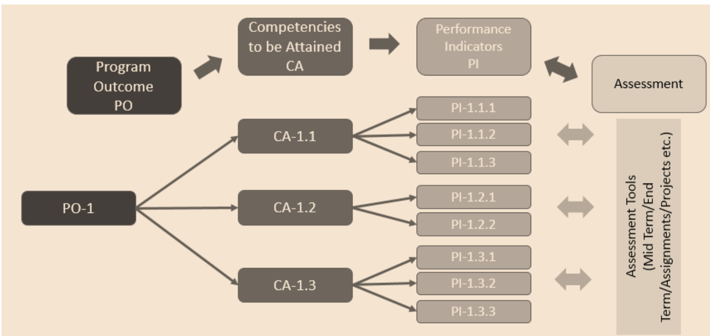

Figure-2 Evaluation of Performance Indicators

The attainment of COs is evaluated through direct and indirect methods. The direct method includes the continuous and terminal assessments. The indirect method includes the student's feedback on the basis of the COs. The same assessment methods (direct and indirect) are used for evaluating the attainment of Pos.

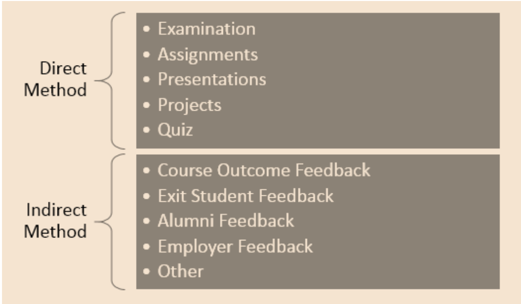

Figure-3 Various Methods of OBE

Rubrics are tools for grading the student's performance and learning for a set of criteria and objectives. Performances criteria are expectation are possible achievements of the students rubric should be communicated to the students.

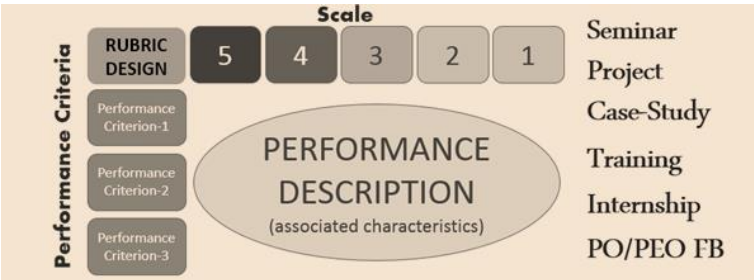

Figure -4 Performance criteria

II. METHODOLOGY

In this section, we will describe the algorithms that are referred in this paper including SE-Net based DBN network model based ranking approach. Predictive and comparative analysis of the student's performance based on academic and personal behavioral dataset using deep learning algorithm and determine most accurate algorithm. The Figure 5 illustrates the proposed architecture. The student dataset would be consisting of academic information and personal information (characteristics of students). The different machine learning algorithm would be applied for predictive and comparative analysis of student's performance. The predictive analysis would be resulted as a prediction of SPI and behavioral analysis which will be (the prediction of most significant personal characteristics which impacts on the marks). The comparative analysis would carry the best accurate machine learning algorithm among all. For the experimental purpose of data analysis, following five objectives are selected. (1) Find the frequent subjects which are the causes of low academic performance, (2) Discriminate the marks of at risk students, (3) Prediction of the result and comparative analysis of algorithms for accurate prediction, (4) Comparison between learning management system with Adaptive approach, (5) Analysis of Quality of Education using student's feedback.

a) Dataset Description and procedure

For experimental purpose, the dataset of the students is used. The first and the fourth objectives use the categorical dataset while second, third and fifth objectives use the numeric dataset, assuming no missing values in each dataset. For 1st objective, the dataset incorporates the four attributes i.e., Name, Maths, science, English.

This dataset holds the information about pass or fail (i.e. Categorical attributes) in maths, science and English. So here the intention is to find out which two subjects together are the causes of failure out of three subjects. For 2nd objective, the student dataset comprises the five attributes which are id, maths, science, English and total. All the records contain numeric values. Maths, science and English contain the scores out of 100 and total contains the marks out of 300 which is total of three subjects. For 3rd objective, the dataset contains the training and test data. Training data contains five attributes id and 1st, 2nd, 3rd and 4th semester SPI and test data contains the four attribute id, 1st, 2nd and 3rd semester SPI. Here 4th semester SPI in training data is actual value, and we will predict 4th semester SPI from test data to determine the accuracy of the algorithm. In the 4th objective there are two datasets i.e. LMS dataset and Adaptive LMS dataset

Table 1 illustrates the dataset of LMS. LMS contains the four attributes: Name (X, Y, Z), Subjects (Maths, Science, English), Level (advance, average, poor) Result (pass, fail). For example, If X knows the advance level of maths then X always passes. As per the dataset if any of the student knows advance level of subjects then they will pass the exams and if they have average or poor knowledge then they will fail.

Table 1 LMS Dataset

Name	Subjects	level	Results
X	Maths	Advance	Pass
Y	Science	Average	Fail
Z	English	Poor	Fail
X	Maths	Average	Fail
Y	Science	Advance	Pass
Z	English	Poor	Fail
X	Maths	Poor	Fail
Y	Science	Average	Fail
Z	English	Advance	Pass

For 5th objective, using feedback for the teachers from the students. There are five attributes: Id, Knowledge, Cooperation, Delivery, and Responsiveness which contain the student’s rating out of 10.

b) Data Collection

For experimental purpose, the dataset of the students is used. The numeric datasets are created with the help of three different sources. The first source of this research work is internal score. Internal consists of Course framework with course outcome and program outcome mapping and Internal score data from respective course teachers like continuous internal assessments, assignments, extra-curricular activity, online tests, practical, seminar, etc. Second, External assessment data will be collected from the Controller of the examinations. Finally, Survey & Feedback was collected from outgoing students and feedback will be collected from alumnus and employers.

c) System Architecture

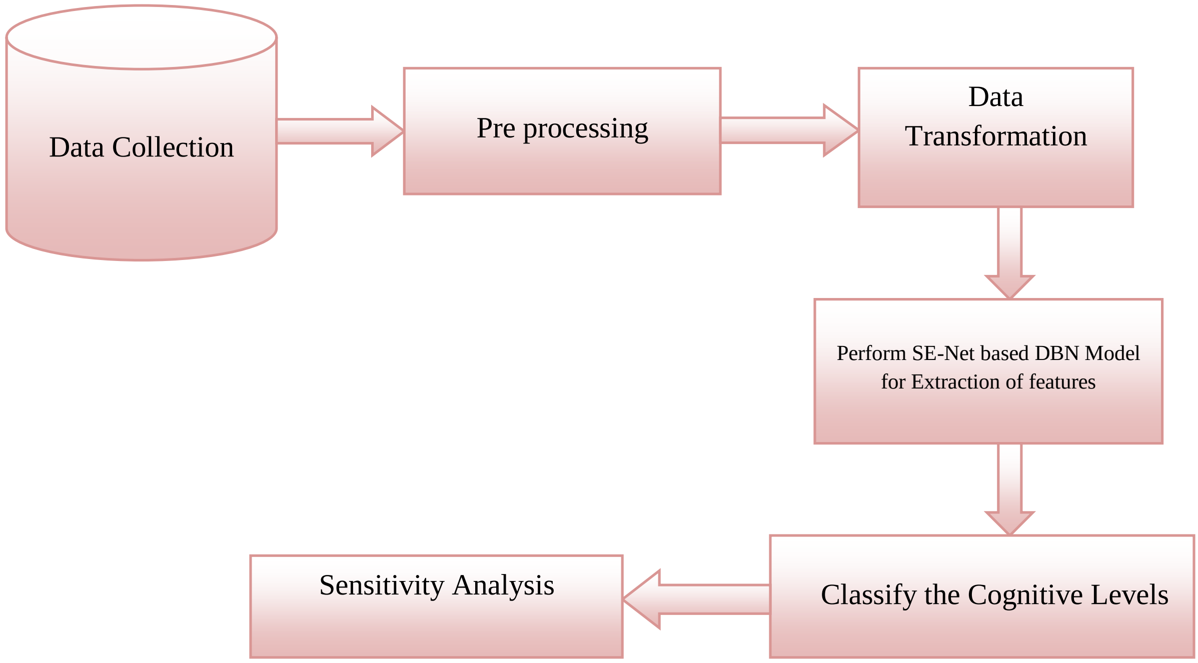

Figure- 5 System Architect

d) SE-Net Architecture

This architecture comprises Squeeze and Excitation operation. SENet is used for extraction of features and can successfully enhance the classification of performance of students SE Block shown in Fig 6 Squeeze operations are executed through global average pooling, which is utilized to get conditions between channels. We perform pressure along the spatial measurement, transforming each two dimensional component channel into a genuine number. This genuine number has a worldwide responsive field somewhat, and the yield measurement coordinates the quantity of info including channels. It describes the worldwide appropriation of reactions on include channels and permits layers near the contribution to acquire worldwide open fields, which is exceptionally helpful in numerous errands. We choose the most straightforward total procedure, global average pooling, which can be acknowledged by Eq. (1).

Excitation mechanism is utilized to produce loads for each module channel by boundaries. What's more, boundaries are found out to unequivocally show the connection between component channels. To utilize the data totaled in the crush activity, we follow it with a second activity, which intends to completely catch channel wise conditions. To satisfy this goal, the work must meet two standards: first, it must be adaptable (in specific, it must be equipped for learning a nonlinear communication among channels) and second, it must get familiar with a non-mutually-elite relationship since we might want to guarantee that numerous channels are permitted to be stressed (as opposed to authorizing a one-hot initiation). To meet these rules, we pick to utilize a straightforward gating instrument with a sigmoid function, which can be represented Eq. (2).

$$z_c = F_{sq}(x_c) = \frac{1}{H*W}\sum_{i=1}^{H}\sum_{j=1}^{w}u_c(i,j) \tag{1}$$

$$Z_C = F_{ex}(Z,W) = \sigma(g(Z,W)) = \sigma(W_2\delta(W_1 z)) \tag{2}$$

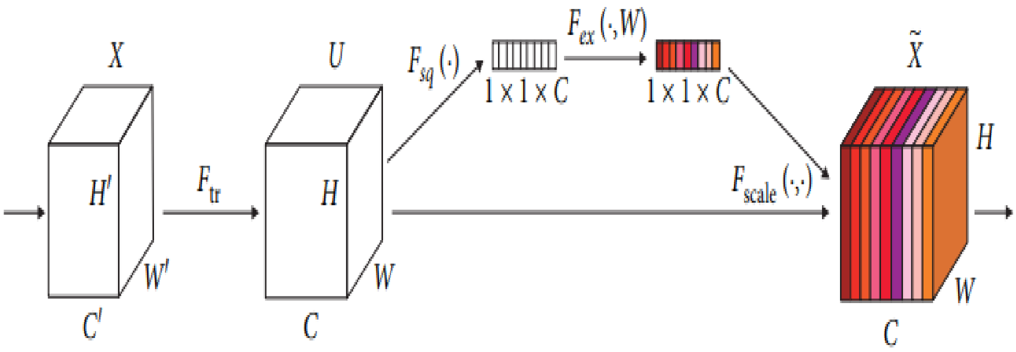

Figure 6: Squeeze – and – Excitation Block

e) DBN Network Model

Several Restricted Boltzmann Machines (RBM) can be stacked and trained in a greedy manner to form Deep Belief Network architecture. RBM is an unsupervised learning method which contains two layers: input and hidden layers. Each and every layer was constructed with nodes. The input nodes process the user dataset. The hidden nodes extract the multilevel features of the dataset. The connection between the input and hidden layers weighted parameters denoted by W [2]. DBN are graphical models which gain to extract a deep hierarchical representation of the training data. The graphical DBN is showed in figure. 7. The standard RBM is presented in figure.8

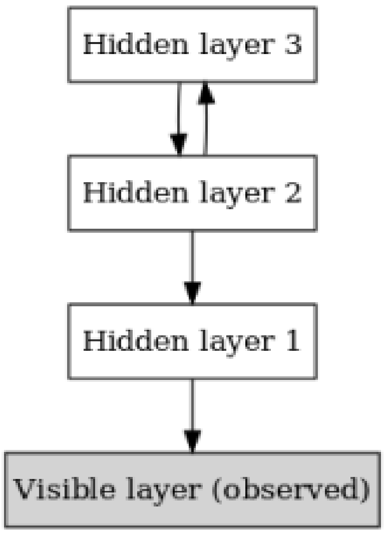

Figure 7 Graphical DBN Model

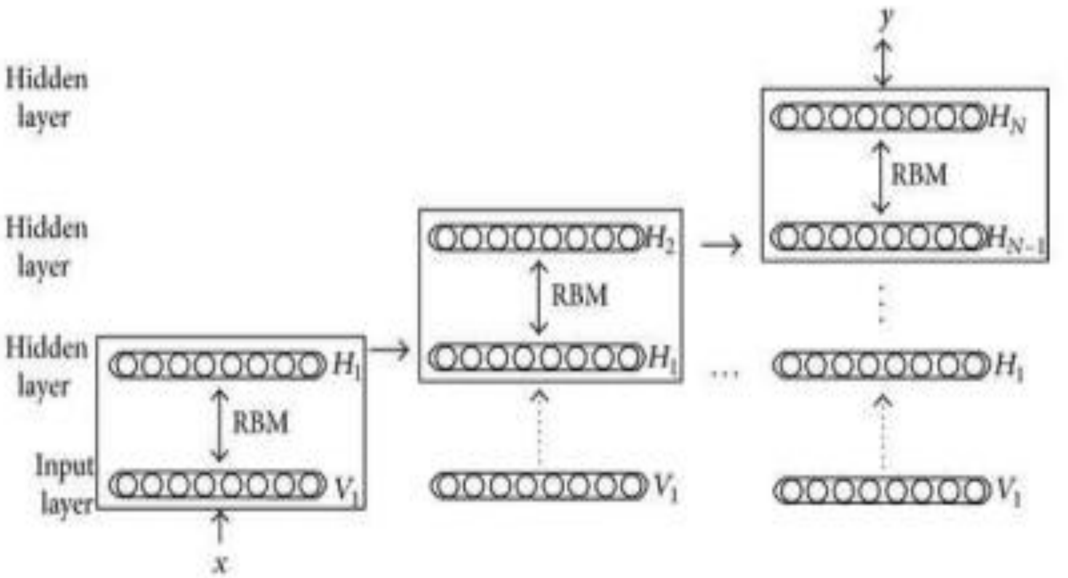

Figure 8 RBM Structure

f) Proposed Algorithm

Begin: SE-Net BASED DBN MODEL
Input: Labeled data set, Training Samples S and test samples set T, Batch size for Training network
Steps

i. Split the dataset into Train, Test, and Validate.
ii. Load and preprocess the sample data
iii. (iii)Train the data using the SE-Net architecture based DBN Model.
iv. Save the features after the train the network.
v. Perform the SVM algorithm with RBF Kernel estimate function
vi. End

Output: Student performance, accuracy

End

Figure-9 Proposed Algorithm

The proposed Algorithm comprises 3D-CNN, SE Block with DBN Network and Support vector Machine. In 3D-CNN, Antecedently the elementary student performance data are elevated to pre-progression stage. An exemplification library is annexed. Then the annexed exemplification data is a parted and classified into various test samples in consonance with various strategies. Subsequently the 3D-CNN network model is entrenched and the exemplified sample data and the corresponding network parameters are fed as input persuasion for paradigmatic training [4-7].

The SE-Block module is mounted with two ployable actions namely squeeze and Excitation. The squeeze action is accomplished by the intricacy of the last layer that renders the pooling average globally. After the reduction of squeeze action a non-linearized function is activated, ReLU function is elevated through the fully connected layer and the weight is promoted by sigmoid, which is the commotion operation. The outcome of the commotion corresponds to the significance of feature selection after the process. The recalibration amplified the original features is also completed. One dimensional vector is derived inexorably by converting the rescaled features. The weights are renovated by the loss function and the optimization of the network is achieved [14]. SVM is embraced to normalize the existing module, which also derives the categorization of student performance data.

III. RESULTS AND DISCUSSION

In this paper, we implemented the application based on the collected data. The collected data is taken for the input and the results shows the outcome analysis of each course. The following figure 10 shows the calculation of the attainment target for the particular course by each student. The calculation is purely based on student's mark attainment in each course outcomes. For each outcome, 3 scale rubrics will be followed,

Level 1: 50% of students secured greater than 50% marks.

Level 2: 60% of students secured greater than 50% marks.

Level 3: 70% of students secured greater than 60% marks.

After calculation of the attainment level, that is mapped with programme outcome for final attainment calculation. Final calculation of the course attainment is considered by University / End semester exam is 80% and remaining 20% is internal assessment components.

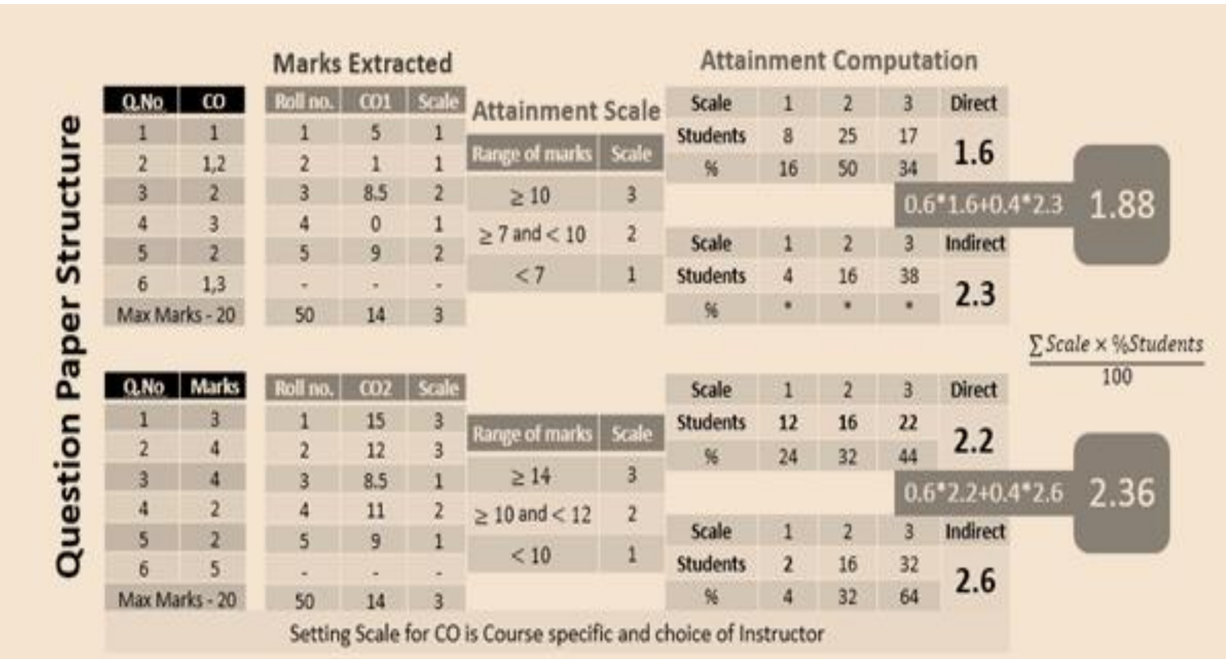

Figure-10 Attainment Computation (Sample 1)

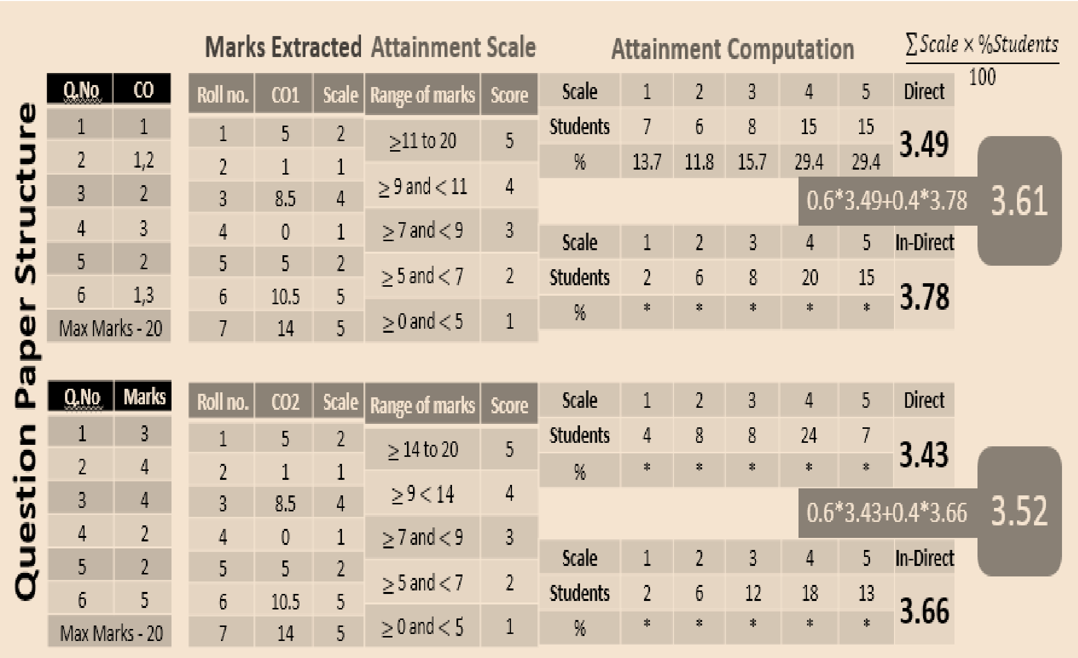

Figure-11 Attainment Computation (Sample 2)

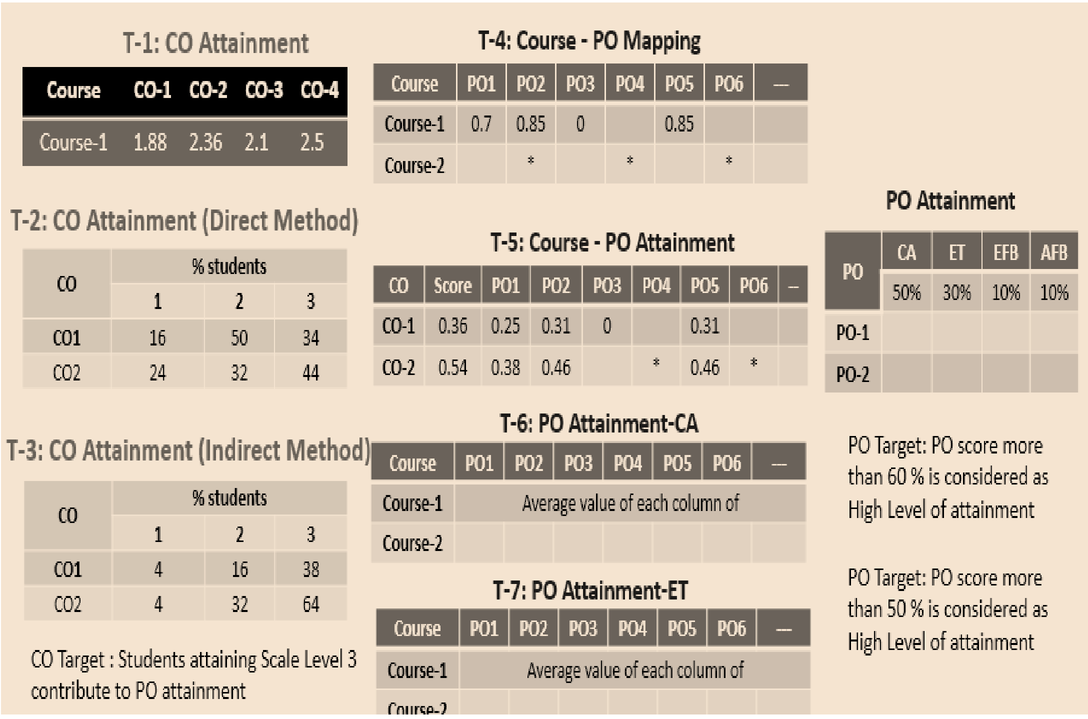

Figure-12 PO Attainment Computation

Table 2.Exploratory data analysis (N=213)

Cognitive level	Basic Topics	Minimum value	Maximum value	Mean	Standard deviation
Remember	K-Selection	0	100	95.02	47.17
	K-Repetition	0	100	93.20	41.20
	K-Modular	0	100	95.25	23.77
	C-Selection	0	100	87.15	43.54

Understand	C-Repetition	0	100	82.80	32.30
	C-Modular	0	100	91.20	15.44
Apply	AP-Selection	0	100	52.56	27.71
	AP-Repetition	0	100	47.26	50.00
	AP-Modular	0	100	54.60	50.00
Analyze	AN-Selection	0	100	22.50	50.00
	AN-Repetition	0	100	15.80	50.00
	AN-Modular	0	100	22.02	50.00
Evaluate	EV-Selection	0	100	32.30	50.00
	EV-Repetition	0	100	15.44	50.00
	EV-Modular	0	100	27.71	50.00
Create	SY-Selection	0	100	15.94	50.00
	SY-Repetition	0	100	17.92	50.00
	SY-Modular	0	100	18.07	50.00

The measured score of all three components are indicating the psychological levels of the optimum value, based on the optimum value suggesting that the student's competence levels are high. The analytical model obtains the table 2 findings. Based on the cluster value three position of selection, repetition and modular nearly center in the upper and lower bounds, suggesting that only two-thirds of students reached the any one of the cognitive level. In addition, the findings of the directive evaluation tool were verified by comparing them to the outcome of manual evaluation. The present paper compares the two-evaluation technique such as rule based and expert judgment. Both techniques are evaluating the proportion of the students at the threshold values. If the threshold value is greater than optimum value, the competency level reached higher concentration. If the competency degree level is low, the evaluation criteria became more complicated. So the p-value should be optimized for getting better classification of the OBE Frame work analysis. Table 3 and Figure 13 describe the accuracy analysis of proposed algorithm.

Table 3 Accuracy Analysis

Model	Accuracy
Ranking Forest with Ranking Algorithm	89.45%
SE-Net based DBN Network model using AHP Method	93.67%

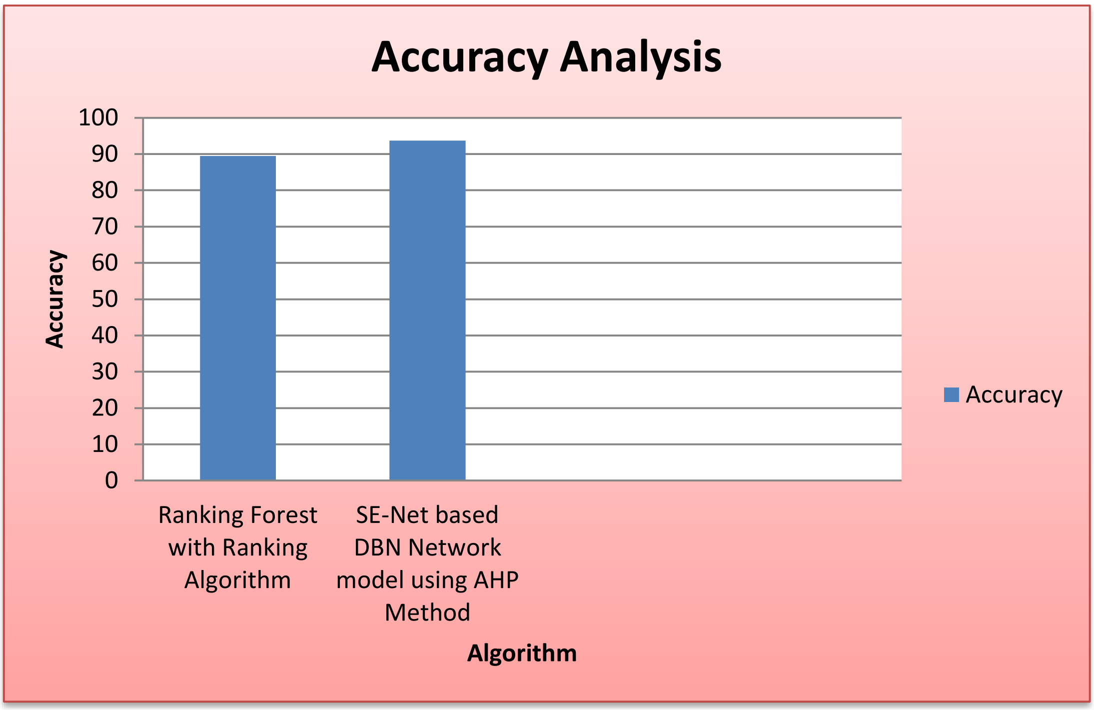

Figure-13 Accuracy Analysis

The performance analysis of the proposed SE-Net based DBN Network model with the existing Random Forest with Ranking Algorithm is displayed in Table 3. Training and testing percentage refers to the percentage of successful training and testing processes. The ratio of the dataset used for training and testing processes is 80 and 20. However, accuracy is generally referred to as the validation accuracy of the model. The proposed algorithm has obtained an overall frequency of 185 which is higher than the Random Forest with Ranking Algorithm. The difference in the frequency analysis shows 58% increase in the proposed SE-Net based DBN Network model. Also, the training & testing and Accuracy results say that the proposed algorithm provides 4.22% increase over than Random Forest with Ranking Algorithm. The proposed algorithm can be trained further based on different rules and to attain some increased performance of the methodology.

IV.CONCLUSION

In this paper, rule based and expert judgment methods are used to assess the competency level of students based on SE-Net based DBN Model and Ranking approach to predict on-time graduation rates of students. Further experiments are needed to replicate and validate the results presented in this paper. In particular, experiments need to be conducted specific institutions. We will use feature selection techniques to identify the most important factors. The proposed algorithm is compared with Random forest algorithm. The proposed algorithm its attain the better classification accuracy of cognitive level of students. The proposed algorithm attains 93.67% accuracy.

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