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Discovering Student Learning Style using Min Max Cascade Neural Network

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Abstract

Objectives: This paper develops a scale to effective and efficient determination of individual student learning style identification. **Methods**: It proposes a Fuzzy Min Max Cascade Correlation Neural Network (FMMCasCorNN) for identifying the student learning behavior based on Kolb's experiential learning style. It uses questionnaires for determining a student learning style; and then adapting their behavior according to the students' styles. After preprocessing step, the student data is then input to an FMMC as CorNN for predicting the student learning style. **Findings**: The performance of the proposed method has been evaluated through experimental results. The proposed work is compared to the existing classification algorithms (Naïve Bayes, SMO, and Back Propagation) with precision, recall, and f-measure metrics. The experimental results shows that proposed work has better classification accuracy compared to other methods. **Application**: The proposed model will be highly beneficial in the field of education and the instructor will have the provision of offering better insights for the students.

Keywords: Cascade Correlation Neural Network, Classification, Fuzzy Min Max Neural Network, Kolb Learning Style, Student Learning Style

1. Introduction

In an educational environment there seems to be more way for finding, thinking and retrieving the information and solving it out. Each individual student thinks and understands according to his learning style. The learning differs for each individual either through visual or theoretical understanding i.e., graphs, pictures, listening and presentation. In other scenarios students prefer to collaborate in performing experiments. Through this the instructors can provide a appropriate learning format for the students to improve their learning process.

Learning styles provides a greater way for preparing the learning materials. The materials prepared by the instructors should match and it should be according to the individual student learning style. The teaching approach is the instrument for the students provided by the instructors for a deeper kind of the contents. In general there are various models for learning styles have been proposed by many researchers across[1-4] and more have involved them self for the finding of students' learning style.

In an author[5], figured around 71 learning style models and out of all the models he found that the most significant model was Kolb's model. (Kayes,) concentrated on

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the empirical method rather than considering fixed learning qualities. Author[7], proposed a method which gives an acknowledgement of an individual student change. Author[8] proposed an approach with number of hypothetical suggestions, which consists of cognitive aspects, phenomenology, and adult learning[9] and several studies have also been empowered as an empirical support for the model [10-12].

Classify a new learning style for an individual by identifying the environmental stimuli as how they process and access the information[13]. A learning style[14] was proposed as a collection of cognitive, emotional and psychological personality of the individuals. It analyses the rational indicators of the individuals perception and how they cooperate and retort with the learning media[15]. As per Kolb, he suggests learning style as a method chosen by an individual student during the appreciation and dealing out specific information. So learning style is viewed on an emotional and in psychological element.

Experiential learning is viewed as learning by experience and it helps to identify how an individual student study, adapt, and equip themselves. So to address this Kolb have proposed an Model based on experiential learning to have more understanding about the several ways about an individual approach. The Learning Style Inventory (LSI) encompasses four learning styles. They are grouped as diverging, assimilating, converging, and accommodating styles.

In the process of an Education, the individual experience is purely based on experiential learning where each can equip with an immeasurable quantity of knowledge. The opportunity is given for the students to acquire the knowledge form where they discover from various ecological events.

The process of learning is difference from the knowledge because knowledge is created from the experience but where learning cannot be done for the same .So a learning process needs to be seen from the experiential point of view. Knowledge begins with the evolution of adaptation and then it is the transformation procedure where information is being continuously reformed and created. Then the learning projects familiarity in both its objective and subjective forms. Finally, for the understanding, each individual need to have an aware of the nature of knowledge and its reversal.

The proposed research focuses on the identification of student's response after experiential learning courses with varying styles of Kolb model. Then, differences in Kolb learning styles are captured. The paper gives a solution to the problem of identifying student learning style which is based on Neural Networks methodology. As Neural networks are computational models specifically for classification of the neural structure of the brain. These models have given very precise classifiers. So this was used along with Mix Max Cascade Correlation which in turn is used to find out the different learning styles of the students based on composed information.

This paper is categorized as follows: The section 2 discusses Kolb learning style and related work of different learning style using various methods. The Section 3 describes the proposed work of fuzzy min max cascade correlation neural network. Section 4 evaluates the performance of proposed work and section 5 provides the conclusion of this work.

2. Background

2.1 Kolb Learning Style

This model projects the learning process as knowledge acquisition through experiential revolution. This model involves six different propositions. First three propositions stresses upon the necessity of learning through continued process with relearning capabilities. The remaining aspects deal with adaptation requirements, environmental tie up and creation of social knowledge through holistic learning. Figure 1 shows Kolb's Experiential Learning Model.

This principle behind this model is based on the two-levels: a cycle of learning with four stages and four different learning styles. The Level-1 i.e. cycle of learning brings the Concrete Experience - (CE), Reflective Observation - (RO), Abstract Conceptualization - (AC), Active Experimentation - (AE). The four learning style involves Diverging (CE/RO), Assimilating (AC/RO), Converging (AC/AE), Accommodating (CE/AE).

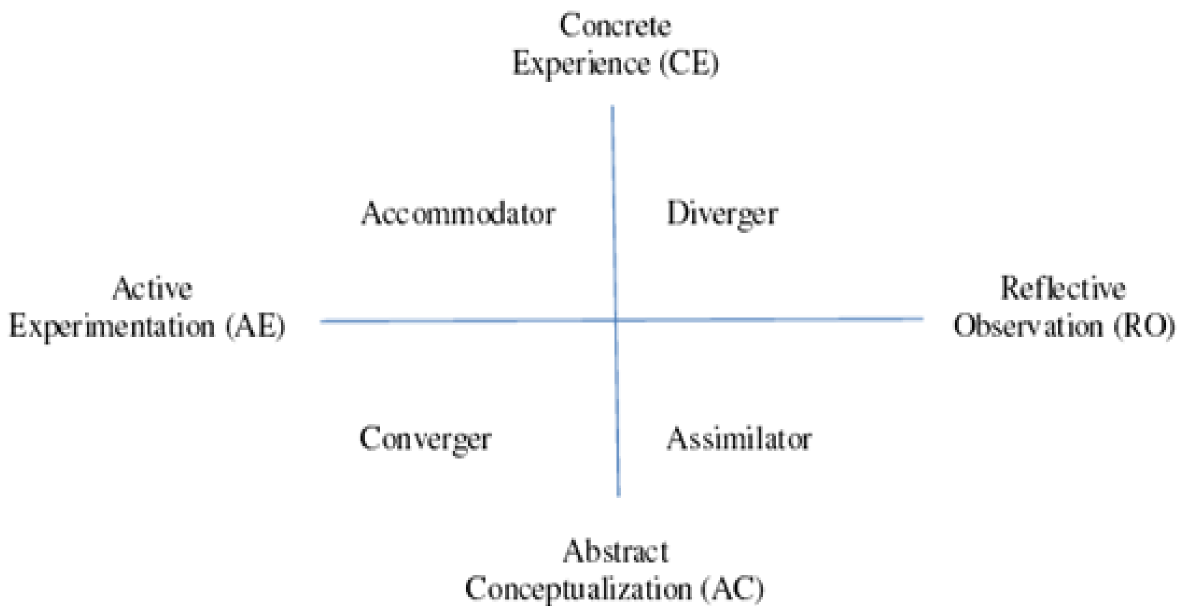

Figure 1. Kolb's Experiential Learning Model.

The concept as follows:

2.1.1 Diverging (Feeling And Watching - CE/RO)

Different people will have different perspectives. These people will collect information from outside world and based on their imagination, the solutions are obtained. These people have extraordinary analytical skills such as brainstorming. These people have high imaginative skills with emotional behavior. They mix with people effectively and they have open-mindness in accepting the suggestions of other people.

2.1.2 Assimilating (Watching And Thinking - AC/RO)

People belonging to this group will strive for good logical conclusions. Rather than depending on external human resources, these groups of people always look for adventurous ideas. Exploring the wealthy information and arriving to a logical conclusion is the focal point**.** This group of people always support strong theoretical inference rather than depending on practical implications. These people involve in the process of learning and analyzing things.

2.1.3 Converging (Doing And Thinking - AC/AE)

These people have the ability to find answers to practical queries. These people are highly proficient in technical domain with less importance to people's emotions.

2.1.4 Accommodating (Doing And Feeling - CE/AE)

The Accommodating learning style stresses upon people's perception. These people choose a practical and experiential approach at various situations. These people explore novel directions only by their instinct feeling. This learning style suits action oriented scenario.. People of this category adapt with the team culture and they actively work to achieve an objective by setting targets themselves.

2.2 Related Work on Learning Style

In[16] the data was collected from the students who are pursuing information science through an online post-graduate program. The results of retrieved data form are analyzed and the experiment was done on the category of Converge and Assimilator and then a study was made on the relationship between learning style. A training based on classroom and computer delivery modes was used[17]. The results stressed the close proximity towards computer-based delivery with respect to coverage and print-based delivery for assimilators.

The different effect of Kolb learning styles was experimented on students' online participation in distributed learning environments[18]. The study shows the impact of is justified by multiple regression analysis.

The association was made between online behavior and Kolb Learning style[19]. The method fails to prove its efficiency on the network. The different learning styles of students are evaluated through online distance education courses against those who have enrolled in traditional in-class courses[20]. The result analysis found that there are no ultimate differences between the online distance education courses when compared to traditional courses.

The Learning style preferences was calculated and checked with their actual visits of linked Web-pages[21]. Here, the learners classified as "Explorers" opted for their own way of learning. In Manochehr's study[22], the comparative analysis of e-learning and traditional learning was done. The Kolb LSI was used to find an apt learning style of various students. The analysis found that there is less impact on traditional learning. But the study stressed the importance of adopting a collection of learning styles in web-based coaching.

The relationships between Kolb Learning Style and the online learning behaviors was studied[23]. The obtained Converges and Assimilators' learning output were higher than Diverges and Accommodators' learning outcomes. The needed for finding different student learning styles and to motivate them to implement an online course design for these styles[24,25].

In[26] various methods were discussed to learn the different student styles in distance learning environment. There is a need to analyze the student's level before processing with the contents. Unterberg[27] compares the various existing learning outcomes of students for a specific course with different learning environments and different learning styles. The author suggested that the classroom or distance environment will have only little impact on learning outcome. Students will have more opportunity to observe in the computer-cultivated environment.

A generic methodology and architecture for developing a novel conversational intelligent tutoring system (CITS)[28] .Oscar CITS was implemented using the Index of Learning Styles (ILS) model to deliver SQL tutorial. This method demonstrates the human instructor's image by modeling their style. Here, Natural language is utilized to throw light on specific topics and the ward's learning style is predicted dynamically.

An efficient learning style model was proposed based on pattern recognition[29]. This method supports intelligent tutoring systems and also makes predictions and update learning style profiles in a recursive manner. This model requires needs a proper standard to specify its functionality and effectiveness. A new mechanism[30] was proposed to improve k-nearest neighbor (k-NN) classification when it combines with genetic algorithms (GA).

A new approach that has the capability of adapting to the curiosity parameters of the students is elucidated in[31]. This scheme identifies the learning style patterns by checking the styles and monitoring the server logs. Clustering models based on different learning styles and algorithmic interpretation of learner's interests is carried out.

A novel prediction model[32] was proposed based on NB Tree and binary relevance classifier. In the proposed approach tutoring system and the learning content are assumed to be independent of the predicted learning methodology. But this model has the limitation of imposing further burden on the learners.

3. Methodology

In this section, the proposed student learning style identification using fuzzy min max cascade correlation is

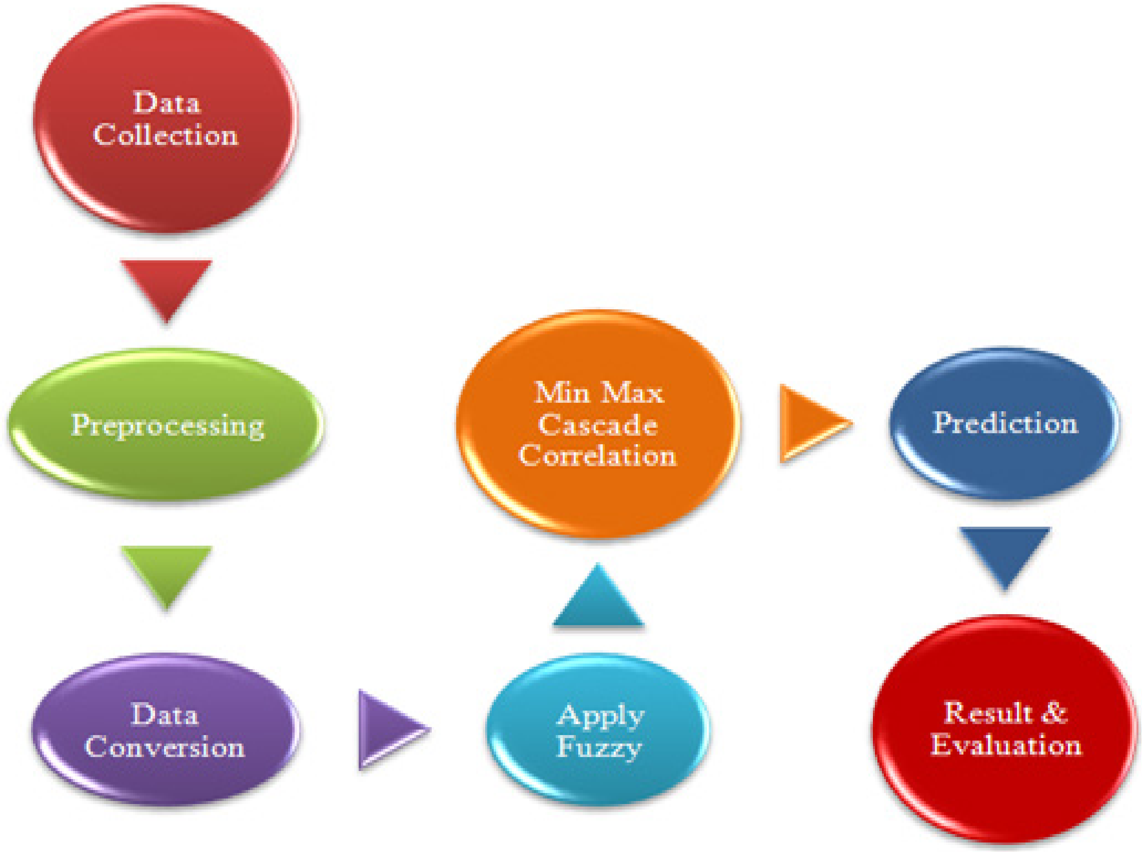

Figure 2. Proposed Work Flow Diagram.

described. Figure 2 shows the flow of proposed system model.

The main components of the system model are as in the following:

3.1 Data Collection

In this process, the data is collected from the students. The data contains the information about students cultural, social, educational background, socioeconomic status, psychological profile and academic progress, and KLSI (Kolb Learning Style Inventory) trait test score. All these information are integrated into single dataset.

3.2 Preprocessing

In this process, the collected data is preprocessed. For privacy and security purpose some personal information of students are removed from the dataset. Any record that contains missing values that student record will be discarded.

3.3 Data Conversion

In this process, the categorical data will be converted into numerical value for further processing. Figure 3 shows the procedure to convert the categorical data to numerical data.

```
Input: Column Values –CV;
1.  Read Distinct Column Values (DCV)
2.  k=1;
3.  For each A value in DCV
4.      Assign A=k
5.      k+1
6.  End for
7.  For all CV
8.      Assign the numerical value
9.  End for
```

Figure 3. Categorical to Numerical Conversion.

3.4 Fuzzy Concept

In this process, the fuzzy membership function is applied to change the data value [0,1]. The fuzzifier technique which is based on triangular is used for this conversion.

Given a data set **X={x_1, x_2, x_3,...... x_n }** find minimum (a) and maximum (b) value of X**.** The value of the membership function presents the possibility value of x, as denoted by F(x).

$$F(x) = \begin{cases} 2*[(x-a)/(b-a)]^2, & a \le x \le (a+b)/2 \\ 1-2*[(x-b)/(b-a)]^2, & ((a+b)/2) \le x \le b \\ 1\,, & x \ge b \\ 0, & otherwise \end{cases}$$

3.5 Min Max Cascade Neural Network

The Min Max Cascade Neural Network is used to predict the student learning style.

Cascade-Correlation deploys input/output layer with automatic training phase that includes sufficient hidden units to form multi-layer structure as shown in Figure 4.

The Cascade-Correlation (CC) combines two ideas:

- The cascade architecture endorses the property of adding hidden units one at a time.
- The second is the learning algorithm, which creates and finds the new hidden units. So the algorithm will maximize magnitude for the each newly created hidden unit, the magnitude is between the new and the residual error signal of the network

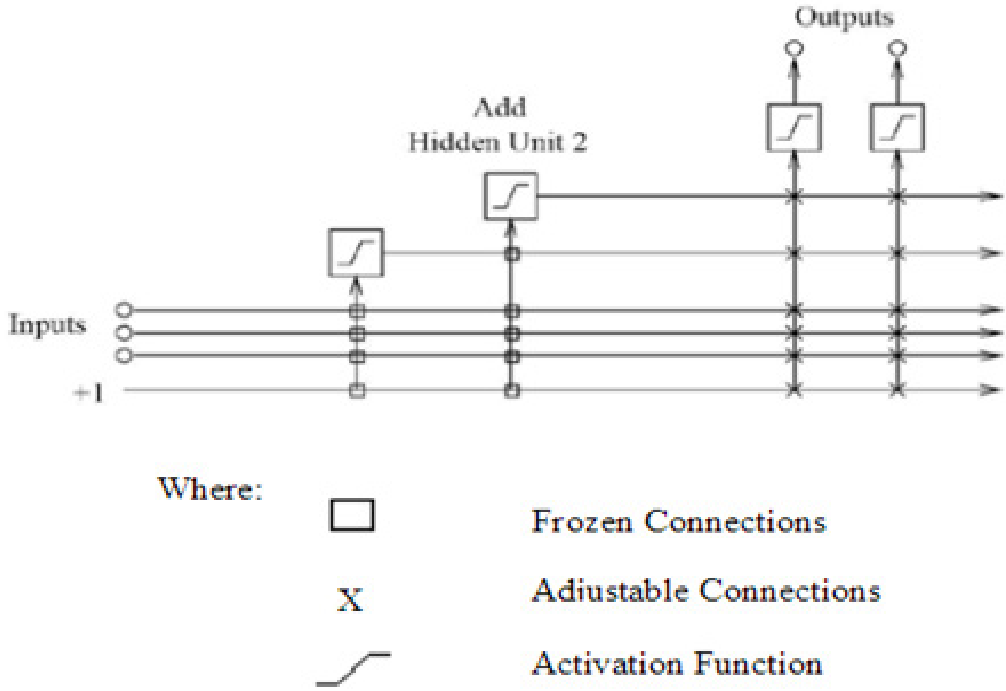

Figure 4. Cascade Correlation Neural Network.

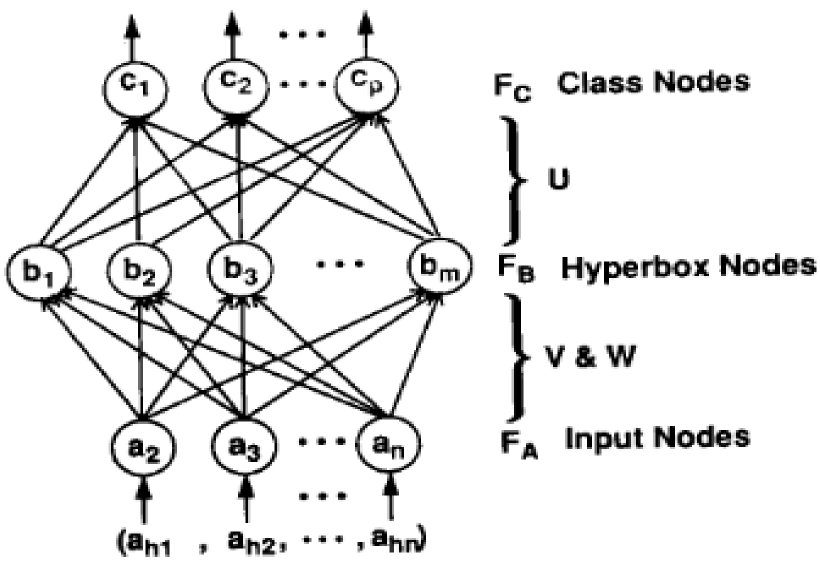

Figure 5. Three Layer FMM Network.

The FMM structure contains hyper boxes with the properties of *n*-dimensional pattern space. The online support of FMM offers fresh hyper boxes with respect to input samples and it can connect with new c-lasses with minimum workload.

The FMM structure has three layers, as shown in Figure 5.

FA denotes the input layer. *FB* represents hyper box layer. Each *FB* node corresponds to a hyper box fuzzy set created during the learning process. The minimum and maximum points are elucidated by the connections between *FA* and *FB* nodes.

The FMMCasCor algorithm is proposed to predict the student learning style. Table 1 shows the notation used in Algorithm.

Figure 6 shows the student learning style prediction algorithm FMMCasCor.

In Step1, the training data is converted into fuzzy value using triangular fuzzy membership function. In Step2, If the hyper box size is lesser than the expansion coefficientΘ. expansion is performed and the input pattern is matched with the respective hyper box class

In Step3, once the expansion process is completed, overlap test is initiated to identify overlapping regions. If the hyper boxes from different classes overlap, a hyper box contraction process is initiated .In Step 4, removal of overlapping regions is carried out.

No of box, minimum value matrix, maximum value matrix and binary class label matrix are extracted based on Step 2, 3 and 4.

Table 1. Symbols and Notation

Symbol	Description
Tr	Training Data Set
Te	Testing Data Set
M	Number of Rows in Tr
N	Number of Columns in Tr
Trv(i,j)	Value in Train Data
Box	Number of Hyper box
VM	Minimum Value Matrix of size B*n
WM	Maximum Value Matrix of size B*n
UB	Binary Matrix (B * No of Class Label)
Thre	Threshold Value

FMMCasCor Algorithm

```
Input: Train Set Tr, Test Set Te, Box=1, Thre =0.5
Output: Learning Style
MMCasCor (Train Set Tr, Test Set Te)
1. Apply Fuzzy Concept
        Convert all Tr values into fuzzy
2. Rule Expansion
3. Rule Overlapping
4. Rule Construction
5. Extract Box, VM, WM, UB
6. Initialize the cascade correlation networks
7. Add new Box as new hidden unit
8. For each Row(k) in Tr
9.      For each B(i) in Box
10.             total=0;
11.             For each Column(j) in Tr
12.                     Compute
        total=total+(max(0,1-max(0,Thre*(min(1,Trv(k,j)-WM(i,j)))))+max(0,1-max(0,Thre
        *(min(1,VM(i,j)-Trv(k,j))))));
13.     End for
14.     Computer e1=1/(2*n) * total;
15. End For
16. Compute Matrix cor=e1*UB(i,:);
17. Find maximum Value
18. Display Predicted Learning Style
19. End For
```

Figure 6. Student learning style prediction.

In Step 6, the cascade correlation is initialized. It consists of only an input and an output layer. Add new hidden units as extracted from step 5. The steps 8 to 19 are used to predicted student learning style. For each row the training data set, the matrix is created based on the computed values. The maximum value of the matrix is assigned as the predicted class label.

In the training process, each hyper box is created with VM, WM and U matrix. If two hyper boxes are overlapped then create a new hyper box.

In the testing process, when a new input pattern is given, calculate membership value corresponding to each hyper box which was generated in training process. Assign class whose hyper box membership value is maximum by using U matrix.

4. Experimental Result

This section explains the performance evaluation of proposed approach. The Min Max Cascade Correlation

Table 2. Learning Style Count

College/ Learning Style	Abstract	Reflective	Active	Concrete
College-A	15	15	23	7
College-B	11	18	20	11
College-C	17	26	10	7

Table 3. Precision, Recall and F-measure

College	Algorithm/ Metric	Proposed	NB	SMO	Logistic	BP
College -A	Precision	0.918	0.749	0.666	0.499	0.604
	Recall	0.926	0.75	0.633	0.5	0.6
	F-Measure	0.922	0.742	0.610	0.499	0.591

Table 3 Continued

College-B	Precision	0.853	0.745	0.546	0.763	0.684
	Recall	0.872	0.75	0.55	0.75	0.83
	F-Measure	0.862	0.738	0.547	0.747	0.679
College-C	Precision	0.891	0.768	0.549	0.661	0.648
	Recall	0.883	0.791	0.567	0.65	0.65
	F-Measure	0.887	0.779	0.557	0.65	0.647

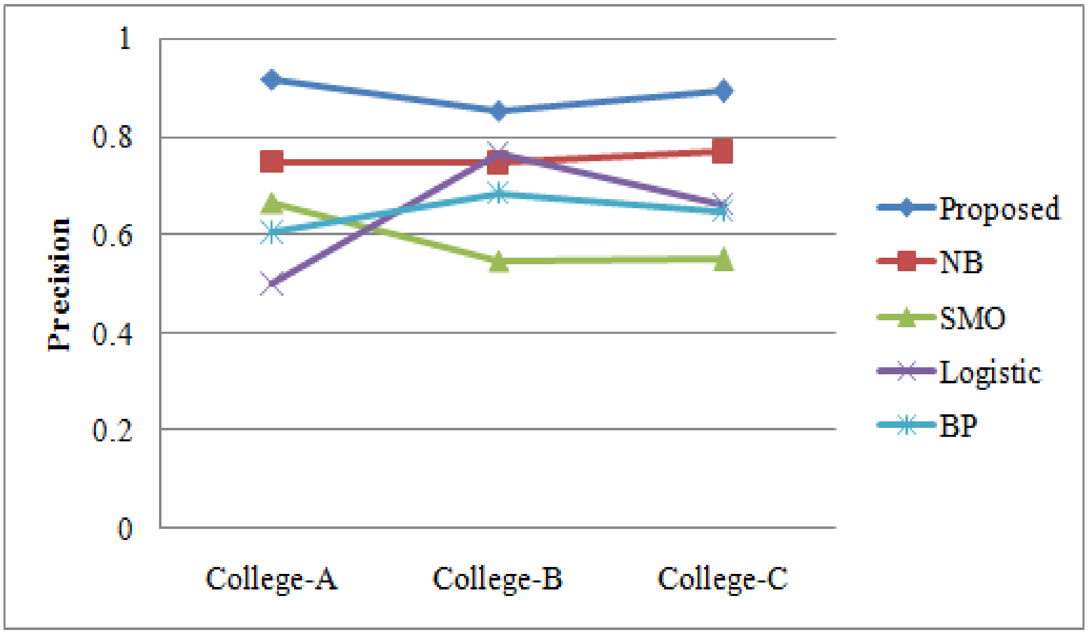

Figure 7. Precision Comparison.

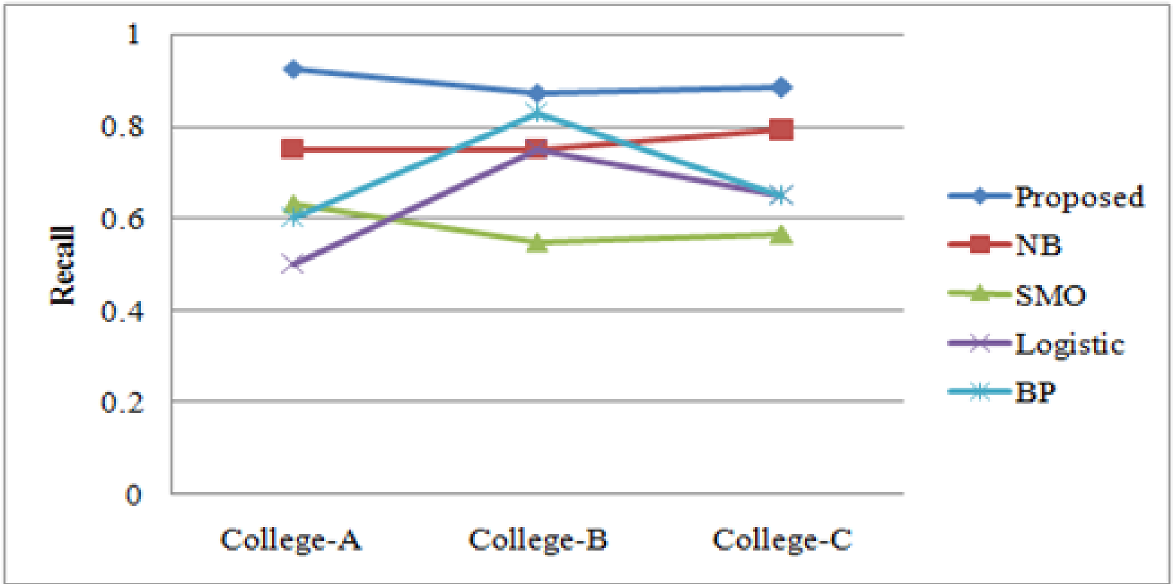

Figure 8. Recall Comparison.

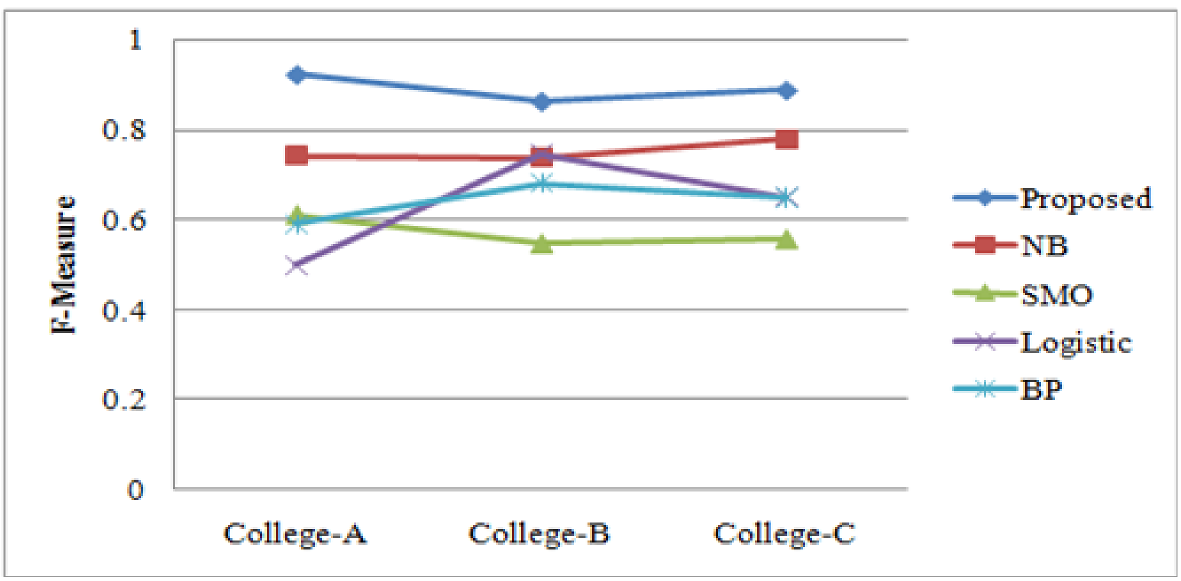

Figure 9. F-Measure Comparison.

Neural Network is implemented using Java (version 1.8), and the experiments are performed on a Intel(R) Pentium machine with a speed 2.13 GHz and 2.0 GB RAM using Windows 7 32-bit Operating System.

For experimental results, the data are collected from 180 students from three colleges. Table 2 shows the count of learning style for 3 different colleges. The proposed method is evaluated using the following evaluation met-

Table 4. Accuracy Comparison

College	Proposed	NB	SMO	Logistic	BP
College –A	93.33	82.27	73.47	66.07	71.38
College-B	85	83.23	69.84	82.89	78.52
College-C	91.67	84.53	69.78	76.32	76.51

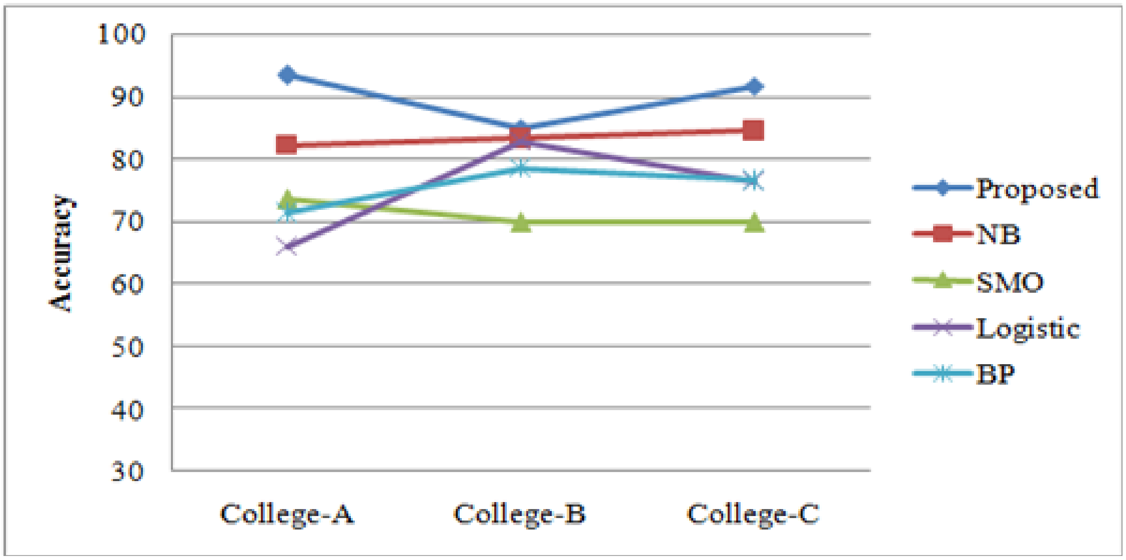

Figure 10. Accuracy Comparison.

ric: False Positive (FP), False Negative (FN), True Positive (TP), True Negative (TN), Recall, Precision, F-Measure and Accuracy.

The min max cascade correlation algorithm is compared with Naïve Bayes, SMO, Logistic and Back Propagation. Table 3 shows the precision, recall and f-measure value of proposed and existing algorithm for three different college students.

Figures 7, 8 and 9 shows precision, recall and f-measure comparison with existing algorithms.

The overall accuracy of the methods are shown in Table 4 and Figure 10

5. Conclusion

The improvement of higher education process requires novel learning style prediction model and it will helps for the betterment of students. The first and important is to find the effective individual learning styles. So we have proposed a new student learning style identification using min max cascade correlation neural network. The proposed work is explored and predicted with the existing learning style of Kolb's and students programming learning ability. Min Max cascade correlation was tested with sufficient number of performance factors and evaluated using real data. A comparative study is also made with other approaches to extract meaningful conclusions. The proposed algorithm is compared to Naïve Bayes, SMO, Logistic and Back Propagation. The experimental result shows that proposed work gives more accuracy than the other methods.

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