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# Enhanced Collaborative E-learning Based on Personality and Learning Style

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**ABSTRACT** Collaborative learning collocations are learning methods in which learners are put together for some purpose and students in each group learn towards a common academic goal. A heterogeneous grouping in such an environment will improve the performance of the students considerably. The personality traits of a student and his/her learning style has been shown to be a necessary forecaster for the student's participation in the group. In existing works, the identification of a student's personality type and his/her learning style has been achieved through questionnaires which are quite tedious for the student and ineffective at times. In this research work, the genetic algorithm was used for heterogeneous grouping, taking the learners personality and learning style as parameters for grouping. The student's personality type and learning styles are detected automatically from his/her text and behavior with the system respectively.

## INTRODUCTION

Collaborative learning is a method in which students study or try to study something together (Liu 2009). Unlike a single student studying, students involved in collaborative learning take on the advantage of everyone's wealth and intelligence (relying on each other's reports, estimating each other's concepts, supervising each other's jobs, and so on). It depends upon the standard that intelligence can be formed in a community in which representatives seriously connect by dividing the knowledge and skills that they have gained through that period of time, put on assumed act. These consist of one-on-one communication as well as artificial arguments (networked conference, conversation rooms, and so on).

Corresponding to partisan of collaborative learning, the case is that learners are seriously transferring, contesting and bargaining concepts within their associations, boosting learners' sympathy in studying. Appealingly, a collaborative learning task would permit for every representative to be authoritative for some needed view to fulfil the task. This means that each association representative will study their designated view and will be authoritative for demonstrating or tutoring the other representative of the association. There are various design models based on this learning style. One of such model is the Felder Design model.

The Felder design model is an informational layout model based on studying style consideration. According to Felder (1988), the model distributes students along the following dimensions: What sort of data does the student conversely realize?: Realizing beginners (focus, factual, adjusted to data and program) or Emotional beginners (theoretic, inventive, adjusted to theories and meanings); Over which method is sensational data most powerfully realized?: Visual beginners (suggest imaged statements of given paraphernalia– images, diagrams, flow charts) or Spoken beginners (suggest reported and oral summary); With which institution of data is the observer most convenient?: Primary beginners (suggest display that progress from the particular to the universal) or Inferable beginners (suggest display that go from normal to particular); How does the learner suggest a data method?: Effective beginners (study by trying things out, engaged with others) or Thoughtful beginners (study by thinking over, engaged alone); How does the learner tolerate other group members?: Succeeding beginners (continuous, regular, study in tiny additional steps) or International beginners (complete, whole thinkers, study in huge jump).

Apart from design models, the researchers have grouping system to group members based on different constraints. One such grouping that the researchers have used here is Dynamic Grouping. Dynamic grouping permits the arrangements of association to be suitable to the public and studying requirements of the learners taking part in a collaborative activity. Heterogeneous (Sabine et al. 2006) association establishment is said to play a demanding act in conditions to improve the achievement of collaborative studying advancement of learners. Further, the learners who ranked low in studying attainment improve in studying in heterogeneous association (Kuan-Cheng et al. 2009). The traits arrangement of association of representative enhancing collaboratively on divided work has been displayed to be a necessary fortune-teller of attainment. Conclusions displayed that the homogenous command association were more difficult at an individual level, instead of the mechanical difficulty. The heterogeneous exploratory association transferred a wider and more different style of analytics and communicates more. Ounnas et al. (2009) developed the framework for learner's group formation based on the survey collected from students learning. Khenissi et al. (2016) proposed the concept of identifying learning style and personality using games, based on the students' interest of games.

Balakrishnan et al. (2015) elaborated the social media acceptance model based on factors affecting student's intensions to use social media learning style. The Big Five Personality traits (Digman 1990) were proposed to be identifiable from a student's interaction with the computer system. A Naive Bayes classifier is trained and tested for personality traits identification. Felder-Silverman's model (Rebecca 2001) arrived at the learning styles that were identifiable from student's performance and interaction within a learning environment. Bayesian Network is constructed and the learning styles are mathematically calculated from the repository maintained in the learning tool. Truong (2016) reviewed fifty-one studies related to adaptive learning system and detected that the learning styles were based on automatic classification with respect to learning styles and applications. Most of the existing research work had not concentrated on grouping in collaborative learning environment. In this research work, the researchers created an enhanced collaborative grouping framework based on personality traits and learning styles.

## METHODOLOGY

The fundamental goal of this research work is to form learner groups in a collaborative learning environment. A studying style is a person's desire about taking in and altering data. Representatives with different studying styles can create various perspectives on a powerful mutual planning. Currently, an expanding number of researchers have recognized studying styles as one of the important observer traits and initiate that they can be used to favourably recover adjusting collaborative activities. The personality traits and learning styles are considered as the grouping characteristics in this research work. In this process, students interacting in a collaborative environment are considered, in which an effective group formation among them helps to increase their performance. Student's individual personality and their learning styles are the main predicted parameters that affect their performance in the group. Automatic detection not only reduces the work of the teacher but helps to provide significant results. Continuous monitoring of the student in a group is done to notice the dynamic change in his/her learning style and personality. Genetic Algorithm (GA) is proposed for grouping the students heterogeneously so that people within a group share differences and learn from each other. This kind of effective group formation can also be applied to non-academic activities. The basic methodology of this process is the grouping of students in a collaborative learning environment. This process of group formation is carried out using the Genetic Algorithm. To increase the effectiveness of the group formed, a student's personality trait and learning style are considered as the main parameters in the Genetic Algorithm. Students may possess different learning styles and may have different personal behaviors in a group. The performance of the student can vary within the group that he/she has put in. So it is necessary to form an effective student group where performance increase of each individual is taken into account.

Student's personal behavior is usually determined with five measures, known as the Big Five. They are Extraversion vs. Introversion (friendly, confident, cheerful vs. remote, silent, afraid), Emotional Stability vs. Neuroticism (peaceful, emotionless vs. uncertain, worried), Agreeableness vs. Disagreeable (friendly, cooperative vs. hostile, fault-finding), Conscientiousness vs. unconscientiously (sober, arranged vs. wasteful, careless), Openness to Experience (thoughtful, intelligent vs. empty predictable).

A classifier can be trained with experimental data and tested to get a precise probabilistic result. One of the main classifier algorithms, Naive Bayes classification is used here to get the probabilistic value of each of the personality traits.

Learning style model classifies students and evaluates the use of Bayesian networks to carry out learning style identification. An effective observer enhances well in associations; thoughtful observers enhance well by themselves or with at most one other person. Here, precisions of personality traits and learning styles are used as the input characteristics for the Genetic Algorithm. This method not only seeks the common achievement of every association but also seeks enough conclusions individually with various traits.

## FINDINGS AND DISCUSSION

The objective of this research work is to form learners group based on personality traits and learning styles. The process of finding personality traits of learners are as follows,

### Finding Personality Traits of Learners

The Big Five personality traits, also known as the five factors model (FFM), is a widely examined theory of five broad dimensions used by some psychologists to describe the human personality and psyche. The five factors have been defined as openness, experience, conscientiousness, extraversion, agreeableness, and neuroticism. Let us take a look at the flow in Figure 1.

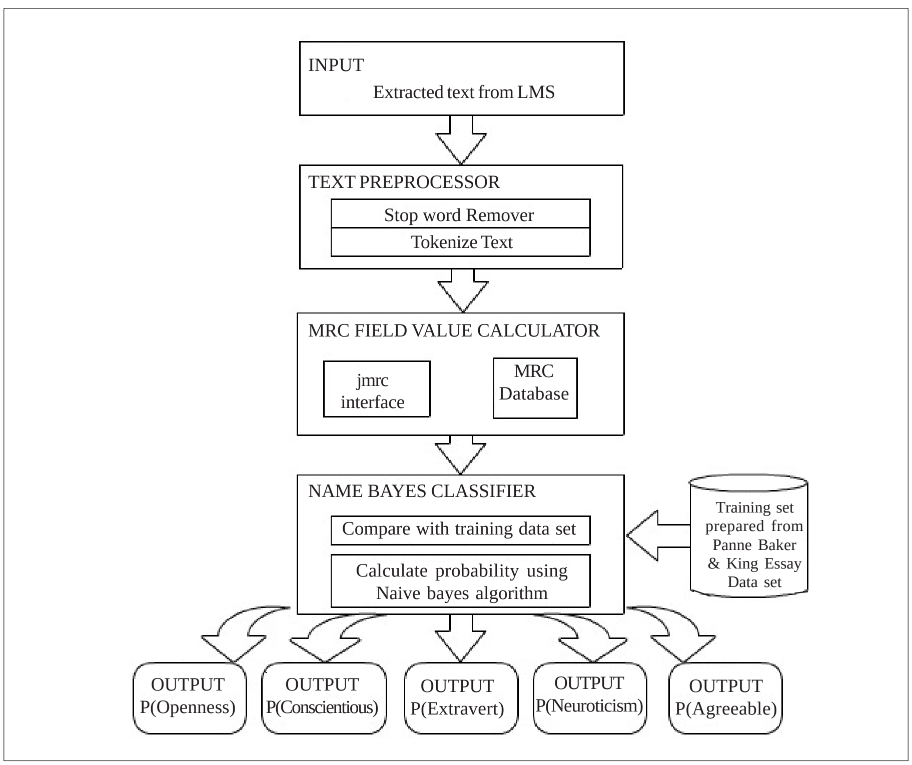


**Fig. 1. Personality identifier process**

The Figure 1 illustrates the personality identifier process consists of a Text Pre-processor which removes the stop words ( and, is, was, etc.) using the Wikipedia stop word list (available on the Internet) and also removes the tokens from the text ( ‘ . ‘ , ‘ , ‘, ‘ “ ’, ‘/’ etc.).The cleaned text is now subjected to the MRC Field value calculator which finds the average value for the text for each of the 14 fields of MRC Database. The details of the MRC fields can be found in the Table 1. This is an input to the Naïve Bayes Classifier (testing data).Similarly, the essay dataset of Pennebaker and King (1999) was processed by subjecting it to cleaning and MRC Field value calculator. The dataset contains conversations of more than 2300 students and their personalities detected by questionnaire. This was then used as the training dataset for the Naïve Bayes Classifier. It consists of average values of each conversation in the dataset for various fields of the MRC Database along with their corresponding personality. The Naive Bayes classifier then classified the text of the students participating in the dataset to one of the personality classes using the Bayes’ Algorithm. The aim of this process was to find the probability of a student belonging to particular personality traits which are Openness, Agreeable, Neurotic, Extravert, and Conscientious. This process has three parts:

### *Training Set Preparation*

Penne-Baker and King Essay Dataset was taken as input. The dataset contains the conversation of various students and their personalities obtained through questionnaire. It had about 2300 entries. Then the text was extracted, cleaned and tokenized and the MRC field values can be found in Table 1.

**Table 1: Range of MRC field values**

| *MRC field name* | *Meaning* | *Range* |
|---|---|---|
| NPHON | Number of phonemes | 1-19 |
| NSYL | Number of syllables | 1-9 |
| KF-FREQ | Kucera and Francis written frequency | 1-69971 |
| KF-NCATS | Kucera and Francis number of categories | 1-15 |
| KFN-SAMP | Kucera and Francis number of samples | 1-500 |
| TLFREQ | Thorndike-Lorge frequency | 1-236472 |
| BR-FREQ | Brown Verbal frequency | 1-6833 |
| FAM | Familiarity | 43-657 |
| CONC | Concreteness | 158-670 |
| IMAG | Imagery | 129-667 |
| MEANC | Mean Colorado meaningfulness | 127-617 |
| MEANP | Mean Pavio meaningfulness | 192-922 |
| AOA | Age of acquisition | 125-697 |
| NLET | Number of letters | 1-21 |

The Table 1 consists of range of MRC field values. The average value for each field was determined from the MRC database which can be accessed from java code using JMRC interface. This was done for each conversation in the dataset and their corresponding personalities were also noted. This was the training dataset for the classifier.

### *Testing Set Preparation*

The texts of the particular student extracted from the discussion forum in chats, self essays, and so on were taken and the MRC field values for each student were calculated. Now this is the other input for the classifier.

### *Classification Using Naïve Bayes Classifier*

The classifier used here was Naïve-Bayes Classifier. From the training dataset, the value of each MRC field was categorized as high, med and low. Then, the testing set was compared and the probability of belonging to a particular personality class was calculated using the Bayesian formula. In this process, the learning style precision for each student was calculated. The probability of effective or thoughtful processing, emotional or perceptive perception and sequential or global understanding were calculated. Various student interactions with the learning tool were recorded and used to build the Bayesian Network involving probability calculations.

The formulas used are:

P (Occurrence of event) = Number of events occurred / Total number of events occurred

$P\,(\text{learning style} = X) = P\,(X \mid A_1, A_2, \ldots, An)\, ^*\, P\,(A_1)\, ^*\, P\,(A_2)\, ^*\, ..\, ^*\, P\,(A_n)$

Where

$P\,(X \mid A_1, A_2, \ldots A_n)$ Is the conditional probability of learning style X given that attribute A1, A2 to An having values.

P (A1) is the probability of occurrence of attribute A1.

### Finding Learning Style of Learners

Learning styles involved in approaches to learning and studying. Expressive styles, involved in verbal or nonverbal communication (for example, tempo, constricted versus expansive). Response styles involved in self-perception and self-report (for example, acquiescence, and deception). Defensive styles involved in accommodating anxiety and conflict (for example, obsessive-compulsive, hysterical). The detailed design for learning style identifier Process is shown in Figure 2.

The Figure 2 consists of the various social network activities such as forum, chat etc, from which the CPT tables are generated to identify the learning styles using Bayesian Network. A Bayesian Network is a directed acyclic graph which consists of nodes and arcs. The Bayesian network used to detect the learning style is shown in Figure 3.

In Figure 3 every bulge has combined CPT which designates measureable possibility of data and the directed arcs mean probabilistic alternation between variables. There are several states in each node of the Bayesian network. They are mentioned in Table 2

The Table 2 consists of several Bayesian network states such as chat, forum, average test score, average time for test, number of sample

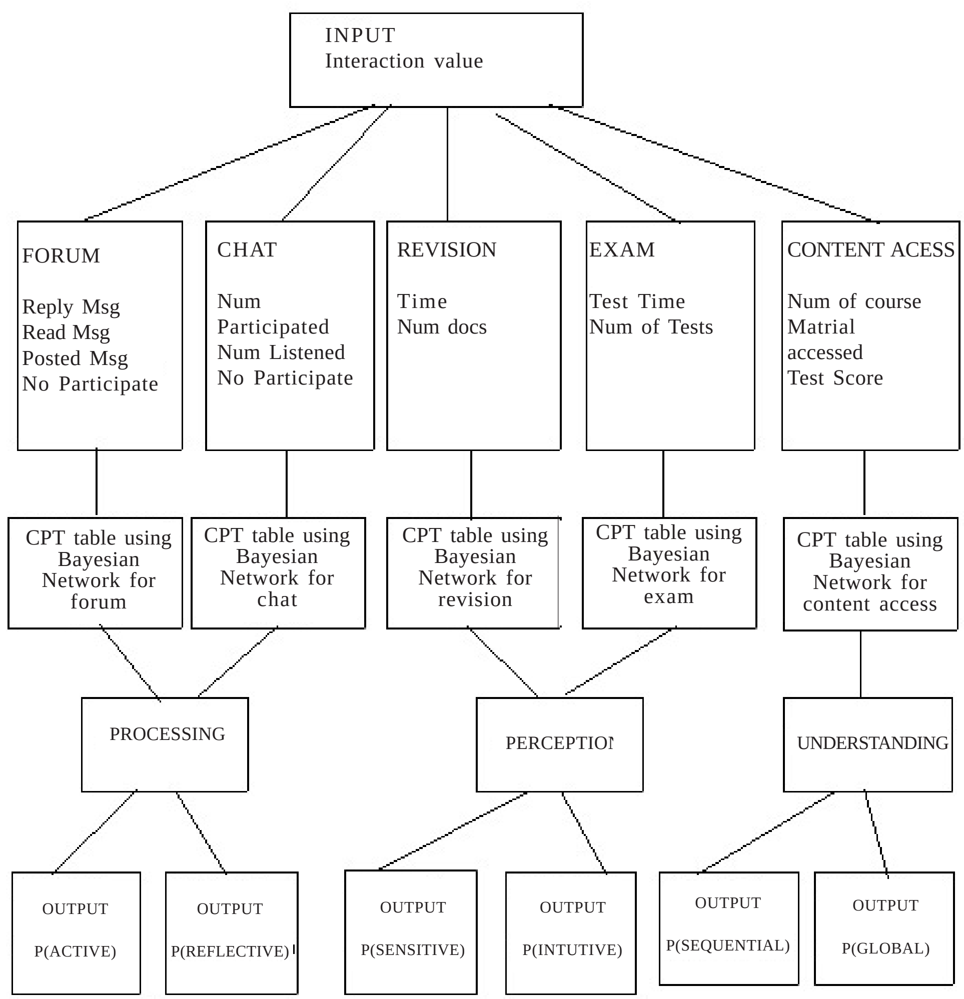


**Fig. 2. Learning style identifier process**
*Source:* Author

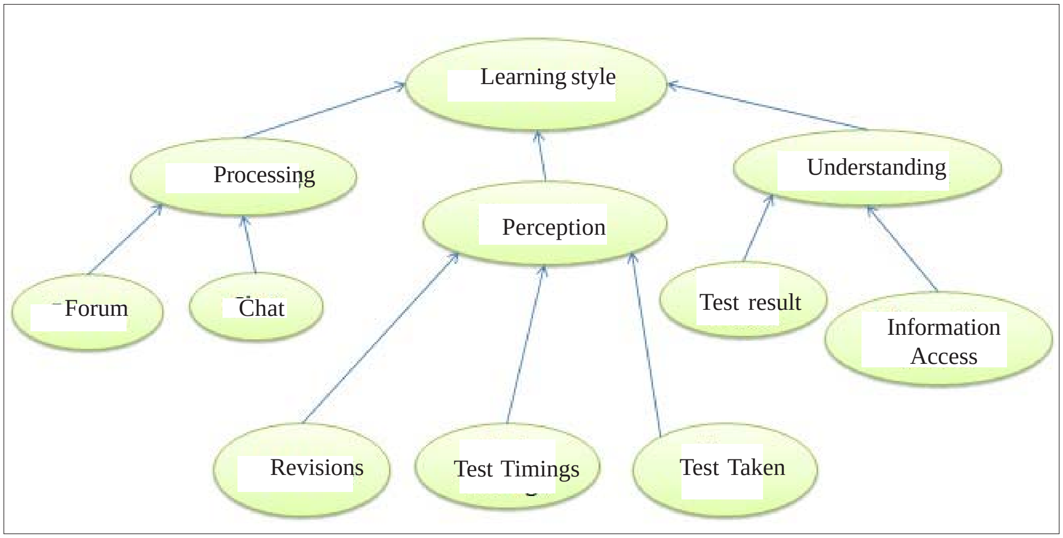


**Fig. 3. Bayesian network to detect learning style**
*Source:* Author

**Table 2: Bayesian network states**

| *Network states* | *Activities* |
|---|---|
| *Chat* | Participate in a chat<br>Listen a chat<br>No participation in a chat |
| *Forum* | Number of read messages<br>Number of replied messages<br>Number of queries posted<br>Number of discussions not participated in |
| *Average Test Score (On a scale of 1 - 10)* | High (more than 7)<br>Medium (4-7)<br>Low (below 4) |
| *Information Access* | Fits and Starts |
| *Average Time for Test* | High (more than 75%)<br>Medium (50-75%)<br>Low (below 50%) |
| *Number of Sample Test Taken* | Many (more than 75%)<br>Few (25-75%)<br>None (below 25%) |
| *Number of Revision Materials Assessed* | Many (more than 20%)<br>Few (10-20%)<br>None (below 10%) |

test taken and number of revision materials-assessed from which CPT are generated. The initial probability tables are built from the values of the states in the learning tool. These initial tables are the leaf nodes in the Bayesian network. The parent nodes are constructed with conditional probability tables which are populated by calculating conditional probability values from their respective children nodes. The probability of a particular learning style is calculated using the formula:

$$P(\text{learning style} = X) = P(X \mid A_1, A_2, \ldots A_n) * P(A_1) * P(A_2) * \ldots * P(A_n)$$

Where X is the learning style.

$A_1, A_2, \ldots, A_n$ are the attributes considered from the learning tool.

$P(X \mid A_1, A_2, ..A_n)$ Is the conditional probability of learning style X given that attribute A1, A2 to An having values.

P (A1) is the probability of occurrence of attribute A1.

## Formation of Heterogeneous Groups

The heterogeneous grouping process is depicted in Figure 4.

The Figure 4, takes as input the eleven probabilities obtained from the Personality Identifier process (five) and Learning style identifier process (six). Initially, three random individuals were generated where each individual represents a grouping scheme. The fitness function was calculated for all the individuals. It was shown that the individuals with low fitness values are considered to be more heterogeneous. Genetic Operators such as election attach and alterations were applied and new individuals were generat-

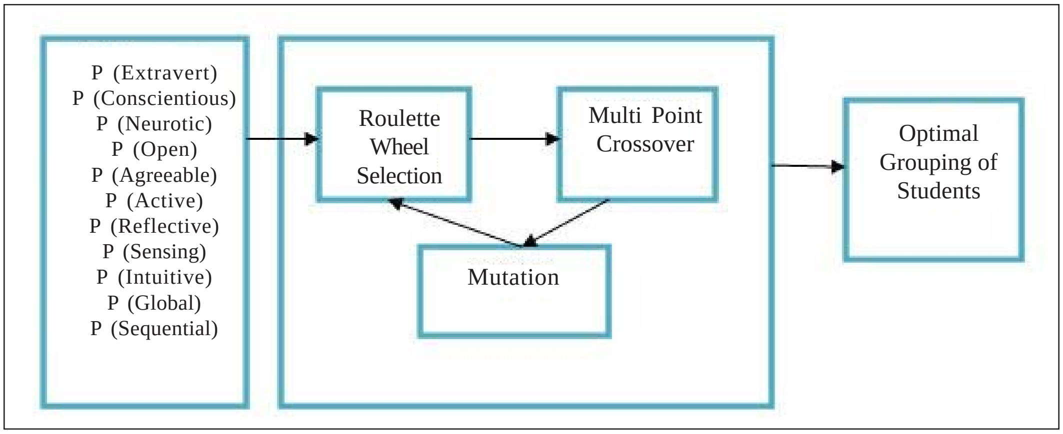


**Fig. 4. Grouping using genetic algorithm**
*Source:* Author

ed for every generation. The number of individuals remained constant for each generation. Initially, three individuals were considered. For the selection process, the Roulette wheel selection mechanism was used. Certain individuals were selected from this process. The other individual was obtained by Multi point Crossover operator from the previously obtained individuals. Finally, mutation was applied and a new individual was obtained. The process continued for a specified number of generations. Finally, the individual with the lowest D value was selected. The aim of this research work was to form optimal heterogeneous groups. Initially, a fixed number of individuals were formed. Fitness function was calculated for all of them and genetic operators selection, crossover and mutation were applied. The individual with the lowest fitness value was considered as the optimal grouping mechanism.

The method for calculation of the fitness function is given below:

Each student is represented as $E_i$ and each student has m characteristics represented by an array:

$E_i = \{C_1, C_2, \ldots, C_m\}$ (here m=11)

The mean of each feature is then calculated as,

$$TM = \left\{ \overline{C1}, \overline{C2}, \overline{C3}, \ldots, \overline{Cn} \right\}$$

Every individual is depicted by a matrix X where rows represent number of groups desired, columns represent maximum size of each group (N/G).

g random groups are formed consisting of N/G members each.

Then for every group g of each single the mean of each depicted is calculated as:

$$IM^i_g = \{ \overline{X_{ig}1}, \overline{X_{ig}2}, \overline{X_{ig}3}, \ldots, \overline{X_{ig}M} \}$$

The squared difference is calculated as:

$$D_i = \Sigma_g = 1 \text{ to } 0 \{ (\overline{C1} - \overline{X_{ig}1})^2 + (\overline{C2} - \overline{X_{ig}2})^2 + \ldots\ldots\ldots + (\overline{Cn} - \overline{X_{ig}M})^2$$

For selection, Roulette wheel Selection mechanism was employed. Each portion of the roulette is represented by Di/ ΣD. On the individuals obtained from selection process. Multi point cross over was applied. A random array whose size is equal to the number of individuals was generated and crossover was done at those points for each row to produce a new individual. Finally, the new individual mutation was applied. The individuals obtained from this process were again subjected to genetic operators for a fixed amount of generations. Finally, the individual with the lowest fitness value was selected for grouping.

The Naive Bayes classifier calculates the probabilities of personality traits of each student and Bayesian network evaluates the precision of learning styles of the student. These probability values serve as the input for the genetic algorithm which is used for grouping the students. The teacher can choose a random group size for grouping. When a group size is chosen, the genetic algorithm generates generations of individuals and keeps calculating their fitness. Finally, after n number of generations the individual with least fitness value is chosen to be the effective group. The lesser the fitness value, the more heterogeneity is observed among the group members.

In conventional learning environment the formation of effective groups is quite complex based questionnaires (kuan-cheng et al. 2009; Truong 2016). But in collaborative e learning environment group formation with the help of genetic algorithm using personality and learning styles are very effective. This research work forms an excellent heterogeneous association by considering the studying style and characteristic traits of the learners. For observation a sample of 60 students was considered. With group size as 10 and 500 generations a fitness value of 0.01944 was obtained which is quite less compared to the initial fitness value of 0.09142.

Table 3 represents first group formation in 1st generation based on genetic algorithm. On observation, it was noted that whenever the group size is small, the genetic algorithm takes lots of generations to arrive at a small fitness value. But if the group size is large, then lesser generations will suffice for an efficient solution. The initial random group size was chosen as 10, so each group had 10 members and there were 6 different groups.

The Table 4 represents first group formation in 500th generation. Tables 3 and 4, slight variations can be observed. In Table 3, all the values are almost similar and have a close homogeneous behavior, where as in Table 4, the values are varying and have slight differences. Thus, heterogeneity among group members was achieved after 500th generations and also performed well.

## CONCLUSION

Generally, students perform better when they are in a group than as individuals. The associating way suggested in this research work will additionally improve the training of any collaborative studying environment. Since it forms an excellent heterogeneous association seeing the studying style and characteristic traits of the learners, it will develop the single attainment of a learner in an association. The intra heteroge-

**Table 3: First group in generation1**

| *Personality/ learning style* | *Student 1* | *Student 2* | *Student 3* | *Student 4* | *Student 5* | *Student 6* | *Student 7* | *Student 8* | *Student 9* | *Student 10* |
|---|---|---|---|---|---|---|---|---|---|---|
| *Extravert* | 0.1395 | 0.1456 | 0.2137 | 0.2111 | 0.2111 | 0.1458 | 0.2111 | 0.1400 | 0.2027 | 0.2136 |
| *Agreeable* | 0.2438 | 0.2109 | 0.2131 | 0.2085 | 0.2085 | 0.2325 | 0.2085 | 0.2132 | 0.1912 | 0.2142 |
| *Neurotic* | 0.1918 | 0.1964 | 0.1964 | 0.1951 | 0.1951 | 0.1609 | 0.1951 | 0.1573 | 0.1908 | 0.1987 |
| *Conscientious* | 0.2366 | 0.2372 | 0.1883 | 0.1903 | 0.1903 | 0.2214 | 0.1903 | 0.2298 | 0.1976 | 0.1896 |
| *Openness* | 0.1903 | 0.2083 | 0.1886 | 0.1945 | 0.1945 | 0.2343 | 0.1945 | 0.2625 | 0.2179 | 0.1843 |
| *Active* | 0.7221 | 0.7493 | 0.7238 | 0.7531 | 0.7109 | 0.6963 | 0.6822 | 0.7174 | 0.6281 | 0.7010 |
| *Reflective* | 0.2778 | 0.2506 | 0.2761 | 0.2468 | 0.2890 | 0.3036 | 0.3177 | 0.2825 | 0.3718 | 0.2989 |
| *Sequential* | 0.79 | 0.6249 | 0.7458 | 0.5611 | 0.2437 | 0.3875 | 0.775 | 0.7307 | 0.3062 | 0.4 |
| *Global* | 0.2099 | 0.375 | 0.2541 | 0.438 | 0.7562 | 0.6125 | 0.2499 | 0.2692 | 0.6937 | 0.6 |
| *Sensory* | 0.76 | 0.72 | 0.8265 | 0.5875 | 0.5708 | 0.7111 | 0.53 | 0.8413 | 0.7192 | 0.8333 |
| *Intuitive* | 0.24 | 0.2799 | 0.1734 | 0.4125 | 0.4291 | 0.2888 | 0.47 | 0.1586 | 0.2807 | 0.1677 |

**Table 4: First group in generation 500**

| *Personality/ learning style* | *Student 1* | *Student 3* | *Student 5* | *Student 7* | *Student 9* | *Student 11* | *Student 13* | *Student 15* | *Student 17* | *Student 19* |
|---|---|---|---|---|---|---|---|---|---|---|
| *Extravert* | 0.1395 | 0.2137 | 0.2111 | 0.2111 | 0.2027 | 0.2027 | 0.2027 | 0.1400 | 0.2027 | 0.2136 |
| *Agreeable* | 0.24382 | 0.21313 | 0.20853 | 0.20853 | 0.19122 | 0.19122 | 0.1915 | 0.21327 | 0.19122 | 0.21421 |
| *Neurotic* | 0.19184 | 0.19641 | 0.19519 | 0.19519 | 0.19089 | 0.19089 | 0.1904 | 0.15737 | 0.19089 | 0.19873 |
| *Conscientious* | 0.23663 | 0.1883 | 0.19039 | 0.19039 | 0.19763 | 0.19763 | 0.19795 | 0.22988 | 0.19763 | 0.18968 |
| *Openness* | 0.1903 | 0.188611 | 0.19451 | 0.19451 | 0.21799 | 0.21799 | 0.21777 | 0.26259 | 0.21799 | 0.1843 |
| *Active* | 0.72215 | 0.72389 | 0.71091 | 0.68224 | 0.62819 | 0.59566 | 0.58848 | 0.71743 | 0.62819 | 0.70107 |
| *Reflective* | 0.27784 | 0.2761 | 0.28908 | 0.31775 | 0.3718 | 0.40433 | 0.41151 | 0.28256 | 0.3718 | 0.29892 |
| *Sequential* | 0.79 | 0.74583 | 0.24375 | 0.775 | 0.30625 | 0.0294 | 0.27692 | 0.73076 | 0.30625 | 0.4 |
| *Global* | 0.20999 | 0.25416 | 0.75625 | 0.24999 | 0.69375 | 0.9705 | 0.723769 | 0.26923 | 0.69375 | 0.6 |
| *Sensory* | 0.76 | 0.82656 | 0.57083 | 0.53 | 0.71923 | 0.905 | 0.85909 | 0.84137 | 0.71923 | 0.8333 |
| *Intuitive* | 0.24 | 0.17343 | 0.42916 | 0.47 | 0.28076 | 0.0199 | 0.13987 | 0.15862 | 0.28076 | 0.16777 |

neous and inter homogeneous group formation which was obtained, would help the students to gain more from the group than when he/she is in a group which is formed in a random manner. Thus, the work of the instructor while forming student groups is minimized since the detection of personality and learning styles and the group formation is automated. This can be integrated with any Learning Management System (LMS) as it only requires features which are commonly found in most of the systems found today.

## RECOMMENDATIONS

On the basis of the results attained in the research work, the following recommendations were made:

The students belonging to the collaborative e learning environment should be effectively grouped based on the personality and learning styles for their improvement in betterment of learning. And also, students belonging to the collaborative e learning environment achieve best in learning than individual learners.

## FUTURE WORK

Future work could involve use of more psychological and lexical databases (for example, Linguistic Inquiry and Word Count (LIWC) database) for improving accuracy of personality classification. More language processing can be done to understand abbreviations and short forms. The precision of a learning style can be improved by taking into account the various other interactions of the student with the learning tool also. Since the genetic algorithm used in this work can adapt to any number of parameters, other characteristics that may affect student's performance can also be included.

## REFERENCES

Balakrishnan Vimala, Lay Gan Chin 2015. Students' learning styles and their effects on the use of social media technology for learning. *Telematics and Informatics*, 33: 808–821.

Digman JM 1990. Personality structure: Emergence of the five-factor model. *Annual Review of Psychology*, 41: 417-440.

Felder RM, Silverman LK 1988. Learning and teaching styles in engineering education. *Journal of Engineering Education*, 78(7): 674–681.

Khenissi Mohamed Ali, Essalmi Fathi, Jemni Mohamed, Kinshuk, Sabine Graf, Chen Nian-Shing 2016. Relationship between learning styles and genres of games. *Computers and Education*, 101: 1-14.

Lin Kuan-Cheng, Mei-Lianshiau, Shu-Ying, Jui Tai 2009. Optimal Grouping by Using Genetic Algorithm and Support Vector Machines. *Joint Conferences on Pervasive Computing, Taiwan,* Dec 3-5: 777-782.

Liu Aihong 2009. Grouping Strategy of Collaborative Learning: Cluster Analysis. *International Conference on E-Business and Information System Security,* Wuhan/ China, May 23-24, pp. 1-5.

Ounnas Asma, Davis Hugh C, Millard David E 2009. A framework for semantic group formation in education. *Educational Technology and Society*, 12 (4): 43–55.

Pennebaker JW, Laura AK 1999. Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology*, 77: 1296-1312.

Rebecca HR 2001. Using Personality Inventories to Help Form Teams for Software Engineering Class Process. *Proceedings of the 6th Annual Conference on Innovation and Technology in Computer Science Education,* Canterbury, UK, June 25-27: 73-76.

Sabine Graf, Rahel Bekele 2006. Forming Heterogeneous groups for intelligent collaborative learning systems with Ant Colony Optimization. *Proceedings of the 8th International Conference on Intelligent Tutoring Systems,* Johngli, Taiwan, June 26-30, pp. 217-226.

Truong Huong May 2016. Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior,* 55: 1185–1193.

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