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SVM and PCA Based Learning Feature Classification Approaches for E-Learning System

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ABSTRACT

E-learning and online education has made great improvements in the recent past. It has shifted the teaching paradigm from conventional classroom learning to dynamic web based learning. Due to this, a dynamic learning material has been delivered to learners, instead of static content, according to their skills, needs and preferences. In this article, the authors have classified eight different types of student learning attributes based on National Centre for Biotechnical Information (NCBI) e-learning database. The eight types of attributes are Anxiety (A), Personality (P), Learning style (L), Cognitive style (C), Grades from previous sem (GP), Motivation (M), Study level (SL) and Student prior knowledge (SPK). In this article the authors have proposed an approach which uses principal components of student learning attributes and have later independently classified these attributes using feed forward neural network (NN) and Least Square –Support Vector Machine (LS-SVM).

KEYWORDS

Adaptive, E-Learning, Least Square Support Vector Machine (LS-SVM), Neural Network (NN), Personalization

1. INTRODUCTION

In order to compete and survive in the twenty-first century internet based economy, it is essential that students are aware of learning programming techniques and acquire these skills in their behaviour (Chen, Warden, & Chang, 2006). The goal of instructing programming is to facilitate students' future by helping them build skills to improve logic to solve real world problem so that they become successful in their academic and professional career. In the conventional classroom learning system instructors deliver the same content to all students without taking into consideration their individuals personality type, learning style, anxiety level, prior knowledge on programming, cognitive styles or result of previous grades. Such type of current learning is based on static learning material but not on dynamic programming based learning (Romero and Bra, 2007). In such type of system if students want to maximize their learning outcome, it is they who have to adapt according to the course content and cannot change the course content to deliver based on their specific attributes or characteristics.

In this paper, our intent is to classify student learning attributes with the help of principal component analysis. Intelligent computing techniques like neural network, principal component analysis and support vector machines are used to investigate students' background and their attributes or characteristics in order to optimize their learning sequence and maximize their learning outcome in computer programming courses.

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An online web based system was designed to analyze various types of student attributes (Gender (G), Personality (P), Anxiety (A), Learning level (L) and Cognitive ability (C)) using Case based reasoning, hybrid neural network and efficient data mining technique in learning C programming course. This system yielded an average accuracy and sensitivity of 71.65% and 70.22% respectively with five different classes (Khamparia and Pandey, 2015). An English language learning system was designed along with mainly three student features (Gender, Personality and Anxiety) as a classifier which mainly used neural network and decision tree algorithm. Gender, study level, Student prior knowledge and intrinsic motivation were classified using hybrid neural network with post-test classification and yielded an accuracy of 67% (Van Seters et al. 2012). Two types of student attributes, cognitive style and learning style, were classified using particle swarm optimization with neural network classifier and achieved more than 64% of sensitivity and 65% of accuracy (Yang et al. 2008).

Even though many works were reported on students' attribute classification, there is a constant need to improve the classification accuracy when more number of attributes are incorporated and operated upon large databases comprising of different instances of individual attributes. Most of the proposed methods involve too many computational overhead, but our intent is to develop a simple methodology for students' learning attribute classification with efficient accuracy for large instances of e-learning database.

The paper is organized in the following ways: Section 2 represents the literature review. It also represents the proposed methodology with involvement of Principal Component Analysis (PCA) and classifiers. Section 3 represents the results and computing description. We present the interpretation of result in Section 4. Finally, we conclude the paper in Section 5.

2. LITERATURE REVIEW

This section demonstrates different intelligent classification approaches used in the context of e-learning. (Wang et al. 2009) proposed an adaptive system for optimizing learning sequences using decision tree algorithm for particular teaching content. (Wang et al. 2011) proposed an adaptive TESL based English learning system which considers student attributes and explores teaching content on the basis of grammar, vocabulary and reading by comparing results with control groups. (Chookaew et al. 2012) presented an e-learning environment which allows personalizing computer programming courses according to learner's level of knowledge and different learning styles. (Hsieh and Wang 2010) developed RBR-ANN based techniques to recognize emotions with the help of production rules to adjust the teaching strategies, (Norsham, Norazah and Puteh 2009) used feed-forward learning network with the help of rules to identify the sequencing of the learner object. (Tang et al. 2008) proposed GA-ontology method in which the personalized course ware is designed on the basis of the difficulty level and time taken to improve the learning of the learner. (Al-Radaei and Mishra 2013) proposed agent based learner which calculates semantic value of keyword based on its occurrence and updates learners' profile based on the score obtained from correct answers. (Van Seters et al. 2012) characterized students groups by collecting demographic data, measuring motivation and prior knowledge of students groups and predicting learning path based on their characteristics and strategies adopted by them. (Lin et al. 2013) used decision tree to predict learning path of students with different learning styles which were used for setting games. (Pandey et al. 2014) proposed CBR based programming system which considers student characteristics and deliver the personalized learning material to students according to their preferences. Very few researchers have involved SVM and PCA into consideration for classification of learning features. (Wu et al. 2012) preferred SVM-PCA integration for reduction and classification of data on the basis of learning time, discussion performed by learner, bulletin reading time, file downloading time, communion and exercises to solve by learner. They have considered sample size of 1000 cases and stabilized the correlation by using SPSS.

2.1. Data Preprocessing (Student Features)

In this work, we have used student learning database from NCBI for the student learning attribute analysis and classification. The classification is performed with help of statistical tool called SPSS through which data is classified or categorized. The normalized data set is comprised of eight important attributes i.e. Anxiety (A), Personality (P), Learning style (L), Cognitive style (C), Grades from previous sem (GP), Motivation (M), Study level (SL) and Student prior knowledge (SPK) each categorized into equal 240 instances.

Wang and his colleagues showed that students' attributes such as: anxiety (A), personality (P), learning (L) Grades from previous semester (GP), Motivation (M), Study level (SL), Student prior knowledge (SPK) and cognitive ability (C) affect their learning performance outcomes in English language (Wang et al. 2009). In the discipline of computers also, the student learning performance is affected by these attributes. This can also be applicable to computer programming language, so we can consider these features to measure the learning performance of students in C programming language (Wu et al. 2012; Khamparia and Pandey, 2015). In present work, we have categorized these features in various levels such as: A in low anxiety (LA), medium anxiety (MA) and high anxiety as (HA); P in introvert (IN), mildly introvert (MI), Neutral (N), mildly extrovert (ME) and extrovert (EX); L in Thinking & belief (TB), Perception of information (POI) and Watching & listening (WAL); M in Extrinsic (E) and Intrinsic (I); SL in High (H), Medium (M) and Low (L); SPK in High (H), Medium (M) and Low (L) ; GP in High (H), Medium (M) and Low (L) and C in Field dependent (FD) and Field Independent (FI).

2.2. Data Set Normalization

In present study, 100 students were selected from North Asia University. These students were asked to take C programming test to understand their Syntax (SY), Logical (LG) and Application (AP) oriented capabilities and to fill out questionnaire gathering information about A, P, L, M, SL, SPK, GP and C. The Syntax (SY) determines the student's ability of understanding syntax required for programming, logical (LG) determines the soundness of student while attempting logical based questions from C programming and application (AP) determines how the student is able to deploy applications using programming constructs. These abilities are divided into low, medium and high level. The programming test assessed the student capability for SY, LG and AP. Test assessment is divided into two phases i.e. mid-term (after 7 weeks) and end-term test (after 14 weeks) each comprised of 20 questions for each SY, LG and AP.

This study used the Computer Anxiety Rating Scale (CARS) developed by Heinssen et al. (1987) to measure the anxiety level of students who participated in test study. Heinssen et al. (1987) computed the scores based on Likert scale which ranges from 33 to 166. The students with scores between 33 and 66 are identified as low anxiety students (LA); with scores between 67 and 132 as medium anxiety (MA); and with scores between 133 and 166 are identified as high anxiety students (HA). Ganschow and Sparks (1996) grouped the students into introverted (IN), mildly introverted (MI), neutral (N), mildly extroverted (ME) and extroverted (E) according to the scores obtained from extroversion scale Eyesenck (1964). Students with scores ranging from 24 to 60 are identified as introverted; scores from 61 to 69 are identified as mildly introverted; with scores ranging from 70 to 87 are identified as neutral personality; with scores ranging from 88 to 96 as mildly extroverted; and finally scores ranging from 97 to 120 are identified as extroverted. Sarasubm (1998) categorized the learning process into Thinking & belief (TB), Perception of information (POI) and Watching & listening (WAL) on the basis of introversion scale which improves profile of students. Oosevert et al. (2012) categorized the motivation into extrinsic (E) and intrinsic (I). Similarly, Witkin et al. (1977) have considered the students' cognitive style as field dependence (FD) and field independence (FI) and analyze their impact on student learning Khamparia and Pandey (2015).

The C programming content was divided into different levels as Syntax (SY), logical (LG) and Application (AP). Each of these contains questions or code snippets related to syntax, logic and

Table 1. Result of partial dataset combination of student characteristics and learning performance levels

Anxiety	Personality	Learning Style	Cognitive Style	Grades From Previous Sem.	Motivation	Study Level	Student Prior Knowledge	SY	LG	AP
1	2	2	1	1	1	1	2	H	L	H
1	2	2	1	2	2	1	2	L	L	H
1	2	2	1	1	1	1	2	L	H	H
1	2	2	1	3	2	1	2	L	H	L
1	3	3	1	1	1	1	3	L	L	L
1	3	3	1	2	2	1	3	H	H	L
2	3	3	1	1	1	1	3	H	L	H
2	3	3	2	2	2	1	3	L	L	L
2	3	3	1	1	1	1	3	H	H	H
2	2	3	2	2	2	1	3	L	H	L
2	3	3	1	1	1	1	3	L	H	H
2	3	4	2	2	2	3	3	H	L	L

application oriented domain Khamparia and Pandey (2015). The number of student attributes are coded as the following Personality types: I=1, MI=2, N =3, ME =4, and E=5; Anxiety level: LA=1, MA=2, HA=3; Learning: TB=1, POI=2 and WAL=3; Motivation: E=1, I=2; Study level: L=1, M=2, H=3; Grade from previous sem: L=1, M=2, H=3; Study level: L=1, M=2, H=3; Student prior knowledge: L=1, M=2, H=3; Cognitive level: FD=1, and FI =2. There are three output nodes: SY, LG and AP which represents the learning performance difficulty levels into High (H) and Low (L). The partial dataset combination is indicated in Table 1.

In proposed methodology as shown in Figure 1, the data has been normalized and student learning features are reduced into different principal components using principal component techniques. The reduced components are treated by different kernel classifiers with help of Multi-SVM for classification of student learning features. Then finally prediction of result is computed by calculating sensitivity, specificity, accuracy and precision values.

2.3. Principal Components Analysis (PCA)

The Principal Component Analysis (PCA) is a linear dimensionality reduction technique that makes easy to visualize and explore data by providing emphasis on variance and store the patterns in dataset (Duda, 2001). In proposed work we have reduced the dimensionality of student features using tool SPSS 17. This data reduction or factor analysis technique involves computation of correlation matrix from the ensemble of student learning features, eigenvalue and eigenvector decomposition of correlation matrix, sorting and rotate eigenvectors in the descending order of eigenvalues and finally projecting the original data in the directions of sorted eigenvectors (Martin et al., 2012). Figure 2 shows the descriptive statistics in terms of Mean and Std. Deviation of student learning features. Figure 3 determines the total variance computed for all features. The first few components will determine the variation among the data which is represented by scree plot as shown in Figure 4. In this work, we have considered only 3 components which were obtained using reduction techniques and used later for classification purpose as shown in Figure 5.

Figure 1. Block diagram of proposed system

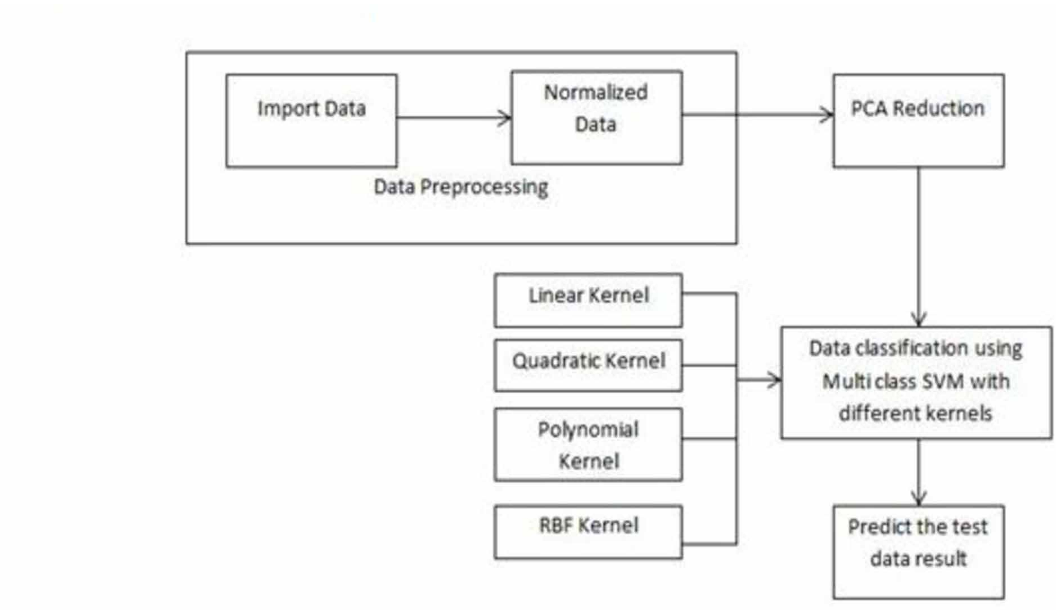


Figure 2. Descriptive statistics

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
Anxiety	1.97	.765	240
Personality	2.10	.976	240
Learning style	2.21	1.018	240
Cognitive style	1.51	.501	240
Grades from previous sem	1.62	.628	240
Motivation	1.50	.501	240
Study Level	1.76	.775	240
Student prior knowLowedge	2.00	.818	240

2.4. Classification

In this study, a fully connected feed forward neural network (NN) and least square support vector machine are used for attribute identification.

2.4.1. Neural Networks

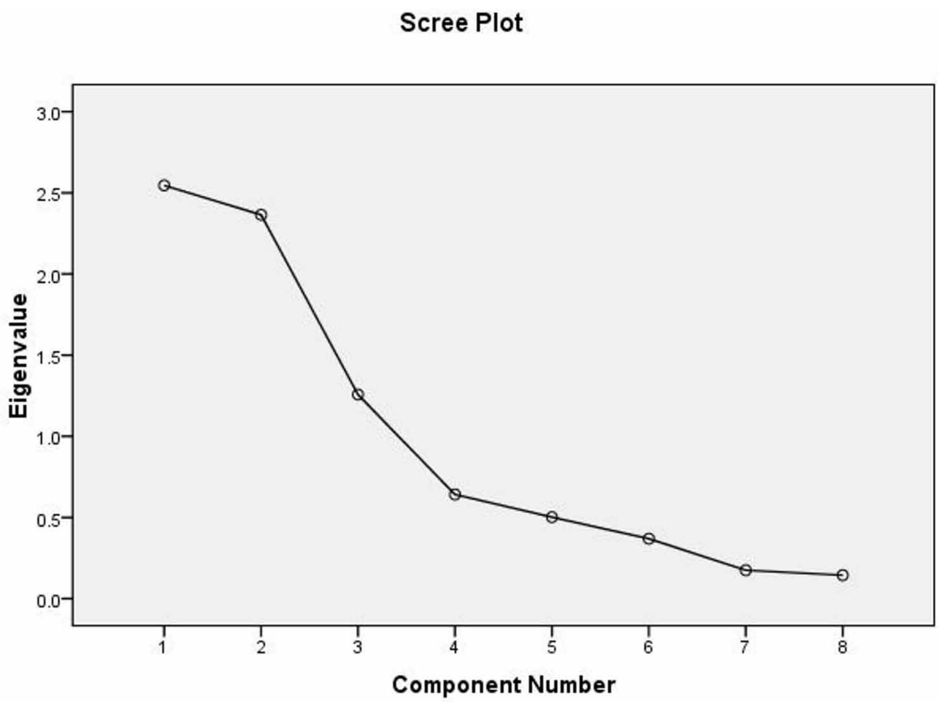
In the current study, a fully connected feed forward neural network is used for feature identification (Bishop, 1995; Haykin, 1999).

Figure 3. Total variance

Total Variance Explained

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total
1	2.546	31.821	31.821	2.508
2	2.365	29.557	61.378	2.358
3	1.257	15.712	77.090	1.402
4	.642	8.019	85.109	
5	.502	6.275	91.384	
6	.369	4.617	96.002	
7	.175	2.191	98.192	
8	.145	1.808	100.000	

Figure 4. Scree plot



The neural network comprised of set of input layers, output layer and hidden layers which comprised of neurons. Weights are assigned to input neurons through which output response has been computed. The error response has been computed by obtaining the difference between the target output and actual output which is obtained. After getting such an error output it has been back

Figure 5. Principal components

Pattern Matrix^a

	Component		
	1	2	3
Student prior knowLowedge	.941	.013	-.012
Learning style	.889	.000	.032
Personality	.854	-.007	-.017
Motivation	-.007	.956	-.077
Cognitive style	.003	.858	.115
Grades from previous sem	.008	.832	-.032
Anxiety	-.173	.016	.857
Study Level	.221	-.007	.760

Table 2. Results of feature extraction using PCA on student learning features

Principal Component	Student Prior Knowledge	Learning Style	Personality	Motivation	Cognitive Style	Grades From Previous Sem.	Anxiety	Study Level
PC1	0.941	0.889	0.854	-0.007	0.003	0.008	-0.173	0.221
PC2	0.013	0	-0.007	0.956	0.858	0.832	0.016	-0.007
PC3	-0.012	0.032	-0.17	-0.77	0.115	-0.032	0.857	0.76

propagated towards the hidden layer to adjust the weight of neurons present at different layers. This process is repeated continuously until error reached or crossed the given threshold. After training the data has been fed for testing and validation purpose to check the simulated output and based on obtained testing set the classification of data has been performed.

2.5. Least Square- Support Vector Machine

Support Vector Machine (SVM) is a highly non-linear and single layered network which is having higher generalization ability; it can classify unseen patterns correctly (Christianini & Taylor, 2000; Gunn, 1998). The classifier minimizes structural risk instead of empirical risk as in other classifiers. It maximizes the distance between the patterns and the class separating hyperplane simultaneously in order to discriminate the patterns belonging to different classes. Generally, the patterns in the given feature space are not linearly separable, therefore they are projected into a high dimensional space where the features are assumed to be linearly separable and classification is performed. The technique is called kernel trick. Commonly used kernels are linear, quadratic and gaussian kernels. In the current study, a modification of original SVM termed as Least Square SVM (LSSVM) is used (Suykens & Vandewalle, 1999).

3. RESULTS

The student characteristics or features from e-learning database were first imported and normalized using data normalization technique. After normalization, the student features were segmented to obtain 240 sample instances as a feature for subsequent analysis.

In the proposed approach, the segmented student attributes were used for its dimensionality reduction using principal component analysis. The dimensionality reduced principal components were used for the classification of eight types of student attributes in learning programming skills according to their syntax, logical and application level. In total 3 components were used for the learner programming skill attributes classification using feed forward neural network and least square support vector machine (LS-SVM). Table 2 provides the result of three principal components extracted from e-learning feature set.

As all 3 statistically features are significant and used for classification using Neural Networks and LS-SVM with different kernel functions. In this study, we have used two fold, five-fold, seven fold and ten-fold cross validation scheme for the training and testing of the classifiers.

Figures 6-9 shows the average sensitivity, specificity, precision and accuracy using different classifiers for various folds of ten-fold cross validation respectively.

It can be seen from Table 3, that LS-SVM with linear kernel classifier provided highest average classification accuracy of 73.15%, average sensitivity and average specificity of 73.12% and 73.01% respectively. The average precision is provided by quadratic kernel classifier with classification precision of 73.23%.

4. DISCUSSION

This paper discusses the learning features classification using PCA and SVM features. Table 4 provides a summary of studies on classification of student's attributes and predicts the programming skill level of students by using the data obtained from NCBI learning database. Three types of student learning attributes (Gender, Personality, and Anxiety) were classified using personalized ANN and

Figure 6. Plot of accuracy versus different folds of cross validation for different classifiers

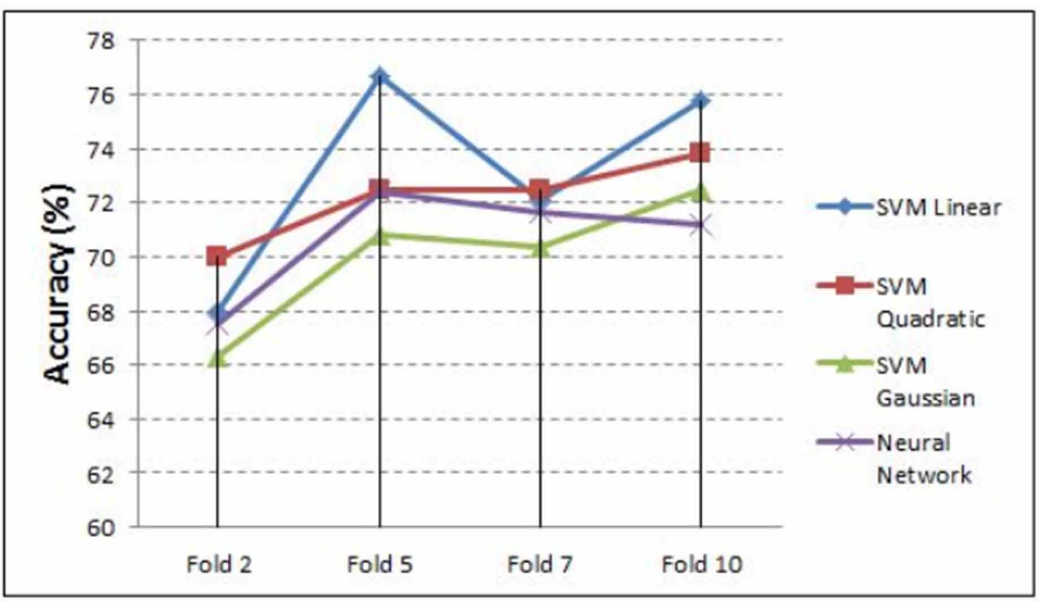


Figure 7. Plot of sensitivity versus different folds of cross validation for different classifiers

Figure 8. Plot of specificity versus different folds of cross validation for different classifiers

Data mining technique for English language learning system and reported 68% of accuracy (Wang and Liao, 2009). The adaptive learning sequencing with Self organized map and data mining were used to classify attributes (Gender, Personality, Cognitive style, learning style and student grades) for English language subject and reported accuracy of 70% (Wang et al. 2011). The GSKM (Gender, Study level, student prior knowledge and intrinsic motivation) features were used to classify different attributes using hybrid neural network classifier with pre-post analysis and achieved accuracy of 67%

Figure 9. Plot of precision versus different folds of cross validation for different classifiers

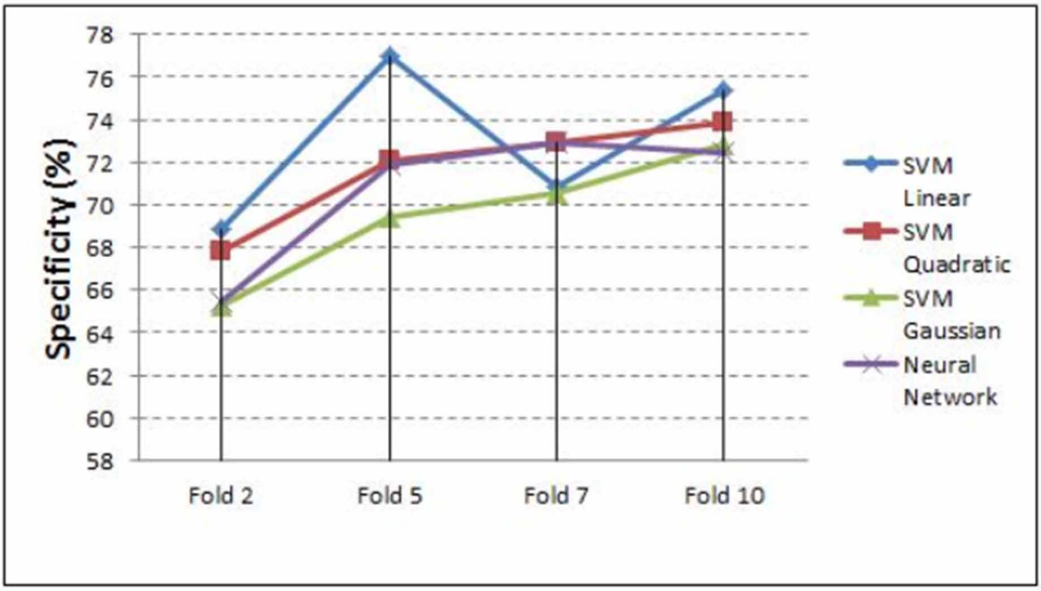


Table 3. Classification results of different classifiers for proposed methodology

	Average Accuracy (%)	Average Sensitivity (%)	Average Specificity (%)	Average PPV (%)
LS-SVM with linear kernel	73.15	73.12	73.01	72
LS-SVM with quadratic kernel	72.2	72	71.68	73.23
LS-SVM with gaussian kernel	70	69.37	69.54	70.61
Neural Network	70.6	71.7	70.67	71.35

(Van Seters et al. 2012). Cognitive and Learning style features were classified using personalized classifier and obtained accuracy of 65% (Yang et al. 2008). Gender, Personality, Anxiety, Learning and Cognitive ability attributes were classified using Case based reasoning, ANN and Data mining techniques with pre-post analysis and reported overall accuracy of 71.65% for computer science programming course (Khamparia and Pandey, 2015).

Our proposed method involves linear kernel classifier with performance yielding the highest average classification accuracy of 73.15, average sensitivity, specificity and precision of 73.12%, 73.01% and 72% respectively compared to other kernel classifiers. Other dimensionality reduction techniques such as Linear Discriminant Analysis (LDA), Canonical correlation (CCA), Independent Component Analysis (ICA) and factor analysis etc. can be used instead of PCA during feature extraction. The best subspace providing highest discrimination among the attributes of different classes can be identified. The performance of classification can be improved and compared using diverse attributes like personality, anxiety, motivation, learning ability etc. and other classification strategies like linear discriminant analysis (LDA), K-nearest neighbour algorithm (KNN), Classification and regression trees (CART) and different multi-layer perceptron networks.

Table 4. Summary of the studies on identification of learning features using e-database

Literature	Features	Classifier	Classes	Accuracy in %	Area
(Wang and Liao, 2009)	Gender, Personality, Anxiety	ANN, Data mining	3	68	English Learning system
(Wang et al., 2011)	Gender, Personality, Cognitive style, learning style and student grades	Self-organized map and data mining	5	70	English Learning system
(Van Seters et al. 2012)	Gender, Study level, student prior knowledge and intrinsic motivation	Hybrid neural network with post test	4	67	Molecular Biology course
(Yang et al. 2008)	Cognitive and Learning style	Particle swarm optimization	2	65	Java Programming course
(Khamparia and Pandey, 2015)	Gender, Personality, Anxiety, Learning and Cognitive ability	ANN, Data mining and CBR	5	71.65	C Programming course
Proposed approach	Anxiety, Personality, Learning level, Cognitive ability, Study level, Grades from previous sem, Motivation, Student prior knowledge + PCA	Linear Square SVM	8	73.12	C Programming course

5. CONCLUSION

In this work, PCA analysis is effectively used as an acute tool for classification of eight varieties of student learning attributes for using e-learning systems, so that effective and personalized learning content can be provided to them according to their needs and preferences. Our proposed method uses principal components of student attributes and later classified using different categories of kernel classifier with support of SVM. Our proposed approach yields an average classification accuracy of 73.15, average sensitivity, specificity and precision of 73.12%, 73.01% and 72% respectively compared to other kernel classifiers. This is the first-time integration of PCA with SVM proposed in area of e-learning domain which can be used to monitor students' learning performance in programming areas and provide more adaptive learning content to them according to their needs and preferences in future. It is also validated and demonstrated that dimension reduction using PCA can significantly improve the generalized performance of least square SVM. Experimental results evidently show that proposed linear SVM had outperformed other kernel classifiers, but due to lack of integration with other computing methods for features hybridization, the accuracy or scaling of proposed system could be marginally ineffective.

In our future work we will further improve parameters with respect to optimization algorithms by using combination of efficient intelligent computing methods to build a more efficient and practical vision system. We will also reduce the rule base formation in dataset by deploying neuro-symbolic rules and add more features to the dataset for experimentation to apply the proposed methodology in assessing a variety of virtual online learning systems.

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