Drop-out Identification model using Data Mining for an Intelligent Recommendation System for Universities in Thailand

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Abstract

In Thailand, many universities face the problems of student dropouts or failures before graduations. In order to improve and support the academic management processes, some universities are developing innovative information systems and services with an aim to enhance efficiency and retain the students to graduations. Moreover, this information technological support can also improve student relationship with universities. One of the key initiatives is the development of Student Relationship Management Systems (SRM) and among their functions, is the provision of recommendation and advice for students. Intelligent Recommendation systems allow personalization for counseling. The proposed system examined the correlation between 9000 student records and their academic results by analyzing student history data to associate with freshmen and current student data. In this experiment, Clustering followed with data mining; Artificial Neuron Networks (ANN), Support Vector Machines (SVM), Chi-squared Automatic Interaction Detector (CHAID) have been employed, the results of prediction techniques have been compared in order to choose the most accuracy. Then two aggregation models; Ensemble method and the Modular Artificial Neural Networks Optimized Weight of Subspace Reconstruction Method (MANN-OWSR) have been used to combine the results from the learning models for better performance. Good results have been obtained from the experiments and the developed system will help counselors, supervisors and academic staff in suggesting appropriate recommendations for the students.

Keywords: *Data Mining, Intelligent Recommendation System, Student Relationship Management, Aggregation Technique.*

Introduction

One of the performance assessments for an educational institute is the number and percentage of successful graduated students. In order to enhance the number of completions, educational institutes establish and implement strategies to improve students' satisfaction and academic development. Furthermore, institutes also utilize technology to assist students to succeed in their study. Prior studies have addressed issues faced by Thai students during their time in the universities. For example, Sarawut [1] studied the causes of dropouts and program incompletion among undergraduate students from the Faculty of Engineering, King Mongkut's University of Technology North Bangkok. It was reported that the general reasons for under achievement were due to teaching and learning issues. Furthermore, the study showed that the three unaccomplished groups have attributed to different reasons. The main reason of the first group is the students' attitude towards the field of study. This group had the perception that their field of study was too hard. The main reasons of the second and third groups were related to teaching and learning. Hence, this indicated the need to match the course requirements with the academic capabilities of the students. Another study at the Dhurakij Pundit University, Thailand looked at the relationship between learning behavior and low academic achievement (below 2.0 GPA) of the first year students in the regular four-year undergraduate degree programs. The results indicated that students who had low academic achievement had a moderate score in every aspect of learning behavior. On average, the students scored the highest in class attendance, followed by the attempt to spend more time on study after obtaining low examination grades. Some of the problems and difficulties that mostly affected students' low academic achievement were the students' lack of understanding of the subject, and the lack of motivation and enthusiasm to learn [2].

One of the possible means to help students and staff is the student counseling service which provides advice and counseling for freshmen in order to achieve a better match between the student's ability and the chances of success in completing the course. In the case of private universities in Thailand, this service is normally provided by counselors or advisors who have many years of experience in the organization or in higher education. However, with the increasing number of students and expanded number of choices, the workload on the advisors is becoming too much. It becomes apparent that some forms of intelligent system will be useful in assisting the advisors and this forms the motivation of this study.

In summary, in the counseling process for students in private universities, it is helpful for advisors and counselors as well as students to give warning for extra extensions. The students' backgrounds may also have a part to play in the matching process. Understanding the student's ability and background will implicitly enhance the student's learning experience and increase their chances of success, thereby reducing the wastage of resources due to drop-outs, and change of programs. These factors are therefore taken into consideration in the proposed recommendation system in this study. In this paper, a drop-out identification model of an Intelligent Recommendation System based on data mining is proposed to assist university students' in studying each course of study by aggregating the results from different techniques to enhance the performance of the system and confidence on the outcomes. Recommendations for the students to enrol in appropriate courses are important as they have implications on required commitment from the students and their families. This paper provides the background of the university system in Thailand and the justification for this study. The techniques and methodology adopted in the proposed Recommendation system are then explained.

The process of the proposed techniques is explained in this paper, which is structured as follows; the next section presents the objectives of the paper, along with a discussion of the instructional techniques which are employed. Following this section, the Intelligent Techniques for the Proposed Recommendation System is discussed in order to justify the techniques used in this study. Section 3 is the procedures of the experiment which are the selection of input and output variable including the explanation of data set, and the experimental design in this section. Then, the experimental results are followed in section 5 respectively. The last section explains the contributions of the techniques used in this paper.

Objective

This paper aims to identify possible drop out during the course of study based on past cases of student database. In this paper, the dropout identification model is proposed, which applies the techniques and methodologies for the intelligent recommendation system for students each academic year in order to identify students who are likely to drop out before graduations. This can help supervisors and lecturers to pay extra attention to students. In the experiment of this study with an aim to find the most accurate recommendations, the classification models are employed in order to classify the relationship between data. The clustering technique is also used to analyze the student relationship and separate to each group before the classification process. In order to improve the performance accuracy, Ensemble and MANN-OWSR are also employed. The proposed techniques are experimented and demonstrated based on the benchmark of three classification techniques. Finally, the proposed techniques are applied and the best model with the highest accuracy is chosen to use in the Intelligent Recommendation System.

Intelligent Techniques for the Proposed Recommendation System

In terms of recommendation systems, Herlocker [3] defined that a recommendation system is one which predicts an interesting or useful items for the user. Within the context of the recommendation system, intelligent techniques used in data mining to find the models and relationships between data, are used to classify and analyse the information in the databases [4]. The basic concepts of the techniques used in this study are described below.

Artificial Neural Networks has been used extensively in machine learning [5] and in various ways for data analysis. For example, ANN has been used to analyse Internet Traffic Data over IP Networks[6], to recognise faces[7] and to enhance the creation of targeted strategies based on computational intelligent techniques for CRM [8]. In addition, Kala el al. [9] also reported that ANN and machine learning have been used in a large number of research dealing with huge data sets such as handwriting recognition. There have been other reports on the application of artificial neural networks in recommendation systems. An example was given by Superby et al.[10]. They used data mining techniques to determine the factors influencing the achievement of the first year university students. Their study classified students into three groups: low-risk, medium-risk and high-risk students. Their report presented the results from the use of machine learning techniques such as neural networks, decision trees and random forests. While the finding stated that the prediction results were not remarkable; the authors mentioned that it was because the dataset from the three universities used in this study were not appropriate for the proposed techniques in their study.

The Decision Tree technique resembles an inverted tree structure consisting of nodes and branches connecting the nodes. Generally, the bottom nodes are called "leaves" which are used to specify different classes, and the top node is called "root" where all the training examples are applied. These examples are then classified into appropriate classes [11]. In this study, the *CHAID, Chi-squared Automatic Interaction Detector*, developed by Kass [12] and Hawkins [13] was used. There are many recommendation systems that have used Decision Tree algorithms. Some researchers have used data mining techniques such as, Vialadi et al.[14]. They proposed the use of a recommendation system to help students' decision in course enrolment by predicting the failure or success in a course using classifier. Their study employed production rules in a pattern discovery module to discover the patterns, and the Decision Tree (C4.5) algorithm in the sub-modules. Their study aimed to develop a system to predict the failure or success in the chosen course of study. The results of the study showed that the global accuracy of the trial was 77.30%. A concern of this experiment was the percentage of inaccuracy which was 22.7% of the total number of students, and it was considered to be a bit high. With a focus on the recommendation system as an important marketing tool in e-commerce, Kim [15] employed several data mining techniques including Decision Trees. Their experimental results showed that the CHAID algorithm performed better than the other models with statistical significance. Hence, CHAID is being incorporated in the proposed system in this study.

Support Vector Machine (SVM) is a classification technique and supervised learning method, developed by Vapnik [16]. SVM [17, 18] creates the input-output mapping functions, which can be either a classification function or a regression function from a set of training data. SVM has also been used in various prediction and recommendation works. Bo and Luo [19] proposed a personalized recommendation algorithm that used SVM to classify the data for collaborative recommendation in a web information recommendation algorithm. Xu et al. [20] used SVM and other techniques to find hidden relational models, the approach of their study realized a solution for recommendations based on the features of the items, features of the users, and their relational information.

K-Mean Clustering techniques are popular in machine learning for the partitioning of groups of similar data in a dataset [21]. Clustering has been applied in diverse problems. For example, clustering was used to analyse the customer relationship in security trading [22], to replicate microarray data for various covariance structure [23], and to classify customers for customer segmentation [24-29]. K-Means is a popular clustering technique and a traditional partition based method [21, 29]. In [30], Sarwar et al. mentioned that K-Means clustering is popularly used because it is fast and it is able to produce a proper size of clusters. In their research, K-Means clustering was employed in order to produce a high quality recommendation for a large number of customers and products. It was found that using K-Means clustering could improve the scalability of the recommendation system. Similarly, K-Means clustering is also employed in this study in order to improve the performance accuracy for the recommendation system for university students.

Confidence Weighted- Voting Ensemble is a widely used method for improving the performance from multiple classification systems. For example, an Ensemble Neural Network could be constructed by training a number of individual Neural Networks and then aggregates their outputs. Kim and Kang proposed an ensemble method based on boosting and bagging methods to improve the performance of neural networks on bankruptcy prediction tasks [31]. Another example, Baruque and Corchado [32], used the weighted voting ensemble to achieve the lowest topographical error for the results of an ensemble of Self Organising Maps (SOM), so as to achieve the best visualization of the data set internal architecture. Rico-Juan and Inesta [33] proposed the confidence voting method ensemble in order to decrease the final equal error rate (EER) for off-line signature verification. In this study, the confidence voting method ensemble is employed in order to achieve the lowest prediction error for the recommendation models.

Modular Artificial Neural Networks-Optimised Weight of Subspace Reconstruction Method (MANN-OWSR) In prediction, Frayman et al. [34] suggested that better results could be achieved by aggregating the forecast results from multiple techniques instead of choosing the best one. Using the concepts of Tobler's first law, "*Everything is related to everything else, but near things are more related than distant things*" [35], Kajornrit et al. [36] proposed the use of Modular Artificial Neural Networks which comprises two aggregation methods: the *Inverse Distance Weighting Method (MANN-IDWM)* and the *Optimised Weight of Subspace Reconstruction Method (MANN-OWSR)* to estimate missing monthly rainfall data. The architectural overview is described below.

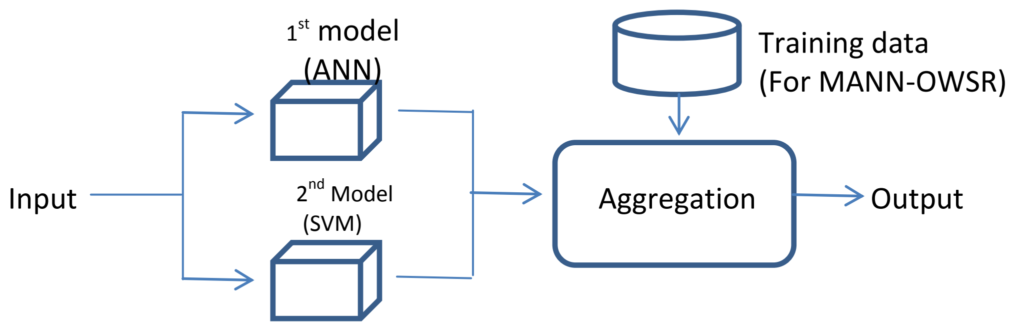

Figure 1: An aggregation model and the training data used in the MANN-OWSR model[36].

MANN-OWSR is an effective aggregation technique in order to improve the accuracy for the classification models. Therefore, MANN-OWSR is chosen to use in this study.

Evaluation metrics of the intelligent recommendation system In order to evaluate the recommendation systems, published works have been used to measure the recommendation system by comparing the prediction numerical recommendation values against and the recorded actual values [37]. The accuracy metric can be formed as follows.

$$accuracy = \frac{number\_of\_correction}{total\_case} \tag{12}$$

There are many metrics which could be used to evaluate the recommendation algorithms, for example, the *Means Square Error (MSE)* and the *Root of the Mean square error (RMSE)* values. There have been many research conducted on recommendation systems which used *Mean Absolute Error (MAE)* as a metric to measure the performance of the system. However, Willmott and Matsuura [38] found that MAE is more advantage than RMSE which is a function of three types of set of errors rather than one set, the authors also stated that "*MAE is a more natural measure of average error, and (unlike RMSE) is unambiguous*". MAE is therefore employed in the study for the purpose of comparing with previous studies and a measure of the deviation of the recommendations from the actual values. It is formulated as follows:

$$MAE = \frac{\sum_{i=1}^{n} |Oi - Pi|}{n}$$

Where *Oi* is the observed value, *Pi* is the predicted value and *n* is the number of predicted data. If the MAE value is low, it means the performance of the recommendation system is more accurate than predictions with a higher value of MAE. There are many researches used MAE as an evaluation metrics [39-46]. Consequently, MAE is used to measure the prediction error in the subsequent papers. Another common evaluation metric is Correlation Coefficient *(r)*[36] used in this study. In the percentage accuracy, MAE and Correlation are therefore chosen to evaluate the intelligent recommendation system in this study.

This paper has provided a background of this study with outline and descriptions of the relevant techniques involved. The university system of Thailand was described together with discussion on relevant issues and the need to establish a student relationship management system. In particular, the intelligent recommendation system was introduced as an aid to assist the students and the university counsellors. The paper then provided the principles of various intelligent techniques such as ANN, Decision tree based on CHAID algorithm, Support Vector Machine (SVM), K-Mean Clustering and ensemble methods. A new technique MANN-OWSR was introduced and used in this study to improve the overall performance of the system. Evaluation metrics are then given in order to assess the performance of the recommendation system.

Procedures

Selection of Input and Output Variables

In the selection of Input and Output variable process, the data source used in the experiment was obtained from a private university in the south of Thailand. In the process of choosing the variables for the training data, it is significant for the recommendation system. In the experiment of this paper, the variables used are chosen from the university's database based on the 11,400 student records, which have been eliminated due to GPA missing in some semesters after student's dropouts. Therefore, the records of student are composed of the 9001 student records and the 2,399 dropout student records. In the total of 11,400 student records, it is illustrated below.

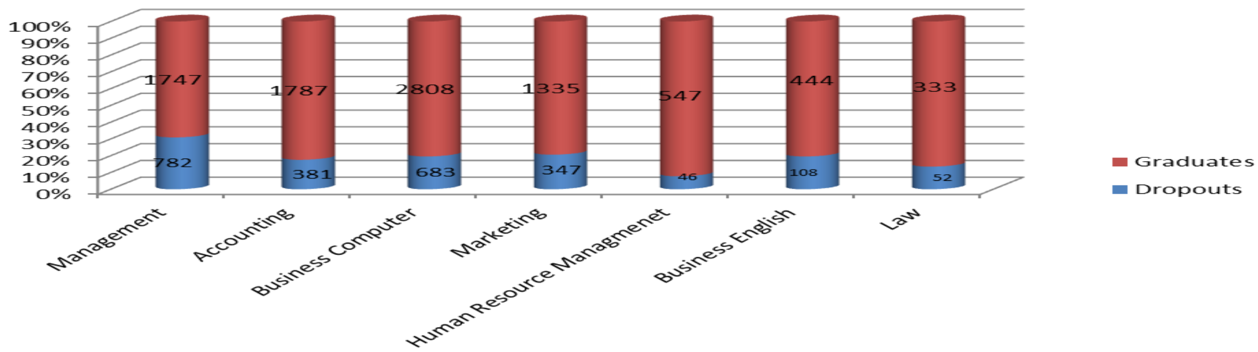

Figure 2: The number of undergraduate students includes dropouts by course of study (2001-2007)

In figure 2, the sets of data were organized in the data preparation process; the selection process involves a dataset from six academic years of undergraduates (2001-2007 academic year excluding summer). The figure demonstrates the undergraduate student data, which is composed of 30.62% of students from Business computer, 19.02% from Accounting, 22.18% from Management, 14.75% from Marketing, 5.2% from Human resource management, 4.84% from Business English and 3.38% from Law. Similarly, the numerical data which are overall GPA from previous school and overall GPA in university is transformed to categorical classes based on Mean and Standard Deviation of all data. Other variables are transformed in the categorical data or binary. However, the data variables used in these three modules are illustrated in table 1.

As explained, some variables in the process of collecting the suitable variables for the experiment are suggested by the participants from the survey results. Nevertheless, some variables cannot be included in the experiment because of insufficient data. Therefore, the data set are used in this module are as shown in the table below,

Table 1 shows variable name and type of the input data and output data (target)

Variable name	Type
Previous GPA, previous major, type of school, number of previous awards, talent and interest, motivation channels, admission round, guardian occupation, Gender, University major, Overall GPA (or GPA before dropouts)	Input
Dropout Identify	Target

Experimental Design

In this study, the proposed techniques have also been applied against the benchmark techniques; ANN, CHAID and SVM. In the proposed techniques, K-means clustering, an unsupervised learning is employed in order to classify student dropouts, the three benchmark techniques; SVM, CHAID and ANN are then applied in each cluster. All outputs of each cluster are compared and the two higher accuracy models are chosen, all clusters of the same models are combined before the steps of aggregation. In the combination process, two aggregation techniques; Ensemble method based on confidence-weight voting and Modular Artificial Neural Networks-Optimized Weight of Subspace Reconstruction Method (MANN-OWSR) are employed to aggregate two models that gives higher accuracy with the combination of all cluster of the same models. The outputs of these two aggregation models are compared, and the best accuracy model is then chosen. In the final step, the chosen model is again compared with the benchmark models. In the final step, the best model is chosen for the module of dropout identification in the intelligent recommendation system. In the proposed model, SVM, Neural Networks, CHAID and K-Means clustering algorithms are employed and the proposed model is shown in the diagram as shown in figure 3.

In the figure 3, it shows the processes of the student dropout identification model. The first process is the bench mark techniques which input data have trained, validated and tested by SVM, CHAID and ANN in three times of each techniques to ensure that the results are not obtained by chances. The results of these three techniques are compared with the final results of the proposed technique. The second process is applied by K-Means clustering. The survey results by interviewing the supervisors and counselors' show that the dropouts can classify for two main groups; low level of GPA and personal reasons; for example, family problem or financial problem. Therefore, the input data are clustered into two groups of related data. Each cluster is applied in the next process. Third process used the same techniques as benchmark, but these three techniques are employed to train, validate and test the data in each cluster and in three time training, validating and testing data. The results of each cluster in each model are compared in the 1st comparison stage. Then the models that give the highest accuracy in each cluster are combined by Ensemble in order to improve the accuracy. Similarly, the fifth process is the combinations of the models that give the second accuracy in each cluster using Ensemble in order to improve the accuracy. The results of these two processes are compared in the second comparison stage. Next process is applied by MANN-OWSR to aggregate the results of cluster 1 and cluster 2 of the highest accuracy model in the comparison of process 4 and 5. This process gives the final output of the proposed techniques. In the final comparison stage, the final results of the proposed techniques are compared with the results of the benchmark techniques. Then the model which gives the best results is chosen for the intelligent recommendation system. However, the results of these models are in binary type which is told that if students are high risk of dropouts, the results are "1" and if students can complete the degree, the results are "0". In regarding to the results shown in binary format, the metrics used to validate the results in this experiment is the accuracy percentage which is presented in the possibility table and graph format.

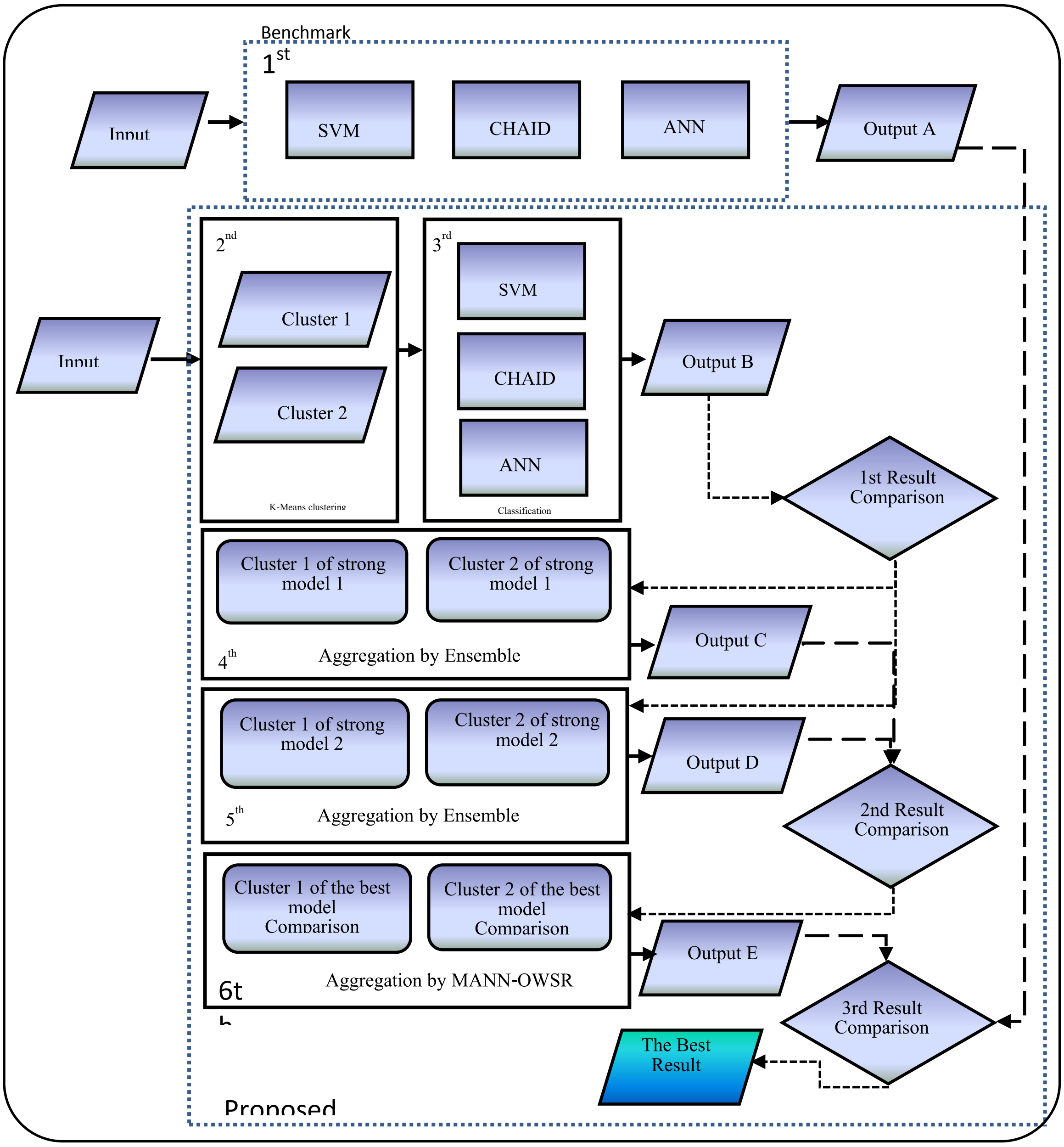

Figure 3: The student dropout identification model

Experimental Results

The research based on the experimental results, concentrates on the improvement of the prediction results in order to choose the best results for the intelligent recommendation system. The comparison of the accuracy rate of the recommendation system are shown in figure 4-9

The comparison results of the benchmark techniques show that SVM model returned the highest accuracy of 93.68; therefore, SVM based model can be utilised to predict the student dropout identification with the best degree of accuracy, and this model is chosen to compare with the final results of proposed techniques in the last process.

In the second process, K-Means clustering is employed to separate data. This experiment used two clusters due to the survey results shown that the dropout can classify for two main groups; low level of GPA and personal reasons; for example, family problem or financial problem. Then, the results obtained that the number of cluster 1 and 2 are 4608 and 6792 records respectively. In the next section, the two clusters are applied by three techniques as shown below

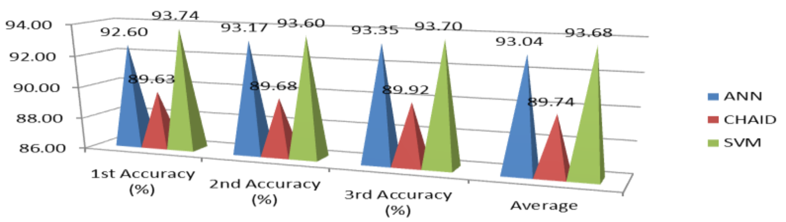

Figure 4: Accuracy of benchmark classification model; ANN, CHAID and SVM models in three time testing data

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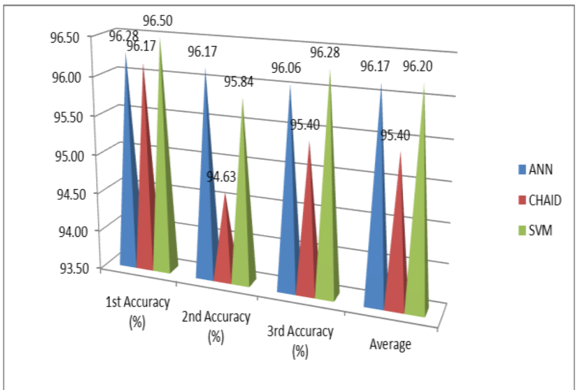

Figure 5: Accuracy cluster 1 of three classification models in three time testing data

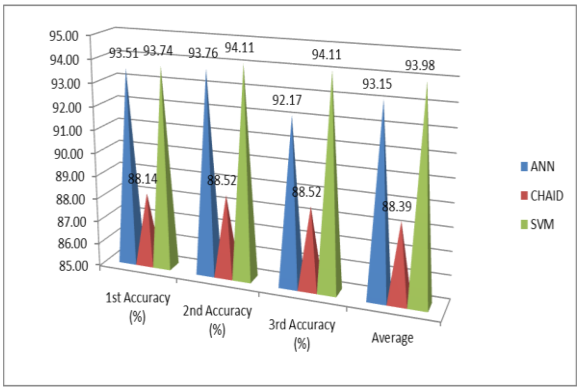

Figure 6: Accuracy of cluster 2 of three classification models in three time testing data

The comparison results demonstrate that SVM and ANN model return the higher accuracy than CHAID in both cluster 1 and 2; therefore, these 2 models are chosen to aggregate in the next process.

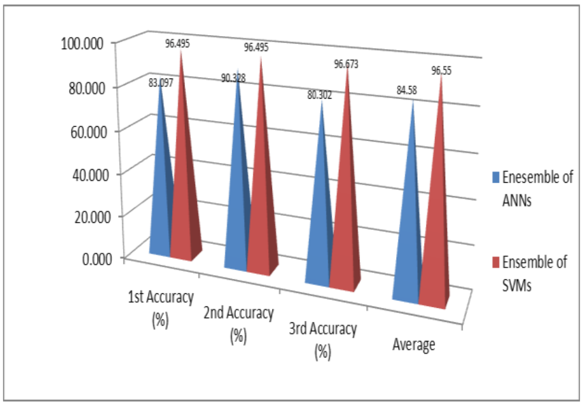

Figure 7: Accuracy of Ensemble of cluster 1 and 2 of SVM models in comparison with the combination of cluster 1 and 2 of ANN models method in three time testing data

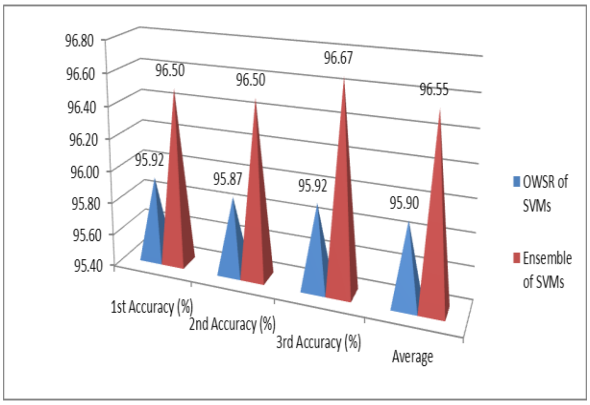

Figure 8: the accuracy of the Ensemble of cluster 1 and 2 of SVM models in comparison with the results of MANN-OWSR of cluster 1 and 2 of SVM models.

In figure 7, the comparison results of aggregation show that Ensemble of SVM combined cluster returned the highest accuracy of 96.55 whereas Ensemble of ANN return the accuracy of 84.58 percentage. Therefore, SVM clusters are chosen to aggregate using MANN-OWSR and Ensemble in the next process. In figure 8, the comparison results of Ensemble of SVM clusters return the highest accuracy of 96.55 percentages whereas the results of MANN-OWSR return 95.90 percentages.

It can be noted that Ensemble of SVM clusters is chosen to compare with the benchmark model in the last process as shown in figure 9.

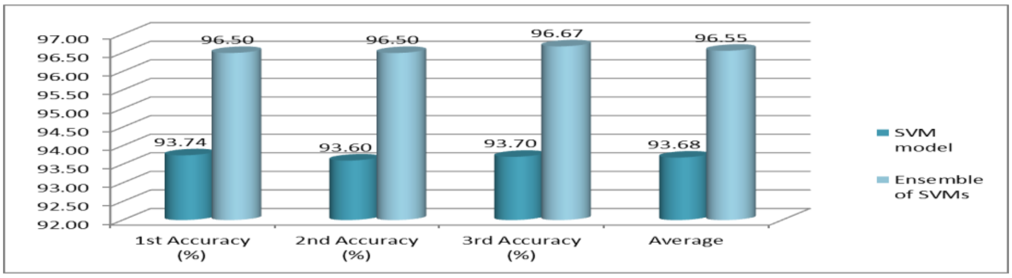

Figure 9: the accuracy of the Ensemble of cluster 1 and 2 of SVM models in comparison with the results of SVM model from benchmark techniques.

In figure 9, the accuracy of the Ensemble model of SVM cluster models in comparison with the results of SVM model from benchmark techniques. The results indicates that Ensemble of SVM models returned the highest classification accuracy of 96.55 percentages, while SVM models from the benchmark techniques returned the average accuracy 93.68 percentage. Therefore, Ensemble of SVM models outperforms the SVM models from the benchmark techniques.

Conclusions

In this experiment, it is found that Ensemble of SVM models outperforms the SVM models from the benchmark techniques and every model which has tested with this dropout identification model. In this study, the experiment results show that Ensemble of SVM models can be utilised to predict the student dropout to identify students who are risk of leaving the study before graduation with the greatest degree of accuracy. Therefore, the best model with highest accuracy is chosen to use in the Intelligent Recommendation System.

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