

PREDICTION OF STUDENT'S PERFORMANCE BASED ON THEIR INTERACTIVITY IN E-LEARNING ENVIRONMENT

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ABSTRACT

Academic performance of students in e-learning environment depends on how meaningful the student learning behavior is. Therefore, the success factor of e-learning is greatly dependent on meaningful learning characteristics that define student 's way of interaction with the learning environment. Some students may have similarities in terms of learning behavior and vary with other students. Different learning behaviors produce different learning performance. Some learning behaviors can lead students to success while some can lead students to failure. It is therefore, very necessary to understand individual student's behavior in eLearning so as to reduce the number of failures. Understanding individual learning behavior is monotonous especially when they are many. Which means it's very difficult or nearly impossible to understand students' individual behavior in eLearning system as the system stores data in a log file which is unstructured and unorganized. Therefore, it is necessary to use advanced tools like data mining classification and prediction algorithms to extract meaningful learning characteristics from the log file. In this research, we employed five different classification algorithms namely, Support Vector Machine (SVM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Decision Tree and Random Forest (RF) in order to determine the best classification algorithm to predict student's performance based on their behavior and interactivity in eLearning environment. The results of this research shows that both K-Nearest Neighbor (KNN) and Support Vector machine (SVM) are good classifiers for students' performance prediction in eLearning environment.

KEYWORDS:

eLearning, Prediction, Student Performance, Classification algorithm.

INTRODUCTION

The advancement in information technology has enhanced the effectiveness of web-based education (e-learning) system[1]. The e-learning system allows students from anywhere and at any time to carryout different learning activities such as reading, presentations, chatting and assignment. These activities usually take place via a platform called Learning Management System (LMS), a platform that utilizes various technologies mostly on the internet to provide access to the courses and facilitates communications between students and tutors and/or among the students[2]. The LMS provides a large volume of heterogeneous data for use by the students and the tutors as well. The learning materials are enough to meet the requirements to achieve the learning objectives and accommodate student needs. The learning management system also contains information about students 'personal information, learning styles & behaviors and usability preferences [3], this information is stored in log files.

Even though the learning management system contains such huge amount of data, it however, does not provide a useful means of knowledge discovery about the data in the system 's log files especially, the students' performance, thus making it challengeable to manually analyze the data [4].

Another factor is the growth of data in the LMS, making the data unstructured, thus making it difficult to extract the desired information in the best or average case time [5]. When considering the fact that

learners are from different background such as educational, cultural and psychological, their learning styles and behaviors may also vary [6][7]The success of e-learning depends greatly on the learner 's positive interest toward e-learning. To make the e-learning more effective, the e-learning environment must be adjusted to meet individual/student needs, but this is very difficult in terms of cost, time and storage management.

Although performance on standardized tests receives the greatest attention in discussions of students' academic performance, teachers' evaluations of performance as indicated in course grades represent a common metric of student performance that often is more directly tied to the day-to-day business of teaching and learning than are annual standardized test scores. Grades serve a number of important functions. They communicate to students and parents' information about students' mastery of course content. In high school, a passing grade also is the criterion for a course's contributing to accumulated credit for graduation. Finally, grades provide information for consideration in college admissions [2]. However, as a measure of academic performance, teacher-given grades have well-known limitations. Grades are composite measures that account not only for students' content mastery but often for other factors, such as their class participation, attitudes, progress over time, and attendance. Both general and special educators are known to consider these various factors when grading, but to emphasize different factors. For example, special education teachers are less likely than general educators to consider homework or attendance to be important in grading student performance, but are more likely to consider in-class participation to be important [8]. Moreover, substantial variations in grading practices occur across teachers, schools, and school districts. Despite these complicating factors, student grades still are an important indicator within the academic performance outcome domain for students for that participate in different learning environment being it physical or virtual, because they indicate success by a teacher's standards regardless of the learning environment.

Prediction of student academic performance has long been regarded as an essential research topic in many academic disciplines for a number of reasons. First, predictive models can help the instructor predict student academic performance and then take some proactive measures[9]. With a validated predictive model, an instructor can identify academically at-risk students. The instructor may consider adopting specific instructional strategies for those academically at-risk students. For example, if a model predicts that a student will receive a final exam score below 50 (out of 100), he or she will be identified as potentially academically at-risk. The student might first be interviewed, followed by the observation of his/her classroom performance. This will help the instructor to develop a clear understanding of that student's learning skills and difficulties. Based on the instructor's judgment, additional instructional interventions may be implemented on that student. A detailed discussion of these instructional interventions is beyond the scope of this research; however, some examples of additional instructional interventions may include one-on-one tutoring and review of important concepts and principles after class, assigning more representative technical problems for additional student, providing remedial lessons to improve the student's mathematical skill, and asking the student to review previously learned concepts in relevant courses

In e-learning, identifying students who may be at risk of failure is very important in that early identification of such students can lead to providing them with necessary assistance which may prevent them from failure (Dewan et al., 2015). The earlier the at-risk students can be identified, the quicker their problems can be addressed by the education managements by taking appropriate actions to prevent them from poor performance. The prediction of students' performance is expected to help develop some special arrangements that educational institutions organize in order to help students perform better in their courses. As a result of technological development, e-learning platforms now provide a means of monitoring students learning behaviour and their interactions with the system through the system's log files, the data can then be analyzed using data mining techniques. However, careful selection of those activities and machine learning techniques is critical. Inappropriate choice of activities and machine learning techniques may result in an unreliable prediction result.

LITERATURE REVIEW

Student performance in educational institutions such as Universities and Colleges is not only a pointer to the effectiveness of the institutions but also major determinant of the future of students in particular and the nation in general. Learning outcomes have become a phenomenon of interest to all and this account for the reason why scholars have been working hard to find out factors that militate against good academic performance[10]. Academic achievement of learners has attracted attention of scholars, parents, policymakers and planners. [11]noted that the major goal of the school is to work towards attainment of academic excellence by students. This student academic performance can be regarded as the observable and measurable behavior of a student in a

particular situation. Performance is defined as the final mark acquired by a student at the end of the term/semester in a subject enrolled through learning management system [12]. The final mark is a cumulative sum of the internal assessment (quizzes, assignments, midterm test) and the final examination score.

Performance of students may be influenced by several factors such as gender, age, parent's socioeconomic situation, area of resident, nature of school being attended, school medium of teaching, number of study hours spent daily, and nature of accommodation which may be school own hostel or otherwise[13]. number of researches about factors affecting students' performance at different study levels have been conducted by many authors. [14] suggests that "A student educational success contingent heavily on social status of student's parents/ guardians in the society". [15] noticed the same that "parent's income or social status positively affects the student test score in examination". [16] observed that "the measurement of student's previous educational outcomes are the most important indicators of student's future achievement", This concludes that the better the performance of students in previous studies, the better their performance in future attempts.

Students' performance prediction is one of the earliest and most valuable applications of Educational Data Mining (EDM) and its objective is to measure the hidden value of students' performance, understanding or grade from the other information, attitude or behavior of those students (Romero and Ventura, 2013). This is a difficult issue to address because of the diverse number of factors or attributes that influences the performance of students such as cultural, family background, psychological history, previous academic performance, parent's economic situation, previous schooling, interaction between student and faculty, etc.[17].

Several EDM techniques have been used in the prediction of students' performance such as classification, regression and density estimation for predicting variable with categorical value, continuous valued variable and probability density function respectively. It is essential to note that most recent researches on EDM for students' performance prediction were primarily applied to cases of University of high school students[18] and specifically, in most cases to e-learning or related mode of instruction (Romero et al., 2013). This is fundamentally as a result of increase in the use of learning management systems (LMSs) such as Moodle, Blackboard, Edmodo, Cornerstone, Schoology, ConnectEdu, Kalboard 360 etc. is increasing rapidly because of its ability to provide unlimited access to learning materials, easily tracks learner performance, and enables easy and convenient expansion of e-learning courses. The LMS collects huge amount of information related to user visits and interactions such as viewing of resources, submission of assignments, participation in discussion forums etc. which are very essential in predicting students' performance, analysing students behaviour and assisting instructors, detecting problems and providing improvements.

The research in e-learning domain is facilitated by the extensive amount of data stored by the e-learning systems, most of these systems have the ability to collect data about the student activities, tracking navigational pathways through educational resources, time spent on various topics, or number of visits. Also, the e-learning systems capture data about the amount and type of resources usage[19]. These data often are the basis of the research. One way to better understand the information gathered in educational databases is through the application of data mining techniques. By data mining, it is possible to discover patterns to be used in predicting student performance and to provide necessary assistance to students at risk of failure. A number of researches have been conducted by several researchers in attempt to predict the performance of students who use learning management system as a medium of learning.

Romero and Ventura (2007) present the main findings of an educational data mining survey covering the period 1995-2005. [20] made another survey covering the latest data mining approach in education domain. Both surveys show that the number of data mining applications in education is constantly increasing, and they cover a lot of educational processes such as: enrollment management, academic performance, web-based education, retention.

Many case studies on data mining techniques in education are cited in the literature[21][19][17]. These case studies aim at predictions of student performance, mainly through cluster analysis to identify relevant types of students[22] proposed a model for the application of data mining in higher education. [2] developed a model to find similar patterns from the data gathered and to make predication about students' performance.

Luan et al. (2004) presented different case studies on educational data mining. One of these studies intended to highlight factors that determine the academic success of first-year students. The methods used are classification and regression trees and neural networks. There were generated decision trees, and association rules. A sensitivity analysis was performed to analyze factors. Variables considered were demographic variables and performance indicators before college. By this analysis can be achieved overall average prediction in the year achieved on average in high school.

CLASSIFICATION ALGORITHMS

Classification consists of predicting a certain outcome based on a given input. In order to predict the outcome, an algorithm processes a training set containing a set of attributes and the respective outcome, usually called goal or prediction attribute. The classification algorithm tries to discover relationships between the attributes that would make it possible to predict the outcome. Next the algorithm is given a data set not seen before, called prediction or testing set, which contains the same set of attributes, except for the prediction attribute which is not yet known. The algorithm analyses the input and produces a prediction. The prediction accuracy defines how "good" the algorithm is (Mallick, 2015). In addition to accuracy there exist other measures such as precision, recall, sensitivity, f-measure etc. which are also considered in determining the performance of a particular algorithm.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) or connectionist frameworks are computing frameworks that are propelled by, but not indistinguishable to, natural neural systems that constitute creature brains. Such frameworks "learn" to perform errands by considering illustrations, for the most part without being modified with task-specific rules[23]. For case, in image identification, they might learn to distinguish images that contain cats by analyzing case pictures that have been physically labeled as "cat" or "no cat" and utilizing the comes about to recognize cats in other images. They do this without any earlier information of cats, for case, that they have hide, tails, hairs and cat-like faces. Instep, they naturally producedistinguishing characteristics from the cases that they process[24]. An ANN is based on a collection of associated units or hubs called artificial neurons, which freelyshow the neurons in anorganic brain. Each association, just like the neural connections in a natural brain, can transmit a flag to other neurons.

Artificial Neural Network (ANN)for classification such as Multi-Layer perceptron (MLP) is a machine learning algorithm that is effective for classification of dataset. ANN has been experimentally tested for classification in different domain and produce excellent resultsmore than many classification algorithms[25].

Support Vector Machine (SVM)

In machine learning, support-vector machines (SVMs, too support-vector networks) are directed learning models with related learning calculations that analyze information utilized for classification and relapse investigation[26]. Given a set of preparing cases, each checked as having a place to one or the other of two categories, an SVM preparingcalculation builds a show that allocatesunusedcases to one category or the other, making it a non-probabilistic paralleldirect classifier (in spite of the fact thatstrategies such as Platt scaling exist to utilize SVM in a probabilistic classification setting)[26]. An SVM demonstratecould be a representation of the illustrations as focuses in space, mapped so that the illustrations of the partitioned categories are separated by a clear holethat's as wide as conceivable. Unusedcases are at that point mapped into that same space and anticipated to have a place to a category based on the side of the crevice on which they fall. In expansion to performing direct classification, SVMs can productively perform a non-linear classification utilizing.

Decision Tree (DST)

A Decision tree could be a flowchart-like structure in which each innerhubspeaks to a "test" on antrait (e.g. whether a coin flip comes up heads or tails)[27], each branchthe outcome the test, and each leaf hubspeaks to a class label (choice taken after computing all traits). The ways from root to leaf represents theclassification rules. In choiceinvestigation, a decision tree and the closely related impactgraph are utilized as a visual and explanatorydecisionbackapparatus, where the anticipated values (or anticipated utility) of competing options are calculated.

Decisiontrees are commonly utilized in operations research and operations management. In the event that, in hone, decisionought to be taken online with no reviewbeneathdeficientinformation, a decision tree ought to be paralleled by a likelihoodshow as a best choice show or online determinationdemonstratecalculation[28]. Another utilize of choice trees is as a clearimplies for calculating conditional probabilities. Decision trees, impactgraphs, utility capacities, and other choiceinvestigationapparatuses and strategies are instructed to undergrad understudies in schools of commerce, wellbeingfinancial matters, and open wellbeing, and are illustrations of operations research or management science strategies

Naïve Bayes (NB)

In machine learning, naïve Bayes classifiers are a family of basic "probabilistic classifiers" based on applying Bayes' hypothesis with solid (naïve) freedom suspicions between the highlights[4]. They are among the best Bayesian organize models. Naïve Bayes has been examined broadly since the 1960s. It was presented (in spite

of the fact that not beneath that title) into the content recovery community within the early 1960s, and remains a prevalent (standard) strategy for content categorization, the issue of judging reports as having a place to one category or the other (such as spam or genuine, sports or legislative issues, etc.) with word frequencies as the highlights. With suitable pre-processing, it is competitive in this space with more progressed strategies counting back vector machines. It moreover finds application in programmed therapeutic diagnosis. Naïve Bayes classifiers are highly adaptable, requiring a number of parameters direct within the number of factors (features/predictors) in a learning issue.

Random Forest (RF)

Random Forest or random choice Forest are ensemble learning strategy for classification, regression and other tasks that works by building a huge number of choice trees at preparing time and yielding the course that's the mode of the classes (classification) or cruel forecast (regression) of the person trees. Arbitrary Random Forest rectify for choice trees' propensity of overfitting to their preparing set[29]. The to begin with calculation for Random Forest was made by Tin Kam Ho utilizing the Random subspace method, which, in Ho's formulation, may be a way to actualize the "stochastic separation" approach to classification proposed by Eugene Kleinberg. An expansion of the calculation was created by Leo Breiman and Adele Cutler,[8] who registered "Arbitrary Random Forest " as a trademark (as of 2019, possessed by Minitab, Inc.).

EXPERIMENTS AND RESULTS

The experiment was conducted using the dataset obtained from 21 undergraduate students taking data structure from school of computing, University Teknology, Malaysia. The dataset is available in a master degree Dissertation by Musa Wakil Bara, 2016. Five (5) different classification algorithms which are Artificial Neural Network (ANN), k-Nearest Neighbor (KNN), Support vector Machine (KNN), Decision Tree (DST) and Random Forest (RF) were implemented in matlab to determined the best classifier for predictions student's performance based on their interactivity in eLearning. The results of each classifier were validated using 10-fold cross validation and accuracy performance metrics was used to assess the performance of each classifier using confusion matrix.

EXPERIMENTAL SETUP

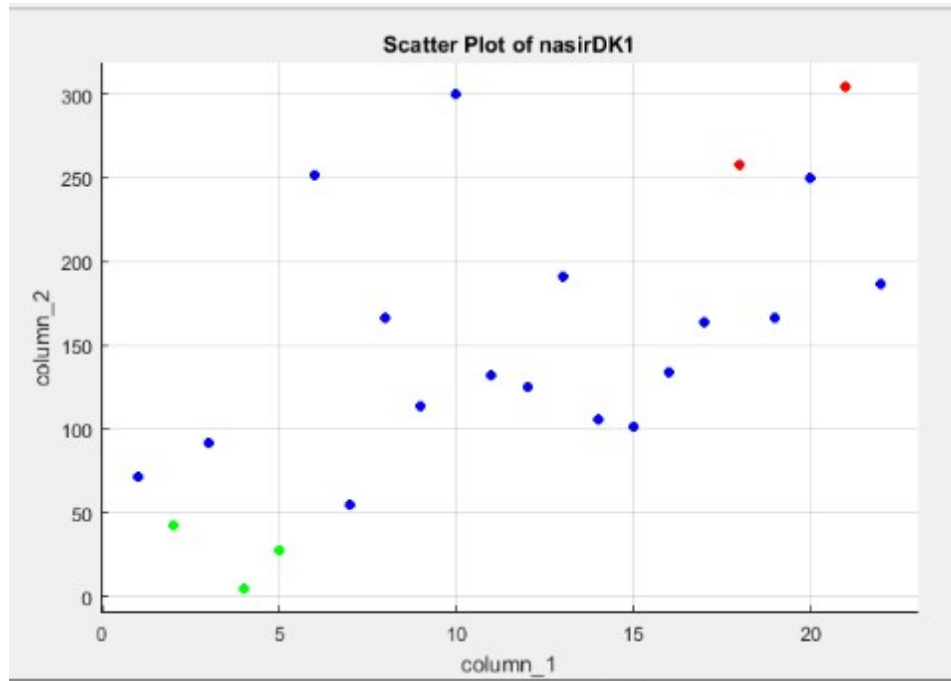
The dataset after preprocessing was taken to Matlab and the experiment was conducted using set of classification algorithms. Table 4.1 shows the preprocessed data which was later fed in to the various classifiers, the result of each classifier is presented in order to evaluate the performance of each classifier in carrying out prediction. A 10-fold cross validation was used to evaluate each classifier and confusion matrix was used to measure the efficiency of the algorithms. The main aim was to determine the best classifier than be suitable for student's performance prediction in eLearning. The dataset of 21 undergraduate students was obtained from school of computing, faculty of engineering UniversitiTeknology Malaysia the dataset consists of three (3) classes which are excellent pass represented as **High**, good pas represented as **Medium** and poor as resented as **Low**. The scatter plot of the dataset set is shown in figure 4.1 which shows the three (3) class distribution.

Table 4.1: Preprocessed dataset.

Student_ID	Course View	Assignment Submit	Forum View	Resource Downloads	Forum Discussion	Online Assessment	Class
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IJETRM**International Journal of Engineering Technology Research & Management**

1	71	167	48	14	3	2	3
2	42	51	35	9	0	0	2
3	92	171	65	19	3	1	3
4	5	4	0	0	0	0	2
5	27	14	14	0	3	3	2
6	252	198	132	16	0	0	3
7	55	104	34	10	0	0	3
8	166	135	63	12	3	4	3
9	114	102	50	13	1	0	3
10	300	201	98	20	3	3	3
11	132	100	57	11	2	2	3
12	125	160	104	18	6	15	3
13	191	121	104	16	1	4	3
14	106	84	72	21	0	0	3
15	101	106	59	15	6	12	3
16	134	85	69	17	1	3	3
17	164	106	110	15	2	0	3
18	258	226	113	20	27	32	1
19	166	138	93	18	6	9	3
20	250	152	179	23	3	3	3
21	304	140	136	19	26	22	1
22	187	233	86	18	4	4	3

**Figure 4.1: Dataset Scatter plot**

The performance of predictive model is evaluated using confusion matrix. The matrix is $N \times N$ where N is the number of target values (classes), it shows the number of correct and incorrect predictions made by the predictive model compared to the actual outcomes in the data. Performance the predictive models is commonly evaluated using the data in the matrix. The entries in the confusion matrix are identified as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) which are used to find the Accuracy as shown in table 4.2.

Table 4.2:Confusion Matrix

PREDICTED CLASS	ACTUAL CLASS	
	Positive	Negative
	Positive	True Positive (TP)
Negative	False Positive (FP)	True Negative (TN)

From Table 4.2, the labels that constitute the confusion matrix are True Positive (TP) which represents the number of instances which were actually positive and were predicted to be positive, False Positive (FP) is the number of instances which were actually negative but were predicted to be positive, False Negative (FN) represent the number of instances which were actually positive but predicted to be positive, True Negative (TN) is number negative instances and were predicted to be negative.

Accuracy is the proportion of total number of predictions that were correct. The accuracy of a predictive model is calculated as follows: (Hsu, Chang, & Lin, 2011).

$$A(\%) = \frac{TP + TN}{TP + FP + FN + TN} \times 100$$

1.1 Results

The results of each experiment by each classifier is summarized in table 4.3 and each confusion matrix is shown in the following figures:

Table 4.3 Results Summary of Classifiers

S/N	Classifier	Accuracy (%)
1.	Artificial Neural Network (ANN)	77.3
2.	Support Vector Machine (SVM)	95.5
3.	Decision Tree (DST)	81.8
4.	K-Nearest Neighbor (KNN)	95.5
5.	Random Forest (RF)	86.4

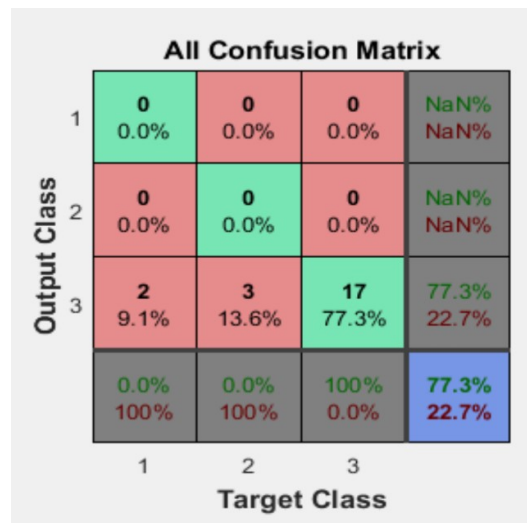


Figure 4.2: confusion Matrix for Artificial Neural Network Classifier

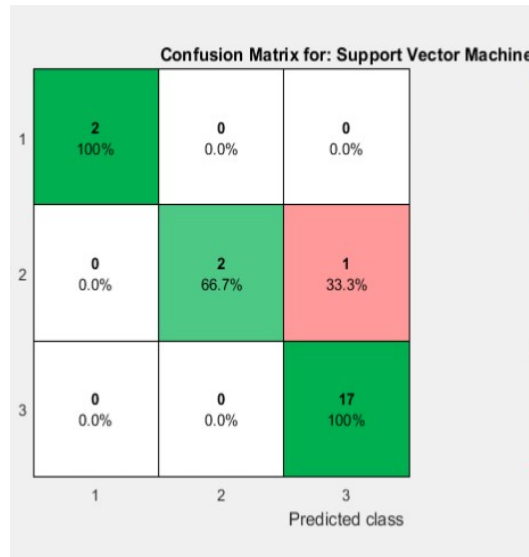


Figure 4.3: confusion Matrix for Support vector Machine (SVM) Classifier

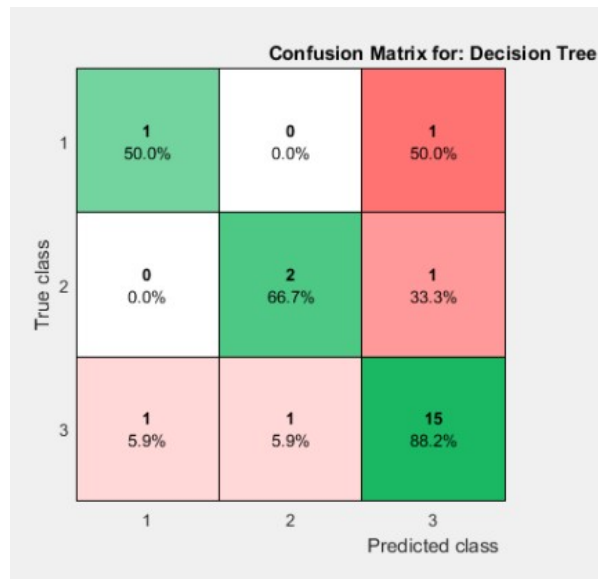


Figure 4.4: confusion Matrix for Decision Tree Classifier

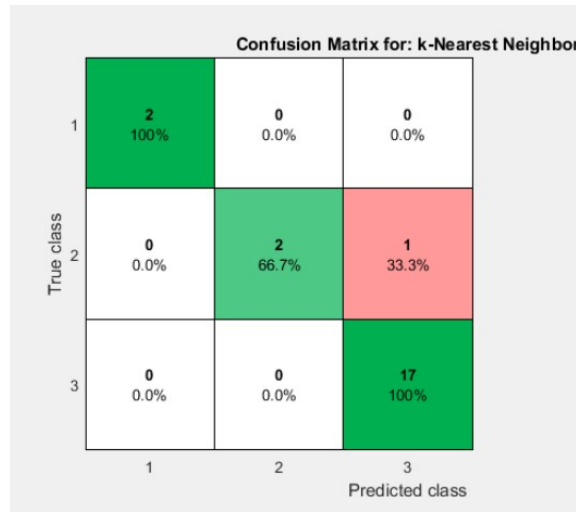


Figure 4.5: confusion Matrix for K-Nearest neighbor Classifier

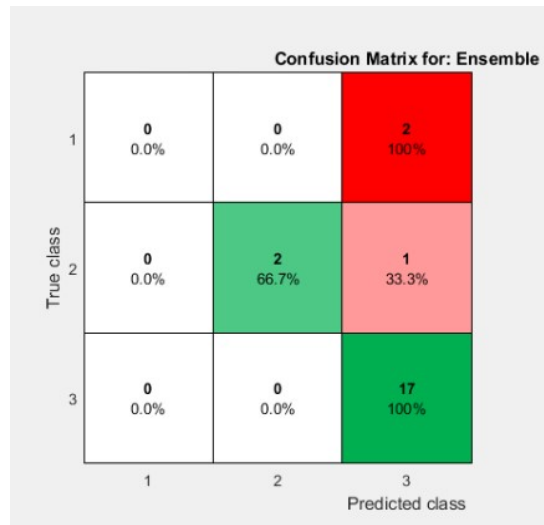


Figure 4.6: confusion Matrix for Random forest Classifier

RESULTS DISCUSSION

All the classifiers show an interesting performance in terms of students' performance prediction in eLearning environment based on their interactivity. However, Support vector Machine (SVM) and K-Nearest neighbor (KNN) has shown the best performance with a classification accuracy of 95.5% each. Another interesting thing is that, considering the class distribution in the dataset, the data is skewed such that the students that belongs to class 3 (Low performance students) constitutes more than 70% of the dataset while those in class 1 (High performance) and class 2 (Medium performance) constitutes less than 30% of the dataset but yet the two classifiers (KNN and SVM) were able to differentiate between the instances of the classes. On the other hand, Artificial Neural Network (ANN) stance to be the worst with an accuracy of 77.3 as it was on able to be sensitive on the skewed distribution of the dataset. Therefore, this research reveals that Both SVM and KNN are reliable classification algorithms that can be used to predicts students' performance in eLearning environment based on their interactivity.

REFERENCES

- A. García-Holgado and F. J. García-Peñalvo, "Architectural pattern to improve the definition and implementation of eLearning ecosystems," *Sci. Comput. Program.*, vol. 129, pp. 20–34, 2016.
- [2] M. I. Al-Twijri and A. Y. Noaman, "A New Data Mining Model Adopted for Higher Institutions," *Procedia Comput. Sci.*, vol. 65, no. Iccmit, pp. 836–844, 2015.
- [3] R. S. Baker, A. T. Corbett, and K. R. Koedinger, "Detecting student misuse of intelligent tutoring systems," in *International conference on intelligent tutoring systems*, 2004, pp. 531–540.
- [4] S. Sasikala, S. A. alias Balamurugan, and S. Geetha, "A Novel Feature Selection Technique for Improved Survivability Diagnosis of Breast Cancer," *Procedia Comput. Sci.*, vol. 50, pp. 16–23, 2015.
- [5] J. D. Cryer and K.-S. Chan, *Time Series Analysis: With Applications in R*, no. January. 2008.
- [6] J. M. Diaz, S. Dormido, and D. E. Rivera, "ITTSAE: A Set of Interactive Software Tools for Time Series Analysis Education [Lecture Notes]," *IEEE Control Syst.*, vol. 36, no. 3, pp. 112–120, 2016.
- [7] Harwati, A. P. Alfiani, and F. A. Wulandari, "Mapping Student's Performance Based on Data Mining Approach (A Case Study)," *Agric. Agric. Sci. Procedia*, vol. 3, pp. 173–177, 2015.
- [8] Q. Huang, H. Su, and J. Wang, "A Prediction Method for Aero-engine Health Management Based on Nonlinear Time Series Analysis."
- [9] P. Kaur, M. Singh, and G. S. Josan, "Classification and Prediction Based Data Mining Algorithms to Predict Slow Learners in Education Sector," *Procedia Comput. Sci.*, vol. 57, pp. 500–508, 2015.
- [10] R. P. Lederman, "Time series analysis.," *MCN. Am. J. Matern. Child Nurs.*, vol. 18, no. 3, p. 177.
- [11] S. Lu, Y. Cheng, X. Wang, Y. Du, and E. G. Lim, "Exploring the Effectiveness of Student-generated Video Tutorials in Electronic Lab-based Teaching," 2017.
- [12] P. Misra, "Machine Learning and Time Series: Real World Applications," pp. 389–394, 2017.
- [13] A. Sarasa Cabezuelo and J. L. Sierra Rodriguez, "A System to Manage Non-Formal Higher Education Activities," *Rev. Iberoam. Tecnol. del Aprendiz.*, vol. 11, no. 3, pp. 205–212, 2016.
- [14] K. Mitsuhashi, S. Yokota, H. Hashimoto, S. G. Shin, and D. Chugo, "Education system of skill succession based on 3D evaluation and improvement in time series," *IEEE Reg. 10 Humanit. Technol. Conf. R10-HTC 2015 - co-located with 8th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM 2015*, 2016.
- [15] O. Moscoso-zea and S. Luján-mora, "Minería de Datos Educativos : una visión holística Educational Data Mining : an holistic view," *Inf. Syst. Technol. (CISTI), 2016 11th Iber. Conf.*, 2016.
- [16] X. Qin, M. Liao, L. Zhang, and M. Yang, "Structural health and stability assessment of high-speed railways via thermal dilation mapping with time-series InSAR analysis," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 10, no. 6, pp. 2999–3010, 2017.
- [17] A. M. Shahiri, W. Husain, and N. A. Rashid, "A Review on Predicting Student's Performance Using Data Mining Techniques," *Procedia Comput. Sci.*, vol. 72, pp. 414–422, 2015.
- [18] R. S. Society, "Source : Journal of the Royal Statistical Society . Series A (General), Vol . 145 , No . 3 (1982) Published by : Wiley for the Royal Statistical Society Stable URL : <http://www.jstor.org/stable/2981880> JSTOR is a not-for-profit service that helps scho," vol. 145, no. 3, 2017.
- [19] M. Sweeney, H. Rangwala, J. Lester, and A. Johri, "Next-Term Student Performance Prediction: A Recommender Systems Approach," pp. 1–27, 2016.
- [20] T.-O. Tran, H.-T. Dang, V.-T. Dinh, T.-M.-N. Truong, T.-P.-T. Vuong, and X.-H. Phan, "Performance Prediction for Students: A Multi-Strategy Approach," *Cybern. Inf. Technol.*, vol. 17, no. 2, pp. 164–182, 2017.
- [21] J. Yeom, J. Jung, A. Chang, M. Maeda, J. Landivar, and C. Christi, "COTTON GROWTH MODELING USING UNMANNED AERIAL VEHICLE VEGETATION INDICES Texas A & M University Corpus Christi , USA ; 2 Texas A & M AgriLife Research Extension Service," pp. 5050–5052, 2017.
- [22] A. Zalewski, W. Long, A. E. W. Johnson, R. G. Mark, and L. H. Lehman, "Estimating Patient ' s Health State Using Latent Structure Inferred from Clinical Time Series and Text," pp. 449–452, 2017.

- [23] A. Y. Alsabawy, A. Cater-Steel, and J. Soar, "Determinants of perceived usefulness of e-learning systems," *Comput. Human Behav.*, vol. 64, pp. 843–858, 2016.
- [24] S. Mishra, "A New Meta-heuristic Bat Inspired Classification Approach for Microarray Data," *Procedia Technol.*, vol. 4, pp. 802–806, 2012.
- [25] D. Chakraborty, S. Saha, and S. Maity, "Training feedforward neural networks using hybrid flower pollination-gravitational search algorithm," *Futur. Trends Comput. Anal. Knowl. Manag. (ABLAZE), 2015 Int. Conf.*, pp. 261–266, 2015.
- [26] J. C. Hernandez Hernandez, B. Duval, and J.-K. Hao, "SVM-Based Local Search for Gene Selection and Classification of Microarray Data," in *Bioinformatics Research and Development: Second International Conference, BIRD 2008 Vienna, Austria, July 7-9, 2008 Proceedings*, M. Elloumi, J. Küng, M. Linial, R. F. Murphy, K. Schneider, and C. Toma, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2008, pp. 499–508.
- [27] C. Ching-Ter, J. Hajiyev, and C. R. Su, "Examining the students' behavioral intention to use e-learning in Azerbaijan? The General Extended Technology Acceptance Model for E-learning approach," *Comput. Educ.*, vol. 111, pp. 128–143, 2017.
- [28] R. Yilmaz, "Exploring the role of e-learning readiness on student satisfaction and motivation in flipped classroom," *Comput. Human Behav.*, vol. 70, pp. 251–260, 2017.
- [29] Z. Hussein, "Leading to Intention: The Role of Attitude in Relation to Technology Acceptance Model in E-Learning," *Procedia Comput. Sci.*, vol. 105, no. December 2016, pp. 159–164, 2017.