International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 12, Issue 11 [November. 2023] PP: 88-95

Analysis of ECE students academic performance using ECE-CAPA

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ABSTRACT: *The objective is to predict the students' final grades based on the features which are extracted from their (and others') homework data. We design, implement, and evaluate a series of pattern classifiers with various parameters in order to compare their performance in a real data set from the ECE-CAPA system. This experiment provides an opportunity to study how pattern recognition and classification theory could be put into practice based on the logged data in ECE-CAPA. The error rate of the decision rules is tested on one of the ECE-CAPA data sets in order to compare the performance accuracy of each experiment. Results of individual classifiers, and their combination, as well as error estimates, are presented.*
Keywords: *Python, MATLAB, ECE, prediction, branch, data.*

Date of Submission: 09-11-2023 Date of acceptance: 23-11-2023

I. INTRODUCTION

1.1 Data set and Class Labels

As the first step in our study, in order to have an experiment in *student classification*, we selected the student and course data of a ECE-CAPA course, ECE-PHY (Physics for Scientists and Engineers I), which was held at MSU in spring semester 2002. Then we extend this study to more courses. This course integrated 12 homework sets including 184 problems. About 261 students used ECE-CAPA for this course. Some of the students dropped the course after doing a couple of homework sets, so they do not have any final grades. After removing those students, 227 valid samples remained. You can see the grade distribution of the students in the following chart (Figure 2.2.1)

We can group the students regarding their final grades in several ways, 3 of which are:

1. The possible class labels are nine similar to that of students' grades, as shown in table 1.1.1.
2. We have classified into three classes, "*high*" representing grades from 3.5 to 4.0, "*middle*" representing grades from 2.5 to 3, and "*low*" representing grades less than 2.5, as shown in table 1.1.2.
3. The students are also categorize with one of two class labels: "*Passed*" for grades above 2.0, and "*Failed*" for grades less than or equal to 2.0, as shown in table 1.1.3.

Table 1.1.1. 9-Class labels regarding students' grades in course ECE-PHY_ SS02

Class	Grade	# of Student	Percentage
1	0.0	2	0.9%
2	0.5	0	0.0%
3	1.0	10	4.4%
4	1.5	28	12.4%
5	2.0	23	10.1%
6	2.5	43	18.9%
7	3.0	52	22.9%
8	3.5	41	18.0%
9	4.0	28	12.4%

Table 1.1.2. 3-Class labels regarding students' grades in course ECE-PHY SS02

Class	Grade	Student #	Percentage
High	Grade >= 3.5	69	30.40%
Middle	2.0 < Grade < 3.5	95	41.80%
Low	Grade <= 2.0	63	27.80%

We could predict that the error-rate in the first class grouping should be higher than the others, because the sample size among the 9-Classes differs considerably.

Table 1.1.3. 2-class labels regarding students' grades in course ECE-PHY SS02

Class	Grade	Student #	Percentage
Passed	Grade > 2.0	164	72.2%
Failed	Grade <= 2.0	63	27.80%

The present classification experiment focuses on the first six extracted students' features based on the ECE-PHY class data.

1. Total number of correct answers. (Success rate)
2. Getting the problem right on the first try, vs. those with high number of submissions. (Success at the first try)
3. Total number of attempts before final answer is derived
4. Total time that passed from the first attempt, until the correct solution was demonstrated, regardless of the time spent logged in to the system. Also, the time at which the student got the problem correct relative to the due date. Usually better students get the homework completed earlier.
5. Total time spent on the problem regardless of whether they got the correct answer or not. Total time that passed from the first attempt through subsequent attempts until the last submission was demonstrated.
6. Participating in the communication mechanisms, vs. those are working with ECE-CAPA provides online interaction both with other students and with the instructor.

II. EXPERIMENTAL SETUP

2.1 Classifiers

Pattern recognition has a wide variety of applications in various fields; hence it is not possible to develop with a specific single type of classifier that can produce optimal results in each and every case. The optimal classifier in most of the case dependent mostly on the problem domain. In general practice, one might have to face across a case where single classifier can perform threshold or minimum level of accuracy. In such cases it would be better to pool the results of various classifiers to achieve the optimal accuracy. Every classifier performs on different aspects like the training or test feature vector. As a result, presuming appropriate conditions and combining various multiple classifiers may improve standard of classification performance when compared with any single classifier.

2.2 Non-tree based classifiers

The popular non-parametric pattern classifiers and a single parametric pattern classifier is compared based on their error estimates. Six different classifiers over one of the ECE-CAPA data sets are compared. The classifiers used are,

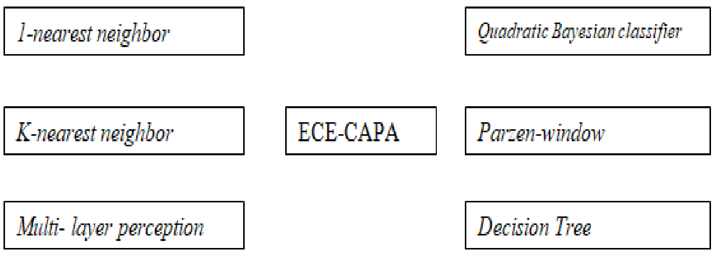

Figure 2.2.1: Non-tree based classifiers

These are the most common classifiers used in practical classification problems. After some pre-processing operations conducted on the data set, the error rate of each classifier is reported. To improve performance, specific combinations of classifiers are presented.

Table 2.2.1 shows the comparison between 3 classes for Error Rate and Standard Deviation for using the classifiers in both normalized and un-normalized data set.

Table 2.2.1 Comparing Error Rate of classifiers with and without normalization in the case of 3 classes

3-Classes	With Normalization		Without Normalization	
Classifier	Error rate	S.D	Error rate	S. D.
Bayes	0.4924	0.0747	0.5528	0.0374
1NN	0.5220	0.0344	0.5864	0.041
KNN	0.5144	0.0436	0.5856	0.0491
Parzen	0.5096	0.0408	0.728	0
MLP	0.4524	0.0285	0.624	0
CMC	0.2976	0.0399	0.3872	0.0346
Oracle	0.1088	0.0323	0.1648	0.0224

Thus, we executed the classifiers with normalization and without normalization. Table 2.2.1 shows an significant improvement in classification results after normalization. The findings are:

1. Without normalizing the data classifiers the Parzen-Window classifier and MLP classifier, not working properly. Therefore, we need to have normalize the data when using these two classifiers.
2. The impact on the Decision tree classifiers did not show any improvement on their classification performance after normalization, so we ignore it in using tree classifiers. At this moment we will not study and discuss the decision tree classifier, even though the Decision Tree classifiers' results are obtained.

2.3 Comparing 2-fold and 10-fold Cross-Validation

In cross-validation of *k*-fold, we have divided the data into k sub-sets of approximately equal size. We would train the data *k number* times, each and every time droping out one of the sub-sets from training, but using only the omitted or dropped sub-set to compute the error threshold of interest. If *k is* equal to the sample size, this condition is called "*LeaveOneOut*" cross-validation. (Duda et al. 2001; Kohavi, 1995). LeaveOneOut cross-validation has provided an unbiased estimate almost of that true accuracy, at an significant computational cost. Both 2-fold and 10-fold cross validation are used in the proposals.

In ***2-fold*** cross-validation, the observation order, in both the training and testing, are randomized before conduct of every trial of classifier. Also, next sample is divided amongst the test and training data, with 50-50, that is 50% going to test, and the other 50% going to training.

In ***10-fold*** cross-validation, the 227 sample data size (ECE-227 students' data) are divided into 10-blocks containing approximately equal numbers of cases and class-value distributions. For each and every block (10% of data) in turn, a training model is developed using the rest of the data in the remaining 90% data blocks (90% of data, *the training set*), and later it is evaluated on the data cases in the hold-out block (*the test set*).

Table 2.3.1 Comparing Error Rate of classifiers 2-fold and 10-fold Cross-Validation in the case of 3 classes

3-Classes	10-fold Cross-Validation		2-fold Cross-Validation	
Classifier	Error Rate	S.D.	Error Rate	S.D.
Bayes	0.5	0.0899	0.5536	0.0219
1NN	0.4957	0.0686	0.5832	0.0555
KNN	0.5174	0.0806	0.576	0.0377
Parzen	0.5391	0.085	0.4992	0.036
MLP	0.4304	0.0806	0.4512	0.0346
CMC	0.313	0.084	0.3224	0.0354
Oracle	0.1957	0.0552	0.1456	0.0462

The tabulated table 2.3.1 shows the comparison of Error Rate and Standard Deviation results performed using the classifiers in both the 2-fold and 10-fold cross-validation in the case of the 3-Classes. We can observe that the 10-fold cross-validation and with the individual classifier has slightly more accurate than 2-fold cross validation, but in relation to combination of classifiers (CMC) there is no a significant difference. Hence, we selected 10-fold cross validation for error estimation in this proposal.

III. RESULTS AND DISCUSSION

3.1 Results, Error Estimation

The experimentally observed results are averaged and presented in the figure charts below. The figure shows the impact of the data random selection on the average error rate. Also the figure shows the average error rate and its standard deviation, which is associated with each classifier, is displayed in the tables as well as the chart. The table concludes and summarizes the results of all the classifiers on our data set.

The standard deviation of error rate is showing the variance of the error rate during cross-validation. The error rate is measured for every round of cross validation using:

$$Error\ rate\ in\ each\ round\ = \frac{Total\ misclassified\ of\ test\ examples}{Total\ number\ of\ test\ examples}$$

After completion of 10 rounds computation, the average error rate and its standard deviation are calculated and then plotted. This metric was chosen due to its ease of computation and intuitive nature. The above Figure 3.1.1 and below figure 3.1.2, show the comparison of classifiers' error rate, when we classify the ECE-students into two categories, "*Passed*" and "*Failed*". The plot shows best performance is for *k*NN with 82% accuracy, and that of the worst classifier is Parzen-window with 75% accuracy. Important observation is CMC has good response in the case of 2-Classes classification has 87% accuracy.

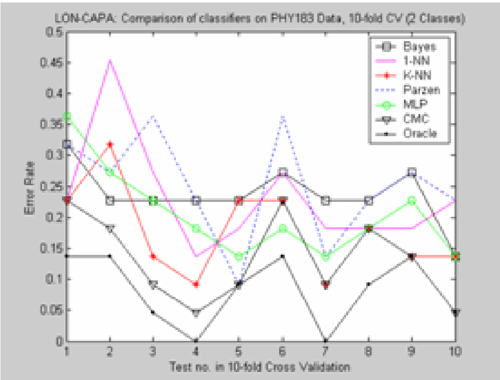

Figure 3.1.1: Comparing Error Rate of classifiers with 10-fold Cross-Validation in the case of 2-Classes

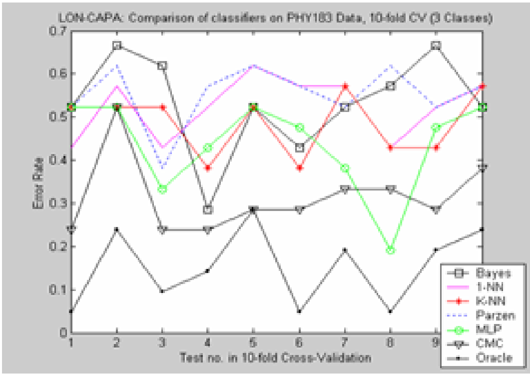

Figure 3.1.2 Comparing Error Rate of classifiers with 10-fold Cross-Validation in the case of 3-Classes

In the case of 9-Classes, 1-NN works better than the other classifiers. Final results in Table 3.1.1 show that CMC is the most accurate classifier compared to individual classifiers. In the case of 2-Classes it improved by **5**%, in the case of 3-Classes itimproved by **20**%, and in the case of 9-Classes it improved by **22**%, all in relation to the best individual classifiers in the corresponding cases.

Table 3.1.1 Comparing the Performance of classifiers, in all cases: 2-Classes, 3-Classess, and 9-Classes, Using 10-fold Cross-Validation in all cases.

	Error Rate		
Classifier	**2-Classes**	**3-Classes**	**9-Classes**
Bayes	0.2364	0.5143	0.77
1NN	0.2318	0.4952	0.71
KNN	0.1773	0.4952	0.725
Parzen	0.25	0.519	0.795
MLP	0.2045	0.4905	-
CMC	0.1318	0.2905	0.49
Oracle	0.0818	0.1619	-

Another important prediction is that when our individual classifiers are working well and each having a high level of accuracy; the benefit of combining classifiers is small. Thus, CMC has little improvement in classification performance while it has a significant improvement in accuracy when we have *weak learner*[8] classifiers.

We tried to improve the classification efficiency, simply from the problems in direct relation to their degree of difficulty. Few specific conceptual sub-sets of the students' data are used, but, we did not achieve a significant improvement in accuracy with this parameter. The upcoming section, we would be explaining the results of decision tree classifiers on our data set, and also discussing the relative importance of student-features and the correlation between these features with category labels.

3.1.1 Decision Tree-based software

Decision trees are to be proved as valuable tools for the description, classification and generalization of data. Many users find decision trees easy to use and understand. As a result, users more easily trust decision tree models than they do "black box" models, such as models produced by neural networks. Many tools and software have been developed toimplement decision tree classification. Lim et al. (2000) has an insightful study about comparison of prediction accuracy, complexity, and training time of thirty-three classification algorithms; twenty-two decision trees, nine statistical and two neural network algorithms are compared on thirty-two data sets in terms of classification accuracy, training time, and (in the case of trees) number of leaves. In this proposal we used C5.0, CART, QUEST, and CRUISE software to test tree-based classification. Some statistical software is employed for multiple linear regression on our data set. First we have a brief view of the capabilities, features and requirements of these software packages. Then we gather some of the results and compare their accuracy to non-tree based classifiers.

3.1.2 Final Results without optimization

The overall results of classifiers' performance on our data set are shown in the Table 3.1.2.1 Regarding individual classifier, for the case of 2-classes, *k*NN has the best performance with **82.3%** accuracy. In the case of 3-classes and 9-classes, CART has the best accuracy of about **60%** in 3-classes and **43%** in 9-Classes

Table 3.1.2 Data-sets of ECE results for two decades.

Year	I - I	I - II	II - I	II - II	III - I	III - II	IV - I	IV - II	I Year	II Year	III Year	IV Year
2004-2005	44.62	44.62	53.52	45.45	44.44	30.16	53.97	87.3	44.62	49.485	37.3	70.635
2005-2006	33.33	33.33	52.53	36.73	55.45	48	40.4	59.6	33.33	44.63	51.725	50
2006-2007	43.82	43.82	59.79	43.75	53.68	59.38	29.79	76.6	43.82	51.77	56.53	53.195
2007-2008	43.94	43.94	51.39	45.14	43.8	55.47	64.23	82.22	43.94	48.265	49.635	73.225
2008-2009	44.62	44.62	53.52	48.94	48.59	60.71	57.14	84.29	44.62	51.23	54.65	70.715
2009-2010	57.5	57.5	50.38	62.31	66.15	69.53	59.54	84.73	57.5	56.345	67.84	72.135
2010-2011	77.12	78.15	57.45	57.86	67.15	71.01	77.86	78.57	77.635	57.655	69.08	78.215
2011-2012	78.89	60.11	56.6	51.43	72.43	60.1	73.58	69.67	69.5	54.015	66.265	71.625
2012-2013	67.5	63.29	56.34	61.7	67.97	65.95	67.03	70.25	65.395	59.02	66.96	68.64
2013-2014	46.84	53.72	50.73	49.27	50.24	50.49	54.9	77.94	50.28	50	50.365	66.42
2014-2015	44.67	38.07	52.73	52.49	53.24	61.32	66.67	81.95	41.37	52.61	57.28	74.31
2015-2016	41.15	41.91	61.19	52.61	53.28	60.85	60.31	80.23	41.53	56.9	57.065	70.27
2016-2017	45.38	50.84	35.25	50.62	57.92	57.32	68.97	75	48.11	42.935	57.62	71.985
2017-2018	50.21	43.46	52.59	60.22	60.59	51.69	67.04	76.78	46.835	56.405	56.14	71.91
2018-2019	50.86	52.42	45.31	51.78	63.49	59.13	65.2	75.5	51.64	48.545	61.31	70.35
2019-2020	38.78	37.14	37.91	42.6	67.53	64.79			37.96	40.255	66.16	
2020-2021	24.9	41.91	50.55	65.2					33.405	57.875		
2021-2022	41.54	45.38							43.46			

However, considering the combination of non-tree-based classifiers, the CMC has the best performance in all three cases. That is we got the **86.8%** accuracy in the case of 2-Classes, **71%** in the case of 3- Classes, and **51%** in the case of 9-Classes.

So far, we have grouped students using multiple classifiers, comparing their prediction accuracy with CMC. In the next section we will study a way to optimize these results in order to find more efficient and more accurate classifiers.

IV. CONCLUSION

4.1 Optimizing the prediction accuracy

We found that a combination of multiple classifiers leads to a significant improvement in classification performance. Through weighting the feature vectors usinga Genetic Algorithm we can optimize the prediction accuracy and get a marked improvement over raw classification. We further show that when the number of featuresis few; feature-weighting works better than just feature selection.

4.1.1 Implementation of a GA to optimize the prediction accuracy

We use the GAToolBox[12] from MATLAB to implement a GA to optimize classification performance. Our goal is to find a population of best weights for every feature vector, which minimize the classification error rate. The feature vector for our predictors are the set of six variables for every student: Success rate, Success at the first try, Number of attempts before correct answer is derived, the time at which the student got the problem correct relative to the due date, total time spent on the problem, and the number of online interactions of the student both with otherstudents and with the instructor.

4.1.2 Experimental Results of GA Optimization

For GA optimization, we used 200 individuals in our population, running the GA over 500 generations. We ran the program 10 times and got the averages, which are shown, in every run 500×200 times the fitness function is called in which we used 10-fold cross validation to measure the average performance of CMC. So every classifier is called 3×10^6 times for the case of 2-classes, 3-classes and 9-classes. Thus, the time overhead for fitness evaluation is critical. Since using the MLP in this process took about 2 minutes and all other four non-tree classifiers (Bayes, 1NN, 3NN, andParzen window) took only 3 seconds, we omitted the MLP from our classifiers group so we could obtain the results in a reasonable time.

4.2 Summary

We proposed a new approach to classifying student usage of web-based instruction. Four classifiers were used to segregate student data. A combination of multiple classifiers led to a significant accuracy improvement in all three cases (2-, 3- and 9-Classes).Weighting the features and using a genetic algorithm to minimize the error rate improved the prediction accuracy by at least 10% in the all cases. In cases where the number of features was low, feature weighting was a significant improvement over selection. The successful optimization of student classification in all three cases demonstrates the value of ECE-CAPA data in predicting students' final grades based on features extracted from homework data. This approach is easily adaptable to different types of courses, different population sizes, and allows for different features to be analyzed. This work represents a rigorous application of known classifiers as a means of analyzing and comparing use and performance of students who have taken a technical course that was partially/completely administered via the web. For future work, we plan to implement such an optimized assessment tool for every student on any particular problem.

REFRENCES

[1]. Dola Sanjay S, B Kalyan Kumar, Prof. S Varadarajan" A moment method solution for spherical structures used in shielding electronic components", Applied Mathematical Science, Vol.6,2012, no.7,333-341.

[2]. Gupta, P., A. Sharma, et al. (2014). "Data Harvesting through Web Mining: A Survey." The International Journal Of Engineering And Science (IJES) 3(4): 21-27. 153

[3]. Guy, I., N. Zwerdling, et al. (2010). Social media recommendation based on people and tags. Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval. Geneva, Switzerland, ACM: 194-201.

[4]. Hernando, A., Jes, et al. (2016). "A non negative matrix factorization for collaborative filtering recommender systems based on a Bayesian probabilistic model." Know.-Based Syst. 97(C): 188-202.

[5]. Hossain, M. and R. M. Rahman (2014). Budget allocation model for the academic library acquisition using data mining technique. Computer and Information Technology (ICCIT), 2013 16th International Conference

[6]. Huaxin, C. and H. Qian (2013). Research on intelligent recommended algorithms of personalized digital library. Conference Anthology, IEEE.

[7]. Jawaheer, G., P. Weller, et al. (2014). "Modeling User Preferences in Recommender Systems: A Classification Framework for Explicit and Implicit User Feedback." ACM Trans. Interact. Intell. Syst. 4(2): 1-26.

[8]. Jie, Y., Z. Haihong, et al. (2012). A Method of Discovering Collaborative Users Based on Psychological Model in Academic Recommendation. Computer and Information Technology (CIT), 2012 IEEE 12th International Conference

[9]. Dola Sanjay S, Prof. S Varadarajan" AMSA as EMI/EMC Sensor", Journal of innovation in Electronics and Communication-Special Issue, Vol. 2, issue 2,ISSN:2249-9946, Jan.2012, 126-129.

[10]. Dola Sanjay S, Prof. S Varadarajan" Implementation of Conducted Emission and Conducted Susceptibility of Pressure Sensor", Proceedings of ICIECE-2012, ISSN: 2249-9946, Jul.2012, 38.

[11]. Chilakanti Sireesha, Dr Dola Sanjay S "Design and Implementation of High Speed Reconfigurable Memory Based FFT" A Journal of Composition Theory, ISSN:0731-6755, Volume XIII, Issue V, May 2020, PP: 360-364.

[12]. Dakhel, G. M. and M. Mahdavi (2011). A new collaborative filtering algorithm using K-means clustering and neighbors' voting. Hybrid Intelligent Systems (HIS), 2011 11th International Conference

[13]. Demovic, L., E. Fritscher, et al. (2013). Movie Recommendation Based on Graph Traversal Algorithms. Database and Expert Systems Applications (DEXA), 2013 24th International Workshop

[14]. Dola Sanjay S, Prof. S Varadarajan, B Kalyan Kumar," Implementation of Conducted Emission and Conducted Susceptibility of Pressure Sensor", IJSER,Vol.4,Jan.2013.

[15]. Dola Sanjay S, Prof. S Varadarajan, "Reduction of Electromagnetic Interference Using Micro-strip Filter", ICPVS 2014, Elsevier Publications, ISBN:978-93-5107-228-7, Mar-2014,90-93.

[16]. Eltahir, M. A. and A. F. A. Dafa-Alla (2013). Extracting knowledge from web server logs using web usage mining. Computing, Electrical and Electronics Engineering (ICCEEE), 2013 International Conference

[17]. Esmailian, P. and M. Jalili (2015). Purchase Prediction and Item Suggestion based on HTTP sessions in absence of User Information. Proceedings of the 2015 International ACM Recommender Systems Challenge. Vienna, Austria, ACM: 1-4.

[18]. Esslimani, I., A. Brun, et al. (2009). A collaborative filtering approach combining clustering and navigational based correlations. 5th International Conference on Web Information Systems and Technologies - WEBIST 2009, Lisbonne, Portugal.

[19]. Dr Dola Sanjay S, P. Geetha Lavanya, P.Jagapathi Raju, M. Sai Kishore, T.N.V.Krishna Priya " Denoising the Spectral Information of Non–Stationary Image using DWT" IJEECS, ISSN 2348-117X, Vol 6, Issue 7 July 2017,pages: 594-598.

[20]. Prof. Dola Sanjay S, G. Pallavi , B. Tarun Kumar, M. Tejaswini , M. Ratna Kireeti "Redundancy Elimination of Stationary Image Using DWT" IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) e- ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 12, Issue 3, Ver. II (May - June 2017), PP 72- 79,10.9790/2834-1203027279(DOI).

[21]. Esteban, B., Á. Tejeda-Lorente, et al. (2014). Aiding in the Treatment of Low Back Pain by a Fuzzy Linguistic Web System. Rough Sets and Current Trends in Computing. C. Cornelis, M. Kryszkiewicz, D. Ślęzaket al, Springer International Publishing. 8536: 250-261.

[22]. Fuchs, M. and M. Zanker (2012). Multi-criteria Ratings for Recommender Systems: An Empirical Analysis in the Tourism Domain. Proceedings of the 13th International Conference on Electronic Commerce and Web Technologies, Vienna, Austria, Springer Berlin.

[23]. Gong, S. (2010). "A Collaborative Filtering Recommendation Algorithm Based on User Clustering and Item Clustering." JOURNAL OF SOFTWARE 5(7): 745-752.

[24]. Dr. Udara Yedukondalu, Sasi Priya Musunuri , Dr. Dola Sanjay. S "VLSI Design of An Area Efficient Architecture of DSP Accelerator Using Dadda Algorithm" IJIEMR, Vol 06 Issue 08, Sept 2017 ISSN 2456 – 5083 Page 327-333.

[25]. Dr. Dola Sanjay.S, Ch.Lakshmi, G.Jayachandra, G. Divya Rupini ,K. Ratnakumar, V Kalpana" Cash less Toll System Using Rppide" International Journal of Engineering Science Invention (IJESI) ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726,Volume 7 Issue 4 Ver. II, April 2018, PP 29-33.

[26]. Dr. Dola Sanjay.S, Sri Durga K, Jayasri M, Mounika S, Eswar Chandu Y , Kumara Varma M" Thermmatology Scan Methodology Using Patel Sensor and Roku Processor" International Journal of Engineering Science Invention (IJESI) ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726,Volume 7 Issue 4 Ver. II, April 2018, PP 34-38.

[27]. Kanimozhi, S. (2011). "Effective Constraint based Clustering Approach for Collaborative Filtering Recommendation using Social Network Analysis." Bonfring International Journal of Data Mining 1(Special Issue): 12-17.

[28]. Keralapura, M. (2009). "Technology and customer expectation in academic libraries: A special reference to technical/management libraries in Karnataka." The International Information & Library Review 41(3): 184-195.

[29]. Konstan, J. A., J. D. Walker, et al. (2014). Teaching recommender systems at large scale: evaluation and lessons learned from a hybrid MOOC. Proceedings of the first ACM conference on Learning @ scale conference. Atlanta, Georgia, USA, ACM: 61- 70.

[30]. Nishnanth.Dulam, Ganesh.Burila, B G Rahul, Dola Sanjay S" Road Accidents Study Based on Regression Model: a Case Study of Vijayawada city to Hanuman Junction" International Journal of Scientific & Engineering Research Volume 9, Issue 5, May-2018 1207 ISSN 2229-5518 PP 1207-1218

[31]. Dr. Dola Sanjay S, P K Ratnam "Reduction of power in confined field multiplier using sorting technique", International Journal of Research e- Volume 05 Issue 16, ISSN: 2348-6848 p-ISSN: 2348-795X PP 712-715 June 2018

[32]. Dr. Dola Sanjay S, P K Ratnam "Reduction of power in confined field multiplier using sorting technique", 2018 IJCRT | Volume 6, Issue 2 April 2018 | ISSN: 2320-2882 PP 798-801 June 2018.

[33]. Dr. Dola Sanjay S, "Implementation of Low Power Transposed FIR Filter using Clock Gating Technique" 2018 IJ | Volume 7, Issue 11 Nov 2018 | ISSN: 2279-543X, DOI:16.10089/IJSRR.

[34]. B S Satish, Dola Sanjay S, A Ranganayakulu, S Jagan Mohan, Ganesan P "Advanced Design of Service Robot for Aged and Handicapped Using Rasberry Pi" 2019 Springer CCIS 922, https://doi.org/10.1007/978-981-10- 8660-1_74, pp854-864, 2019, ISSN: 1865-0929.

[35]. B S Satish, Dola Sanjay S, A Ranganayakulu, S Jagan Mohan, Ganesan P "An Approach to Threshold based Human Skin Color Recognition and Segmentation in Different Color Models" 2019 Springer CCIS 922, https://doi.org/10.1007/978-981-10-8660-1_74, pp 920-931, 2019, ISSN: 1865-0929.

[36]. KHASIM SHAIK, Dr. Dola Sanjay S, Dr. Anupama A " A Study and Approach on Optimization of the Upstream Bandwidth Allocation in Passive Optical Networks Using Internet Users Behaviour Forecast" International Journal of Research, Volume VIII, Issue II, February/2019, pp 372-380, ISSN NO : 2236-6124.

[37]. KHASIM SHAIK, Dr. Dola Sanjay S, Dr. Anupama A " An Approach For Artificial Intelligence Techniques For Combating Cyber Crimes" Universal Review, Volume VIII, Issue III, MARCH/2019, pp 597-601, ISSN NO : 2277-2723.

[38]. Lops, P., M. de Gemmis, et al. (2011). Content-based Recommender Systems: State of the Art and Trends. Recommender Systems Handbook. F. Ricci, L. Rokach, B. Shapira and P. B. Kantor, Springer US: 73-105.

[39]. Ma, L. and J. Xiao (2010). The study on customer-oriented solutions for college library services. Computer and Communication Technologies in Agriculture Engineering (CCTAE), 2010 International Conference

[40]. Mabroukeh, N. R. and C. I. Ezeife (2010). "A taxonomy of sequential pattern mining algorithms." ACM Comput. Surv. 43(1): 1-41.

[41]. KHASIM SHAIK, Dr. Dola Sanjay S, Dr. Anupama A " A Study on mobile AD-HOC Networks: A Detailed survey of QOS Routing Protocols" International Journal of Management, Technology and Engineering, Volume IX, Issue III, MARCH/2019, pp 3416-3424, ISSN NO : 2249-7455.

[42]. KHASIM SHAIK, Dr. Dola Sanjay S, Dr. Anupama A " A Study on performance Analysis of Bandwidth Allocations for Multi Services Using Wireless Networks" Journal of Applied Science and Computations, Volume VI, Issue III, MARCH/2019, pp 1586-1590, ISSN NO : 1076-5131.

[43]. Prof. Dola Sanjay S, B. Madhu Sri, P.Bangaraya, D.B.S.Naveen, Ch.Bala Chandra "Analysis Of Electromagnetic Interference In Pressure Sensor Using Microstrip Low Pass Filter" © 2019 JETIR March 2019, Volume 6, Issue 3, JETIR1903F39, Journal of Emerging Technologies and Innovative Research (JETIR), pp 259-262, www.jetir.org (ISSN-2349-5162).

[44]. Dr. Dola Sanjay S1, M.Gayathri2, N.Gayathri2, P.Vasantha2, Ch. Sai Kiran Chandu2 "Analysis Of Emission And Susceptibility Of Interference On Air Tank Pressure Sensor Using Microstrip Lpf" © 2019 JETIR March 2019, Volume 6, Issue 3, JETIR1903F39, Journal of Emerging Technologies and Innovative Research (JETIR), pp 564-567, www.jetir.org (ISSN-2349-5162).

[45]. Bharathi Lakshmanan, Sangeetha Priya Nachimuthu, Sasikala Ramasamy, S. Dola Sanjay, S. Jagan Mohan Rao" Attribute Table based Energy-Efficient and QoS-of Multipath Routing Protocol Using in Loss-Free Optical Burst Switching Networks" Jour of Adv Research in Dynamical & Control Systems, Vol. 11, 06-Special Issue, 2019, ISSN 1943-023X Received: 02 June 2019/Accepted: 18 June 2019, pp 1339-1348.

[46]. B Varalakshmi , Dr. S Dola Sanjay " Implementation Of Multiplier Architecture Using Efficientcarry Select Adders For Synthesizing Fir Filters" IJRAR19K4739 International Journal of Research and Analytical Reviews (IJRAR), © 2019 IJRAR June 2019, Volume 6, Issue 2, www.ijrar.org (E- ISSN 2348-1269, P- ISSN 2349-5138), pp 457- 465.

[47]. Sangeethapriya Nachimuthu, Bharathi Lakshmanan, Dola Sanjay" Trust Aware Light Weight Secure Routing Protocol for Wireless Body Sensor Network using RCP Measures" International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-1, November 2019, Retrieval Number: L34081081219/2019©BEIESP DOI: 10.35940/ijitee.L3408.119119, PP:5081-8085.

[48]. Ch Murali Krishna, Dr Dola Sanjay S "SRR Inspired Moore Antenna With Fractal Techniques For Multiband Applications" Test Engineering and Management Published by: The Mattingley Publishing Co., Inc. , Jan - Feb 2020 ISSN: 0193 - 4120 PP:11746 – 11752.

[49]. Dez, F., J. E. Chavarriaga, et al. (2010). Movie recommendations based in explicit and implicit features extracted from the Filmtipset dataset. Proceedings of the Workshop on Context-Aware Movie Recommendation. Barcelona, Spain, ACM: 45- 52.

[50]. Joshi1, R. C. and R. S. Paswan (2013). "A Survey Paper on Clustering-based Collaborative Filtering Approach to Generate

Recommendations." International Journal of Science and Research (IJSR) 4(1): 1395-1398.
[51]. Krishnamurthy, V. and R. Balasubramani (2014). An Association Rule Mining Approach for Libraries to Analyse User Interest. Intelligent Computing Applications (ICICA), 2014 International Conference
[52]. Kun, M., L. Tingting, et al. (2014). Hybrid parallel approach for personalized literature recommendation system. Computational Aspects of Social Networks (CASoN), 2014 6th International Conference
[53]. Kuzelewska, U. (2014). "Clustering Algorithms in Hybrid Recommender System on MovieLens Data." Studies in Logic, Grammar and Rhetoric. 37(1): 125–139.
[54]. Lee, D. H. and P. Brusilovsky (2009). Reinforcing Recommendation Using Implicit Negative Feedback. User Modeling, Adaptation, and Personalization: 17th International Conference, UMAP 2009, formerly UM and AH, Trento, Italy, June 22-26, 2009. Proceedings. G.-J. Houben, G. McCalla, F. Pianesi and M. Zancanaro. Berlin, Heidelberg, Springer Berlin Heidelberg: 422-427.
[55]. Lee, S. K., Y. H. Cho, et al. (2010). "Collaborative filtering with ordinal scale-based implicit ratings for mobile music recommendations." Information Sciences 180(11): 2142-2155.
[56]. Master. Lei, M. and Y. Lingshui (2010). Research on digital library knowledge organization methods based-on semantic grid. Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference
[57]. Li, H., Y. Gu, et al. (2009). Review of Digital Library Book Recommendation Models. Available at SSRN: http://ssrn.com/abstract=1513415
[58]. Lomotey, R. K. and R. Deters (2014). Towards Knowledge Discovery in Big Data. Service Oriented System Engineering (SOSE), 2014 IEEE 8th International Symposium
[59]. Lopes, P. and B. Roy (2014). "Recommendation System using Web Usage Mining for users of E-commerce site." International Journal of Engineering Research & Technology 3(7).
[60]. Mahajan, D. S., P. Pawar, et al. (2014). "Analysis of Large Web Sequences using AprioriAll_Set Algorithm." International Journal of Emerging Trends & Technology in Computer Science (IJETTCS) 3(2).
[61]. Malik, S. K. and S. A. M. Rizvi (2011). Information Extraction Using Web Usage Mining, Web Scrapping and Semantic Annotation. Computational Intelligence and Communication Networks (CICN), 2011 International Conference
[62]. Manh Cuong Pham, Y. C., Ralf Klamma, Matthias Jarke (2011). "A clustering approach for collaborative filtering recommendation using social network analysis." Journal of Universal Computer Science J.UCS 17(4). 160
[63]. McGrath, O. G. (2008). Insights and surprises from usage patterns: some benefits of data mining in academic online systems. Proceedings of the 36th annual ACM SIGUCCS fall conference: moving mountains, blazing trails. Portland, OR, USA, ACM: 59-64.
[64]. McNally, K., M. P. O, et al. (2011). "A Case Study of Collaboration and Reputation in Social Web Search." ACM Trans. Intell. Syst. Technol. 3(1): 1-29.
[65]. Meyyappan, N., S. Foo, et al. (2004). "Design and evaluation of a task-based digital library for the academic community." Journal of Documentation 60(4): 449-475.
[66]. Mohd Shuib, N. L., N. Abdullah, et al. (2010). The use of information retrieval tools: A study of computer science postgraduate students. Science and Social Research (CSSR), 2010 International Conference
[67]. Morales-del-Castillo, J. M., R. Pedraza-Jiménez, et al. (2009). "A Semantic Model of Selective Dissemination of Information for Digital Libraries." Information Technology and Libraries 28(1).
[68]. More, N. and K. J. Somaiya (2014). "Recommendation of Books Using Improved Apriori Algorithm." International Journal for Innovative Research in Science & Technology - IJIRST 1(4): 80-82.
[69]. Muralidhar, N., H. Rangwala, et al. (2015). Recommending Temporally Relevant News Content from Implicit Feedback Data. 2015 IEEE 27th International Conference on Tools with Artificial Intelligence (ICTAI).
[70]. Mustafa, A. S. and Y. S. Kumaraswamy (2014). Data mining algorithms for Webservices classification. Contemporary Computing and Informatics (IC3I), 2014 International Conference
[71]. Naak, A., H. Hage, et al. (2009). A multi-criteria collaborative filtering approach for research paper recommendation in papyrus. 4th International Conference MCETECH.
[72]. Nassar, O. A. and N. A. Al Saiyd (2013). The integrating between web usage mining and data mining techniques. Computer Science and Information Technology (CSIT), 2013 5th International Conference
[73]. Neumann, J. and H. Sayyadi (2015). Recommendations for Live TV. Proceedings of the 9th ACM Conference on Recommender Systems. Vienna, Austria, ACM: 228-228.
[74]. Nguyen, T.-T. and P.-K. Nguyen (2012). A New Approach for Problem of Sequential Pattern Mining. Computational Collective Intelligence. Technologies and Applications.
[75]. N.-T. Nguyen, K. Hoang and P. Jędrzejowicz, Springer Berlin Heidelberg. 7653: 51- 60. 162
[76]. Palmer, B. C. (2012). Web usage mining: Application to an online educational digital library service. Instructional Technology and Learning Sciences. Logan, Utah, Utah State University. DOCTOR OF PHILOSOPHY: 263.
[77]. Pani, S. (2011). "Web Usage Mining: A survey on pattern extraction from web logs." International Journal of Control Automation and Systems 1: 10-19.
[78]. Papic, A. and M. Primorac (2014). Introducing e-CRM into academic libraries: Exploration of needs and possibilities. Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2014 37th International Convention
[79]. Park, W.-B. C., Young-Sung; Ko, Hyung-Hwa (2013). "A Study on Hybrid Recommendation System Based on Usage Frequency for Multimedia Contents." Journal of Digital Contents Society 14(4): 419-428.
[80]. Parsons, J., P. Ralph, et al. (2011). Using Viewing Time to Infer User Preference in Recommender Systems AAAI Workshop in Semantic Web Personalization. San Jose, California.
[81]. Patel, V. R. and R. G. Mehta (2011). "Impact of Outlier Removal and Normalization Approach in Modified k-Means Clustering Algorithm." IJCSI International Journal of Computer Science and Information Security(IJCSIS) 8(5): 331-336.
[82]. Peska, L. and P. Vojtas (2013). Negative implicit feedback in e-commerce recommender systems. Proceedings of the 3rd International Conference on Web Intelligence, Mining and Semantics. Madrid, Spain, ACM: 1-4. 164
[83]. Peska, L. and P. Vojtas (2015). Using Implicit Preference Relations to Improve Content Based Recommending. E-Commerce and Web Technologies: 16th International Conference on Electronic Commerce and Web Technologies, EC-Web 2015, Valencia, Spain, September 2015, Revised Selected Papers. H. Stuckenschmidt and D. Jannach. Cham, Springer International Publishing: 3-16.