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UTILIZING GENETIC ALGORITHMS FOR DATA MINING IMPROVEMENT IN AN EDUCATIONAL WEB-BASED SYSTEM

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ABSTRACT
This paper shows a methodology for arranging understudies with the end goal to anticipate their last grade dependent on highlights separated from logged information in an instruction online framework. A mix of different classifiers prompts a noteworthy enhancement in characterization execution. Through weighting the component vectors utilizing a Genetic Algorithm we can advance the forecast precision and get a stamped enhancement over crude arrangement. It further demonstrates that when the quantity of highlights is few; include weighting is works superior to simply highlight choice

KEYWORDS: Web Based Education System, Data Mining, Genetic Algorithm.

1. INTRODUCTION
Many driving instructive foundations are attempting to set up a web based educating furthermore, learning nearness. A few frameworks with various capabilities and methodologies have been created to convey online instruction in a scholarly setting. Specifically, Michigan State University (MSU) has spearheaded a portion of these frameworks to give a framework for online guidance. The exploration displayed here was performed on some portion of the most recent online instructive framework created at MSU, the Learning Online Network with Computer-Assisted Personalized Approach (LON-CAPA).
In LON-CAPA1, we are included with two sorts of vast informational collections: 1) educational assets, for example, website pages, exhibitions, reproductions, and individualized problems intended for use on homework assignments, tests, and examinations; and 2) data about clients who make, change, survey, or utilize these assets. At the end of the day, we have two regularly developing pools of information.
We have been examining information digging strategies for extricating valuable learning from these substantial databases of understudies utilizing on the web instructive assets and their recorded ways through the trap of instructive assets. In this examination, we intend to answer the accompanying two research questions:

[1]. Can we discover classes of students? As such, do there exist gatherings of students who utilize these online assets likewise? Assuming this is the case, would we be able to distinguish that class for any individual understudy? With this data, would we be able to enable an understudy to utilize the assets better, in view of the utilization of the asset by different students in their gatherings?
[2]. Can we arrange the issues that have been utilized by students? Provided that this is true, would we be able to demonstrate how unique kinds of issues affect students' accomplishments? Would we be able to assist educators with developing the homework all the more adequately and proficiently?

We plan to discover comparable examples of utilization in the information accumulated from LON-CAPA, and in the end have the capacity to make forecasts with regards to the most-helpful course of concentrates for every student dependent on their present use. The framework could then influence recommendations to the student with respect to how to best to continue.

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2. MAP THE PROBLEM TO GENETIC ALGORITHM

Hereditary Algorithms have been appeared to be a compelling apparatus to use in information mining and pattern recognition. A vital part of GAs in a learning setting is their utilization in pattern recognition. There are two unique ways to deal with applying GA in pattern recognition:

[1]. Apply a GA directly as a classifier. Bandyopadhyay and Murthy applied GAto find the decision boundary in N dimensional feature space.

[2]. Utilize a GA as an improvement instrument for resetting the parameters in different classifiers. Most uses of GAs in pattern recognition advance a few parameters in the order procedure. Numerous specialists have utilized GAs in highlight determination. GAs has been connected to locate an ideal arrangement of highlight weights that enhance characterization precision. Initial, a customary element extraction strategy, for example, Principal Component Analysis (PCA) is connected, and after that a classifier, for example, k-NN is utilized to figure the wellness work for GA. Blend of classifiers is another zone that GAs have been utilized to advance. Kuncheva and Jain in utilized a GA for choosing the highlights and also choosing the kinds of individual classifiers in their plan of a Classifier Fusion System. GA is likewise utilized in choosing the models for the situation-basedgrouping.

In this paper we will centre around the second methodology and utilize a GA to enhance a mix of classifiers. Our goal is to foresee the understudies' last grades dependent on their web-utilize highlights, which are extricated from the homework information. We configuration, execute, and assess a progression of pattern classifiers with different parameters with the end goal to look at their execution on a dataset from LON-CAPA. Mistake rates for the individual classifiers, their blend and the GA enhanced mix are exhibited.

2.1 Dataset and Class Labels

As test information we chose the understudy and course information of a LON-CAPA course, PHY183 (Physics for Scientists and Engineers I), which was held at MSU in spring semester 2002. This course coordinated 12 homework sets including 184 issues, which are all on the web. Around 261 students utilized LON-CAPA for this course. Some of students dropped the course in the wake of completing two or three homework sets, so they don't have any last grades. Subsequent to expelling those students, there stayed 227 substantial examples. The review circulation of the students is appeared in Fig 1.

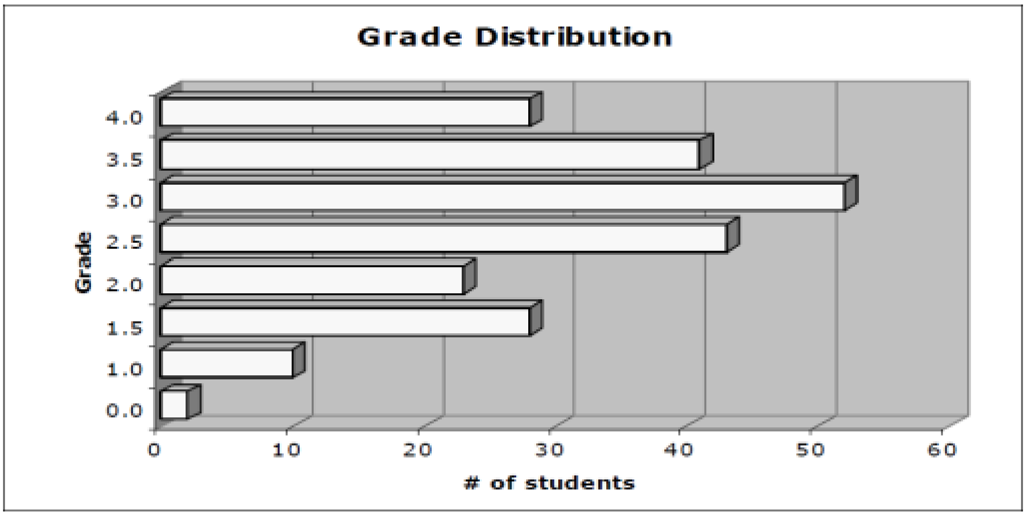

Fig 1.Graph of distribution of grades in course PHY183 SS02

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

[1]. Let the 9 possible class labels be the same as students' grades, as shown in table 1

[2]. We can label the students in relation to their grades and group them 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.

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[3]. We can also categorize the students with one of two class labels: "Passed" for grades higher than 2.0, and" Failed" for grades less than or equal to 2.0, as shown in table 3.

Table 1. Selecting 9 class labels regarding to students' grades in course PHY183 SS02

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

Table 2. Selecting 3 class labels regarding to students' grades in course PHY183 SS02

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

Table 3. selecting 2 class labels regarding to students' grades in course PHY183 SS02

Passed	Grade > 2.0	164	72.2%
Failed	Grade <= 2.0	63	27.8%

We can foresee that the mistake rate in the top of the line gathering ought to be higher than the others, on the grounds that the dispersions of the grades more than 9 classes are so unique. Obviously, we have less information for the initial three classes in the preparation stage, and so the blunder rate would almost certainly be higher in the assessment stage.

2.2 Extractable Features

A fundamental advance in doing characterization is choosing the highlights utilized for order.

Underneath we examine the highlights from LON-CAPA that were utilized, how they can be pictured (to help in determination) and why we standardize the information before order.

The accompanying highlights are put away by the LON-CAPA framework:

1. Add up to number of right answers. (Achievement rate)
2. Getting the issue ideal on the principal attempt, versus those with high number of attempts. (Accomplishment at the primary attempt)

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3. Add up to number of strives for doing homework. (Number of endeavours before right answer is determined)
4. Time spent on the issue until unravelled (all the more particularly, the quantity of hours until right. The contrast between time of the last effective accommodation and the first run through the issue was inspected). Additionally, the time at which the understudy got the issue rectify in respect to the due date. Normally better understudies get the homework finished before.
5. Add up to time spent on the issue paying little heed to whether they found the right solution or then again not. (Contrast between time of the last accommodation and the first run through the issue was analysed).
6. Partaking in the correspondence components, versus those working alone. LONCAPA furnishes online association both with different understudies and with the teacher. Where these utilized?
7. Perusing the supporting material before endeavouring homework versus endeavouring the homework first and after that perusing up on it.
8. Presenting a great deal of endeavours in a short measure of time without looking into material in the middle of, versus those giving it one has a go at, perusing up, presenting another, and so forward.
9. Abandoning an issue versus understudies who kept attempting up to the due date.
10. Time of the primary sign on (start of task, centre of the week, a minute ago) connected with the quantity of attempts or number of tackled issues. An understudy

Passed Grade > 2.0 164 72.2%
Fizzled Grade <= 2.0 63 27.8%

who finds every single right arrangement won't really be in the effective gathering on the off chance that they took a normal of 5 attempts for every issue, except it ought to be checked from this examination.
As of now we could extricate the initial six highlights in the PHY183 SS02 dataset that we have decided for the characterization try.

2.3 Classifiers
Pattern acknowledgment has a wide assortment of uses in a wide range of fields, to such an extent that it isn't conceivable to think of a solitary classifier that can give great outcomes in every one of the cases. The ideal classifier for each situation is profoundly subject to the issue space. By and by, one may go over a situation where no single classifier can arrange with a worthy dimension of exactness. In such cases it is smarter to pool the aftereffects of various classifiers to accomplish the ideal exactness. Each classifier works well on various parts of the preparation or test include vector. As a result, assuming suitable conditions, consolidating various classifiers may enhance grouping execution when contrasted and any single classifier.

The extent of this overview is limited to looking at some famous non-parametric design classifiers and a solitary parametric example classifier as per the blunder gauge. Six distinct classifiers utilizing the LON-CAPA datasets are looked at in this investigation. The classifiers utilized in this examination incorporate Quadratic Bayesian classifier, 1-closest neighbour (1-NN), k-closest neighbour (k-NN), Parzen-window, multi-layer perceptron (MLP), and Decision Tree.2 These classifiers are a portion of the normal classifiers utilized in most down to earth grouping issues. After some pre-processing tasks were made on the dataset, the blunder rate of every classifier is accounted for. At last, to enhance execution, a mix of classifiers is displayed.

2.4 Normalization
Having accepted in Bayesian and Parzen-window classifiers that the highlights areordinarily appropriated, it is vital that the information for each element be standardized. This guarantees each element has a similar weight in the choice procedure. Accepting that the given information is Gaussian disseminated, this standardization is performed utilizing the mean and standard deviation of the preparation information. With the end goal to standardize the preparation information, it is vital first to compute the example mean, and the standard deviation σ of each component, or section, in this dataset, and after that standardize the information utilizing the equation (1).

$$x_i = \frac{x_i - \mu}{\sigma} \qquad \textbf{(1)}$$

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This guarantees each component of the preparation dataset has a typical dissemination with a mean of zero and a standard deviation of one. What's more, the kNN strategy requires standardization of all highlights into a similar range. In any case, we ought to be careful in utilizing the standardization before thinking about its impact on classifiers' exhibitions.

2.5 Combination of Multiple Classifiers (CMC)

In combining multiple classifiers, we want to improve classifier performance. There are different ways one can think of combining classifiers:

- The simplest way is to find the overall error rate of the classifiers and choose the one which has the least error rate on the given dataset. This is called an offline CMC. This may not really seem to be a CMC; however, in general, it has a better performance than individual classifiers.
- The second method, which is called online CMC, uses all the classifiers followed by a vote. The class getting the maximum votes from the individual classifiers will be assigned to the test sample. This method intuitively seems to be better than the previous one. However, when tried on some cases of our dataset, the results were not better than the best result in previous method. So, we changed the rule of majority vote from "getting more than 50% votes" to "getting more than 75% votes". This resulted in a significant improvement over offline CMC.Using the second method, we show in table 4 that CMC can achieve a significant accuracy improvement in all three cases of 2, 3, and 9-classes. Now we are going to use GA to find out that whether we can maximize the CMC performance.

3. UPGRADING THE CMC USING A GA

We utilized GAToolBox3 for MATLAB to actualize a GA to streamline order execution. We will likely discover a populace of best weights for each component vector, which limit the order mistake rate.

The element vector for our indicators are the arrangement of six factors for each understudy: Success rate, Success at the primary attempt, Number of endeavours before right answer is determined, the time at which the understudy got the issue redress in respect to the due date, add up to time spent on the issue, and the quantity of online associations of the understudy both with different understudies and with the teacher.

We arbitrarily introduced a populace of six-dimensional weight vectors with qualities somewhere in the range of 0 and 1, relating to the component vector and tried different things with various number of populace sizes. We discovered great outcomes utilizing a populace with 200 people. The GA Toolbox underpins twofold, whole number, genuine esteemed and coasting point chromosome portrayals. Genuine esteemed populaces might be instated utilizing the Toolbox work crtrp. For instance, to make an arbitrary populace of 6 people with 200 factors every: we characterize limits on the factors in FieldD which is a grid containing the limits of every factor of a person.

```
FieldD = [0 0 0 0 0 0;  % lower bound
          1 1 1 1 1 1];  % upper bound
```

We create an initial population with Chrom = crtrp (200, FieldD), So we have for example:

Chrom = 0.23 0.17 0.95 0.38 0.06 0.26
0.35 0.09 0.43 0.64 0.20 0.54
0.50 0.10 0.09 0.65 0.68 0.46
0.21 0.29 0.89 0.48 0.63 0.89
………………

We used the simple genetic algorithm (SGA), which is described by Goldberg. The SGA uses common GA operators to find a population of solutions which optimize the fitness values.

3.1 Recombination

We utilized "Stochastic Universal Sampling" as our choice strategy. A type of stochastic general testing is actualized by getting a combined entirety of the wellness vector, FitnV, and producing N similarly divided numbers among 0 and sum (FitnV). Hence, just a single arbitrary number is created, all the others utilized being similarly separated starting there. The record of the people chose is dictated by contrasting the produced numbers and the aggregate entirety vector. The likelihood of an individual being chosen is then given by where f(xi) is the wellness of individual xi and F(xi) is the likelihood of that person being chosen.

$$F(x_i) = \frac{f(x_i)}{\sum_{i=1}^{N_{ind}} f(x_i)} \qquad \textbf{(2)}$$

3.2 Crossover

The hybrid crossover task isn't really performed on all strings in the population. Instead, it is connected with a likelihood Px when the sets are decided for reproducing. We chose Px = 0.7. There are a few capacities to make hybrid on genuine esteemed grids. One of them is recint, which performs middle of the road recombination between sets of people in the present populace, Old Chrom, and returns another populace in the wake of mating, NewC hrom. Each line of Old Chrom relates to one individual. recint is a capacity just pertinent to populaces of genuine esteem factors. Middle of the road recombination joins parent esteems utilizing the accompanying equation:

Posterity = parent1 + Alpha × (parent2 – parent1)

Alpha is a Scaling factor picked consistently in the interim [-0.25, 1.25]

3.3 Mutation

A further hereditary administrator, change is connected to the new chromosomes, with a set likelihood Pm. Transformation makes the individual hereditary portrayal be changed as per some probabilistic standard. Transformation is by and large viewed as a back-ground administrator that guarantees that the likelihood of looking through a specific subspace of the issue space is never zero. This has the impact of having a tendency to hinder the likelihood of combining to a neighbourhood ideal, as opposed to the worldwide ideal.

There are a few capacities to make transformation on genuine esteemed populace. We utilized mutbga, which takes the genuine esteemed populace, OldChrom, changes every factor with given likelihood and returns the populace after change, NewChrom = mutbga(OldChrom, FieldD, MutOpt) takes the present populace, put away in the grid OldChrom and transforms every factor with likelihood by expansion of little irregular qualities (size of the transformation step). We thought about 1/600 as our transformation rate. The change of every factor is figured as pursues:

Mutated Var = Var + MutMx ×range ×MutOpt(2) ×delta

where delta is an inward lattice which indicates the standardized transformation step measure; MutMx is an inner cover table; and MutOpt determines the change rate and its shrinkage amid the run. The transformation administrator mutbga can create most focuses in the hypercube characterized by the factors of the individual and the scope of the change. In any case, it tests all the more regularly close to the variable, that is, the likelihood of little advance sizes is more noteworthy than that of bigger advance sizes.

3.4 Fitness Function

Amid the multiplication stage, every individual is appointed a wellness esteem inferred from its crude execution measure given by the goal work. This esteem is utilized in the determination to predisposition towards more fit people. Profoundly fit people, with respect to the entire populace, have a high likelihood of being chosen for mating though fewer fit people have a correspondingly low likelihood of being chosen. The mistake rate is estimated in each round of cross approval by separating "the aggregate number of misclassified precedents" into "add up to number of test models". Thusly, our wellness work estimates the blunder rate accomplished by CMC and our target is expand this execution (limit the mistake rate).

4. EXPERIMENT RESULTS

Without using GA, the overall results of classifiers' performance on our dataset, regarding the four tree-classifiers, five non-tree classifiers and CMC are shown in the Table 4. Regarding individual classifiers, for the

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case of 2-classes, kNN 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. However, considering the combination of non-tree-based classifiers, the CMC has the best performance in all three cases. That is, it

achieved 86.8% accuracy in the case of 2-Classes, 71% in the case of 3-Classes, and 51% in the case of 9-Classes.

Table 4. Comparing the Error Rate of all classifiers on PHY183 dataset in the cases of 2Classes, 3-Classess, and 9-Classes, using 10-fold cross validation, without GA

		Performance %		
Classifier		**2-Classes**	**3-Classes**	**9-Classes**
Tree Classi-fier	**C5.0**	80.3	56.8	25.6
	CART	81.5	**59.9**	**33.1**
	QUEST	80.5	57.1	20.0
	CRUISE	81.0	54.9	22.9
Non-tree Classifier	**Bayes**	76.4	48.6	23.0
	1NN	76.8	50.5	29.0
	kNN	**82.3**	50.4	28.5
	Parzen	75.0	48.1	21.5
	MLP	79.5	50.9	-
	CMC	**86.8**	**70.9**	**51.0**

For GA improvement, we utilized 200 people in our populace, running the GA more than 500 ages. We ran the program multiple times and got the midpoints, which are appeared, in table 5. In each run 500×200 occasions the wellness work is brought in which we utilized 10-crease cross approval to gauge the normal execution of CMC. So, every classifier is called 3 ×106 times for the instance of 2-classes, 3-classes and 9-classes. In this way, the time overhead for wellness assessment is basic. Since utilizing the MLP in this procedure took around 2 minutes and all other four non-tree classifiers (Bayes, 1NN, 3NN, and Parzen window) took just 3 seconds, we excluded the MLP from our classifiers gathering so we could get the outcomes in a sensible time.

Table 5. Comparing the CMC Performance on PHY183 dataset Using GA and without GA in the cases of 2-Classes, 3-Classess, and 9-Classes, 95% confidence interval

	Performance %		
Classifier	2-Classes	3-Classes	9-Classes
CMC of 4 Classifiers without GA	**83.87 ± 1.73**	**61.86 ± 2.16**	**49.74 ± 1.86**
GA Optimized CMC, Mean individual	**94.09 ± 2.84**	**72.13 ± 0.39**	**62.25 ± 0.63**
Improvement	**10.22 ± 1.92**	**10.26 ± 1.84**	**12.51 ± 1.75**

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The outcomes in Table 5 speak to the mean execution with a two-followed t-test with a 95% certainty interim. For the enhancement of GA over non-GA result, a P-esteem demonstrating the likelihood of the Null-Hypothesis (There is no enhancement) is likewise given, demonstrating the criticalness of the GA streamlining. All have $p<0.000$, demonstrating critical enhancement. Along these lines, utilizing GA, in every one of the

cases, we got in excess of a 10% mean individual execution enhancement and around 12 to 15% mean individual execution enhancement. Fig. 2 demonstrates the diagram of normal mean individual execution enhancement.

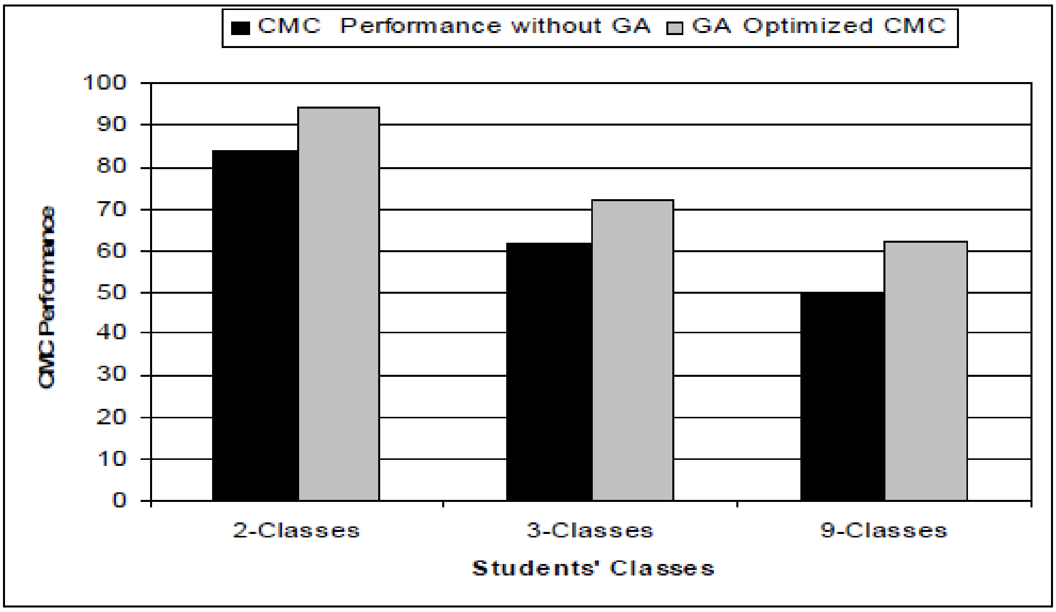

Fig. 2. Chart of comparing CMC average performance, using GA and without GA.

Fig. 3 demonstrates the best consequence of the ten keeps running over our dataset. These outlines speak to the population mean, the best individual at every age and the best esteem yielded by the run.

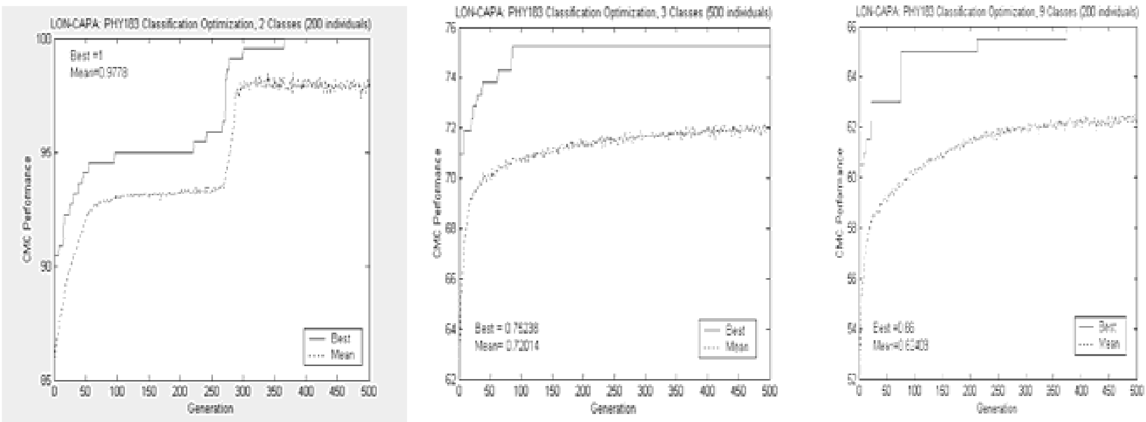

Fig. 3. Graph of GA Optimized CMC performance in the case of 2, 3, and 9-Classes

At long last, we can look at the people (weights) for highlights by which we got the enhanced outcomes. This element weighting demonstrates the significance of each element for making the required arrangement. As a

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rule, the outcomes are like Multiple Direct Regressions or tree-based programming that utilization factual techniques to gauge include significance.

Table 6 demonstrates the significance of the six highlights in the 3-classes case utilizing the Entropy part standard. In view of entropy, a factual property called data gain estimates how well a given element isolates the preparation precedents in connection to their objective classes. Entropy describes debasement of a discretionary

gathering of models S at a particular hub N. In [5] the pollution of a hub N is indicated by i(N) with the end goal that:

$$\textbf{Entropy(S)} = \textbf{i(N)} = -\sum_{j} P(\omega_j)\log_2 P(\omega_j)$$

where $P(\omega_j)$ is the fraction of examples at node N that go to category ω_j.

Table 6. Feature Importance in 3-Classes Using Entropy Criterion

Feature	Importance %
Total_Correct _Answers	100.00
Total_Number_of_Tries	58.61
First_Got_Correct	27.70
Time_Spent_to_Solve	24.60
Total_Time_Spent	24.47
Communication	9.21

The GA results also show that the "Total number of correct answers" and the "Total number of tries" are the most important features for the classification. The second column in table 6 shows the percentage of feature importance.

5. CONCLUSIONS AND FUTURE WORK

Four classifiers were utilized to isolate the students. A mix of different classifiers prompts a noteworthy precision enhancement in every one of the 3 cases. Gauging the highlights and utilizing a hereditary calculation to limit the mistake rate enhances the forecast exactness at any rate 10% in the all instances of 2, 3 and 9-Classes. In situations where the quantity of highlights is low, the element weighting worked much superior to include determination. The effective advancement of understudy arrangement in every one of the three cases exhibits the benefits of utilizing the LON-CAPA information to anticipate the students' last grades dependent on their highlights, which are separated from the homework information.

We will apply Genetic Programming to create various blends of highlights, to remove new highlights and enhance expectation exactness. We intend to utilize Evolutionary Algorithms to order the students and issues straightforwardly also. We likewise need to apply Evolutionary Algorithms to discover Association Rules and Dependency among the gatherings of issues (Mathematical, Optional Response, Numerical, Java Applet, et cetera) of LON-CAPA homework informational collections.

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