Journal of Advances and Scholarly Researches in Allied Education
Vol. 21, Issue No. 5, July-2024, ISSN 2230-7540

https://doi.org/10.29070/0z3q1245

Evaluate the impact of early intervention strategies based on predictive analytics on improving student outcomes and Enhancing the Teaching-Learning process

Vinod K C[1]*, Dr. Suhas Rajaram Mache[2]

[1] Research Scholar, University of Technology, Jaipur, Rajasthan, India

Email: kckcvkc@gmail.com

[2] Professor, Department of Computer Science, University of Technology, Jaipur, Rajasthan, India

Abstract - If we want to see lasting improvements in our economy, education is a must. In light of this, educational institutions on a global scale are working to enhance the educational system for the benefit of both students and instructors. Educational institutions must ensure that low-performing students are identified early and accurately so that they can provide high-quality education and get appropriate assistance to decrease dropout rates. The purpose of this project is to examine data mining techniques as a means to forecast students' academic success. The main goal is to provide methods that may enhance the performance of students on the prediction test. Using the best subset of features determined in Phase I, an improved SVM classifier is used to forecast a student's performance in Phase 2. There are two ways in which the SVM classifier gets improved. The first one eliminates superfluous training support vectors, which improves both the accuracy and the time complexity. To get around knowing the K values before clustering, the K Means clustering technique is tweaked utilising ensemble clustering technology.

Keywords: Teaching learning process, Predictive analysis, K value, algorithm,AI

- x -

INTRODUCTION

The field of predictive analytics in education uses statistical algorithms, machine learning, and student data from the past to make predictions about what could happen in the classroom. Predictive models equipped with AI and ML may achieve an accuracy rate of 90-95%. Using data-driven AI and predictive analytics, educational institutions may better anticipate issues, spot patterns, improve feedback techniques, and advise students on the best services to use. A student dashboard providing evaluation formative feedback and data-driven course suggestions based on performance was created by researchers in a 2021 project that used explainable ML and predictive analytics. Motivated, self-regulated, and with better learning results, the children emerged victorious from the experiment.

In any case, by analysing domain data, professionals may create a collection of degree plans that students can utilise to pick the right ones. In addition, a strategy for intervention has been created to warn students of potential failure. In order to help pupils sooner, the notifications are prepared and sent to the schools' faculty. In addition, the works are used for evaluating how students' activities, assignments, and examinations will impact their future outcomes. Based on it, we can anticipate students' ultimate grades and outcomes and provide teachers early warnings when necessary. When it comes to predictive analytics, artificial intelligence (AI) is crucial. It paves the way for massive data sets to be collected and analysed, revealing patterns and correlations that could otherwise go unnoticed by more conventional techniques of data analysis. The ability of computers to learn from data, recognise patterns, and make judgements with little to no human involvement is what makes machine learning, a branch of artificial intelligence, so useful for predictive analytics. To better assist each student, teachers may use machine learning algorithms to examine a student's past academic data and forecast how well they will do in the future. For more information on this subject, see our article on the use of machine learning in the classroom.

LITERATURE REVIEW

Linda Darling-Hammond (2020) An increasing agreement about the science of learning and development, as detailed in a recent synthesis of the research, is discussed in this article, along with its implications for school and classroom practices. Using a developmental systems framework as a starting point, we compile findings from various areas of educational research and the learning sciences to provide a picture of tried-and-true methods for fostering the connections and experiences that kids need to thrive, grow, and learn. Furthermore, we survey the literature on strategies that might aid teachers in dealing with student diversity, hardship, and resilience, so that schools can pave the road for all students to succeed as adults.

Marco Colizzi et.al (2020) Prior knowledge The field of mental health has followed the trend of other medical specialties in its pursuit of early diagnosis and treatment of mental illness. On the other hand, new information on the efficacy of main prevention and promotion measures for youth mental health is emerging from convergent studies. It was our intention to reevaluate this evidence. Methods To better understand how to promote and prevent mental health issues in young people, we surveyed the existing literature. Final Product Half of all mental problems begin before the age of fourteen, and non-specific psychosocial disturbances are often present before any significant mental condition may develop. Among people aged zero to twenty-five, these disturbances account for forty-five percent of the worldwide burden of disease. Although there has been significant progress in promoting the establishment of youth-specific services, the majority of the mental health requirements during this formative time remain unfulfilled. These call for a rethinking of prevention efforts within a trans-diagnostic paradigm that focuses on adolescents in order to alter potential psychopathological pathways early on. Final thoughts Based on the available evidence, it is unreasonable to assume that mental health practitioners are solely responsible for promoting and preventing mental health issues. In order to reduce the likelihood of unfavourable long-term outcomes, improve the variety of therapies available, and perhaps save money for the healthcare system, integrated and multidisciplinary services are essential. Nevertheless, mental health experts have a scientific, ethical, and moral obligation to point the way for all governmental, social, and health care organisations that are engaged in addressing mental health problems among young.

Mina Fazel et.al (2014) Integrating mental health services into school systems may help children's mental health and academic performance go hand in hand. For optimal child development and to reinforce this continuum, it may be necessary to reorganise the mental health and education systems to facilitate the use of evidence-based therapy. There is a lot of promise in integrative solutions that aim to help both students and teachers. A strong research agenda is required to concentrate on the long-term maintenance and system-level implementation of treatments. Integration of mental health and education has scientific and ethical merits; it broadens people's access to services and, when combined with evidence-based methods, may help kids grow up healthily.

Beth Dietz-Uhler et.al (2013) A growing number of people are taking an interest in learning analytics because of the potential it has to help schools with things like student retention, achievement, and accountability. Academics should think about these systemic problems, but they should also think about how they might utilise learning analytics to improve their own classes. This article provides an overview of learning analytics, its applications in education, the current state of the field, and the tools that educators have at their disposal for analysing course data to forecast and improve student performance. Lastly, we go over some of the problems and worries associated with learning analytics at universities.

Tuomi, (2018) This article provides an overview of the latest advancements in AI and how they might change the face of education. It provides the theoretical groundwork for study, policy, and future endeavours that take into account the possibilities and threats posed by AI's rapid advancements. Though written with policymakers in mind, the paper has valuable insights for those working on artificial intelligence (AI) technologies and academics investigating the field's potential societal, economic, and educational effects.

METHODOLOGY

A number of technical advances and breakthroughs are anticipated in the current century, necessitating the involvement of competent and efficient individuals. Students graduating from schools are expected to be innovative and competent in working with these cutting-edge technology by both private firms and public agencies. Therefore, it is critical that students acquire skills that will serve them well in the workforce. Only until schools deliver high-quality instruction will this be possible.

Student Performance Prediction System

Businesses are increasingly demanding highly qualified individuals due to the ongoing revolutionary developments that are anticipated by various sectors. The educational sector has been driven to seek out ways to enhance learning and teaching habits and adapt to new challenges and advances. They have focused on presenting competitive techniques to help individuals manage these changes. The betterment of pupils' education is the shared goal of all approaches. The institutions are looking for an easy-to-use solution that is both very precise and quick to pinpoint trouble spots. Institutions like to see particular methods tested and validated before incorporating them into existing educational systems and resources.

Development Methodology, Phases And Interactions

Using methods built on the efficient and cooperative integration of many schemes, this study introduces a Student Performance Prediction (SPP) System.

- Effectively eliminate superfluous and unneeded data points to derive a feature vector that may enhance prediction accuracy
- Forecast how well students will do in class by integrating ensembling, clustering, and classification approaches.

DATA ANALYSIS

Feature Selection

Conventionally, a student dataset is shown using a two-dimensional matrix (Figure 1), whereby each row contains information on a single student, each column shows the values of the student's features, and the final column shows the class or target label to which each student belongs.

	SF1	SF2	...	SFN	Target Label
Student 1	V_{11}	V_{12}	…	V_{1N}	c_1
Student 2	V_{21}	V_{22}	…	V_{2N}	c_2
...	…	…	…	…	…
Student M	V_{M1}	V_{M2}	…	V_{MN}	c_M

Figure 1: Representation of a Student Dataset

Finding a close approximation of the functional connection between two inputs, I and O, is the goal of the machine learning issue. It is usually possible to decide on the output O using just a small subset of I, rather than the whole set of I. For better discriminatory power, use the whole student dataset while making predictions.

Consider the Student Features (SF) dataset, which contains a fixed-length collection of features (assignments) and the values (V) that go along with them. In other words, SF is equal to {SF1, SF2, …, SF N, SF N+1| whereas V is equal to {VSF1, VSF2,, …, VSFN,, VSF1} and N is the number of characteristics retrieved from the student's courses or institution. Its comparable value is VSFN+1, while the target class is SFN+1 in this case. The collection of labels for the target class or category is denoted by C, which is equal to {CL1, CL2, …, CLK}. K = 2 and may take on the values "Pass" or "Fail" in this study. The goal of the suggested predictor is to generate a hypothesis that, given fresh student data, can reliably forecast the labels. The benefits of using FS into TD prediction systems are outlined below.

Steps in FS Algorithm

The fitness function and the search method are the two primary parts of FS algorithms (Tsymbal et al., 2003). The search methods scour the feature space for the best subsets to include, and the fitness function takes the best subsets from the search, analyses them, and then gives a numerical assessment of how well they predict. Typically, the goal of the search part is to maximise the fitness function's function. As seen in Figure 2, the FS algorithm follows a four-step process to choose the best features (Liu and Yu, 2005). This section lays out the four stages.

Proposed Hybrid Feature Selection Algorithm

So far, feature selection methods have been underutilised in SPP solutions, with the majority of proposals aimed at enhancing classifier performance. When it comes to choosing the best characteristics, not even these scarce research use more than one method. Everyone knows that there are advantages and disadvantages to any feature selection algorithm. Finding the best characteristics might be a challenge, but this study suggests using a combination of feature selection methods to get the most of each one. Specifically, we provide a two-stage feature selection technique that integrates several wrapper- and filter-based algorithms. In this study, this technique is called EASOF, which stands for Enhanced technique for Selecting Optimal Student Features. The proposed EASOF combines several types of feature selection algorithms, such as those based on filters and wrappers, with genetic algorithms and Ant Colony Optimisation.

The EASOF algorithm selects optimal features using the two steps (Figure 2) as listed below.

• Step 1: A method for selecting features using multiple filters (MFFSMI)

• Step 2: Optimisation of Ant Colonies using Wrapper-Based Genetic Algorithms and Support Vector Machines (WAGS)

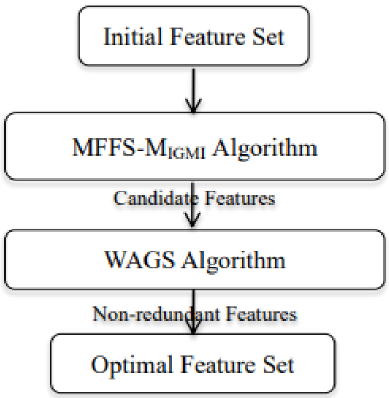

Figure 2: Steps in EASOF

PROPOSED WRAPPER-BASED FEATURE SELECTION ALGORITHM

A number of novel, population-based stochastic search and optimisation algorithms have emerged in the last ten years; these algorithms draw inspiration from evolutionary principles and aim to solve real-world problems as efficiently as possible with as little computing resources as possible. More and more researchers in this field are turning to Evolutionary Computation (EC) and Swarm Intelligence (SI) techniques. Evolutionary conservation strategies are based on the notion of "survival of the fittest" as it occurs in nature. The learning process in humans and the social behaviour in insects are the main sources of inspiration for SI approaches. Both approaches are reliable in finding the best possible answers and give effective solutions. In order to choose the best characteristics from a student dataset, this study combines the two approaches.

ACO-Based Feature Selection Method

Colonies of social insects, such as ants, bees, schools of fish, and flocks of birds, are studied for their collective intelligence, which is known as swarm intelligence. The effectiveness of insects in completing complicated tasks, such as determining the quickest route from their nest to their food supply or organising their nest, is the primary focus of insect research. These bugs aren't very smart, and they can only do basic things by themselves.

GA-Based Feature Selection

Holland (1975) first proposed GA, a technique that draws on natural genetics and the processes of natural selection. As shown in many studies (Lu et al., 2008; Bhanu and Lin, 2003; Kharrat et al., 2011), GA is often used to identify feature subsets optimally. Finding solutions in a population of initially produced, randomly, hypotheses (named individual or chromosome) is the first step of the GA algorithm. In the FS issue, each chromosome stands for a possible solution, or feature subset. Bit strings, which consist of strings of zeroes and ones, are used to encode the chromosomes. Over the course of many generations, the algorithm refines these starting points by applying a fitness function to each chromosome in the population. Stochastic selection of the fittest individuals in the present population is used to produce the new population. By modifying and/or recombinating the pieces of these chosen people, new individuals may be produced. The following generation inherits some of these chosen people unaltered. The algorithm then uses the updated population in the subsequent algorithm iteration.

Analysis of ACO and GA

There are two stochastic search methods: GA, which is based on the fitness survival principle, and ACO, which mimics the pheromone trial laying behaviour of ant colonies. To generate the next generation, GA makes use of mutation operators and crossovers, whereas ACO makes use of heuristic information and pheromone trials. Table 1 compares the ACO and GA algorithms' shared capabilities.

TABLE 1

SIMILAR CHARACTERISTICS OF ACO AND GA ALGORITHMS

S.No.	ACO	GA
1	Number of Ants	Population Size
2	One Iteration	One Generation
3	Based on the foraging behavior of ant colonies	Trial solutions are based on the principle of survival of fittest
4	Probabilistic process is defined by pheromone intensities and local heuristic information	Probabilistic process is defined by crossover and mutation operators
5	Search space is guaranteed by pheromone evaporation	Achieved by using mutation operator

The trial solutions are generated by different algorithms. ACO algorithms iteratively build experimental solutions based on environmental data, which are then tweaked to make them better. While GA builds new solutions by changing old ones, genetic algorithms employ genetic materials.

Naïve Bayes has the worst prediction accuracy compared to other approaches. This is because Naïve Bayes assumes that the characteristics have a strong independent connection, which is not always true.

DESIGN OF HYBRID PREDICTION SYSTEM

The achievement gap and students' progress are seen as critical performance metrics by educational institutions across the globe. Their goal is to narrow the achievement gap and the difference in academic functioning between high- and low-performing pupils, and they devote a lot of time and energy to this end. Mathematical models have been used in the past to try to figure out how to help children who are at risk (Mariel et al., 2012; Merwe et al., 2018; Huang and Fang, 2013).

K means Clustering Algorithm

Data is grouped into k groups (where k is the number of pre-chosen groups) using the K Means clustering method, one of the simplest unsupervised learning techniques. Squaring the distances (Euclidean distances) between each item and its centroid is how the grouping is done. It plays an essential role in several data mining applications and is among the most popular and long-standing clustering algorithms (Patil and Khan, 2015). The standard K-Means method is shown in Figure 3. The student dataset (SF) and the number of clusters (K) are inputs to this method, which then outputs a set of clusters (C) and a set of labels (L).

```
for each ci ∈ C do
        ci = ej ∈ E  // random selection of initial centroids
end for
for each SFi ∈ SF do
        l(SFi) = argminDistance(SFi, cj) j ∈ {1..K}
end for
ClusterChange = false;
repeat
        for each SFi ∈ C do
                updateCluster(ci);
        end for

        for each SFi ∈ E do
                mindist = argminDistance(SFi, cj) j ∈ {1..K};
                if mindist ≠ l(SFi) then
                        l(SFi) = mindist;
                        ClusterChange = true;
                end if
        end for
until ClusterChange = true or convergence is reached
```

Figure 3: Conventional K-Means Algorithm

The goal of this approach is to minimise the sum of squared errors (SSE) (Equation 1), which is the criterion for convergence.

$$SSE = \sum_{j=1}^{k} \sum_{x_i \in c_j} \| x_i - \mu_j \|^2$$

$$\mu_j = \frac{1}{n_j} \sum_{x_i \in c_j} x_i$$

Where where nj is the number of instances in cluster cj and represents the mean of cluster cj. There is a guaranteed minimum that the K Means algorithm will converge to. It is the beginning cluster centroids that determine which local minimum is discovered. In order to find the local minimum, the K Means method updates the cluster centroids. Euclidean distance is the measure of distance employed.

$$d_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2}$$

The following characteristics are shown by the efficient K Means method:

- At all times, K clusters are present.
- The groups do not overlap and do not form a hierarchy.
- Closeness does not always entail the 'centre' of clusters, therefore every member of a cluster is closer to its cluster than any other cluster.

The key benefits of the K Means method are its speed, robustness, and clarity. Additionally, for the method to work well, the data sets must be unique or at least physically isolated. But there's a big problem with picking the right K number before clustering.

CONCLUSION

Education is undergoing a sea change as a result of technological advancements in electronics and information technology. A more robust, powerful, location-independent, and student-centric model of education is emerging as a result of the widespread availability of educational resources made possible by the expansion of the Internet. One way to do this is by implementing a system to anticipate which students would perform poorly in class. Teachers may utilise this information to aid students who are struggling and reduce attrition rates by giving them extra support. The primary goal of this study is to provide a framework for predicting students' future academic success by analysing their past performance in the classroom and using new methods to make the predictions more accurate. Research technique begins with the proposal of a hybrid feature selection algorithm that takes the best parts of both filter and wrapper-based methods and uses them together. To locate the best student traits, the traditional hybrid model is tweaked by making the filter and wrapper algorithms operate better together. Using ensemble technology, the K Means clustering method is improved such that the user-defined K value is no longer a need. While adaptively deciding on the necessary number of clusters, the ensemble clustering algorithm organises data. To train the improved SVM classifier, the clustering results are then used.

REFERENCE

1. Beth Dietz-Uhler et.al "Using Learning Analytics to Predict (and Improve) Student Success: A Faculty Perspective" Volume 12, Number 1, Spring 2013 ISSN: 1541-4914

2. Tuomi, I. The Impact of Artificial Intelligence on Learning, Teaching, and Education. Policies for the future, Eds. Cabrera, M., Vuorikari, R & Punie, Y., EUR 29442 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-97257-7, doi:10.2760/12297, JRC113226.

3. Colizzi, M., Lasalvia, A. & Ruggeri, M. Prevention and early intervention in youth mental health: is it time for a multidisciplinary and trans-diagnostic model for care?. *Int J Ment Health Syst* **14**, 23 (2020). https://doi.org/10.1186/s13033-020-00356-9

4. Linda Darling-Hammond et.al "Implications for educational practice of the science of learning and development" https://doi.org/10.1080/10888691.2018.1537791

5. Fazel M, Hoagwood K, Stephan S, Ford T. Mental health interventions in schools 1:

Mental health interventions in schools in high-income countries. Lancet Psychiatry. 2014 Oct;1(5):377-387. doi: 10.1016/S2215-0366(14)70312-8. PMID: 26114092; PMCID: PMC4477835.

6. Aulck, L.; Velagapudi, N.; Blumenstock, J.; West, J. Predicting student dropout in higher education. arXiv **2016**, arXiv:1606.06364.

7. Ahadi, A.; Lister, R.; Haapala, H.; Vihavainen, A. Exploring machine learning methods to automatically identify students in need of assistance. In Proceedings of the Eleventh Annual International Conference on International Computing Education Research, Omaha, NE, USA, 9–13 July 2015; pp. 121–130.

8. Kursa, M.B.; Rudnicki, W.R. Feature selection with the Boruta package. J. Stat. Softw. **2010**, 36, 1–13.

9. Almarabeh, H. Analysis of students' performance by using different data mining classifiers. Int. J. Mod. Educ. Comput. Sci. **2017**, 9, 9–15.

10. Xu, J.; Moon, K.H.; Van Der Schaar, M. A machine learning approach for tracking and predicting student performance in degree programs. IEEE J. Sel. Top. Signal Process. **2017**, 11, 742–753.

11. Asif, R., Merceron, A., Ali, S. A., & Haider, N. G. (2017). Analyzing undergraduate students' performance using educational data mining. *Computers & Education, 113*, 177–194.

12. Bernacki, M. L., Chavez, M. M., & Uesbeck, P. M. (2020). Predicting achievement and providing support before STEM majors begin to fail. *Computers & Education, 158*, 103999. https://doi.org/10.1016/j.compedu.2020.103999

13. Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial intelligence trends in education: A narrative overview. *Procedia Computer Science, 136*, 16–24. https://doi.org/10.1016/j.procs.2018.08.233

14. Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 1*, 100002. https://doi.org/10.1016/j.caeai.2020.100002

15. Dillenbourg, P. (1999). What do you mean by "collaborative learning"? In P. Dillenbourg (Ed.), *Collaborative learning: Cognitive and computational approaches (Vol 1)* (pp. 1–15). Oxford: Elsevier.

Corresponding Author

Vinod K C*

Research Scholar, University of Technology, Jaipur, Rajasthan, India

Email: kckcvkc@gmail.com