An Enhanced Machine Learning-Based Approach for Analysis and Prediction of Student Performance in Classroom Learning

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Many students at higher education institutions have to work hard to finish different courses since there is no specialized help supplied to students who require particular attention in the registered courses. Students' grades may be predicted using machine learning approaches in a wide range of courses. Such strategies would encourage students to improve their performance based on expected grades, and teachers would be able to identify those students who would benefit from extra guidance in the classroom. Students' conduct reveals the link between students and a Web-based education system's Learning Management System. In this research, we propose a novel model for students to forecast their performance based on machine learning approaches that include new characteristics known as student behavior and a sequential feature selection used to identify important features. The suggested output model is being evaluated using ANN, SVM, KNN, Logistic regression, and a Decision Tree. We also used Bagging, Boosting, and Random Forest as collaborative approaches to improve classification accuracy. The results show that the student's activities and academic progress are linked. Using collaborative ways to improve academic performance in the classifier resulted in a 96% accuracy rate. As a result, the ML techniques are found to be better than the other techniques used in predicting the students' performance in the classroom learning.

Keywords: Educational data mining, Machine learning, prediction of student performance, classroom learning, Prediction accuracy.

1. Introduction

Students' retention in prestigious colleges and universities is a major problem because of their status as sites of higher learning [1]. According to [2], a majority of students drop out of college within their first year owing to a lack of assistance in undergraduate courses [3]. First year of college is referred to be a "make or break year" because of this. In the absence of any assistance, a student may get demotivated and decide to drop out of the course. To help students stay on track in colleges and universities, there is a pressing need to find a suitable solution. As a result of early grade prediction, the University's degree courses will be monitored more closely and the students' learning process will be improved based on their expected grades.

This is because computers and portable gadgets have evolved in the last three decades, allowing access to a wide range of electronically available materials. Educators may now connect with students in new ways because to these innovations [2]. Modern schooling has becoming increasingly technologically oriented [3]. Human-machine collaboration is necessary to develop a learning environment that is both successful and efficient for the human learner [4] because of the technology's involvement with humans. Higher education institutions have begun incorporating blended learning approaches into their standard teaching methods due to the relevance of both instructor-generated and learner-generated material [2]. There is also a rise in the popularity of massive open online courses (MOOCs). As mentioned in [5,] researchers are now able to tackle issues that were previously inaccessible. There has been a startling development of Artificial Intelligence (AI) in the educational system recently. One of the ten most common reasons for using new technology in education is to assist students accomplish their educational goals. The importance of AI-enabled educational technology has grown to draw attention to the improvement of educational quality and the enhancement of traditional teaching and learning methods [6]. Research shows that artificial intelligence (AI) technology is allowing computers to execute a variety of activities by emulating human problem-solving skills [7]. AI technology has also been identified as one of the most significant uses in the field of special educational needs (SEN) [8].

Organization for Economic Co-operation and Development (OECD) members have a dropout rate of around 45% [2]. In response to this issue, higher education institutions are establishing and implementing interventions. A student's first year of college is the best time to implement these methods, according to researchers and practitioners. Because of this, a lot of attention has been paid to figuring out which students are most likely to drop their classes as early as possible [2,3]. Machine Learning has recently been used to enhance corporate decision-making in predictive analysis. The importance of Machine Learning research in a variety of business tasks may be seen in the fields of finance, operations, and risk management, to name a few. It has been shown that machine learning may help forecast business process performance [4] and identify credit card fraud [5]. The application of Machine Learning in higher education management is increasing. Educators are increasingly interested in applying Machine Learning to forecast student performance and identify students at risk based on their initial data acquired during their years of study [6]. Fewer studies have been done on how to predict a student's academic achievement based on their past academic experience [2,3]. As seen in Figure 1, some of the most important statistics from the literature study are shown graphically.

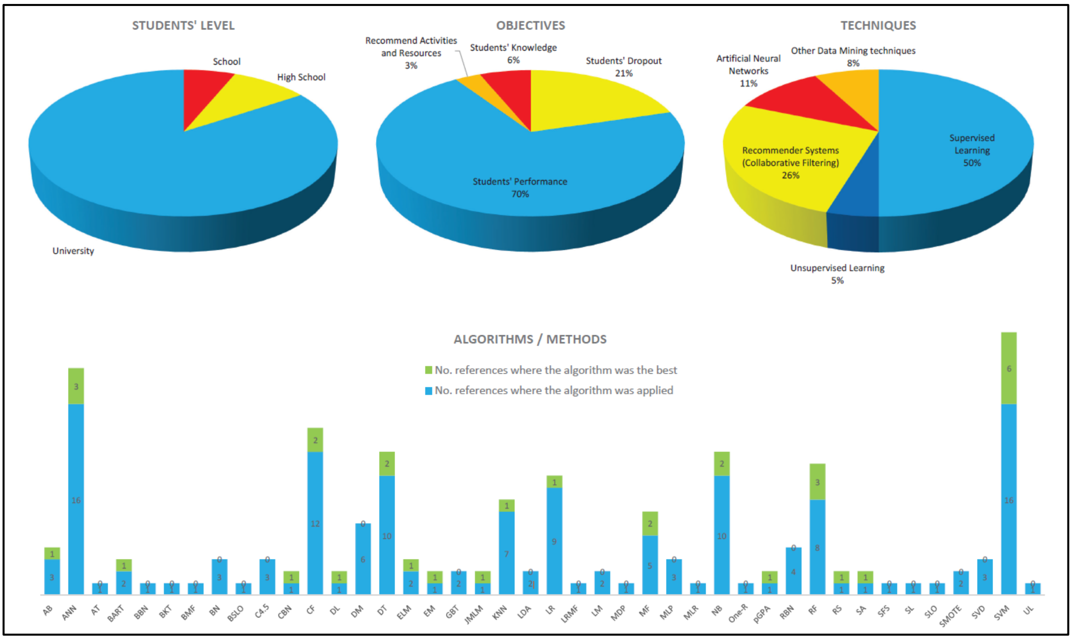

Figure 1. Basic data about the approaches, goals, and methods used.

In order to better forecast student exam success, this research examined and compared the latest state-of-the-art machine learning algorithms. For this type of prediction, supervised machine learning approaches are preferred over unsupervised ones since they don't need the use of an unlabeled dataset. Similarity-based, model-based, and probabilistic machine learning techniques were all considered in this study. The technique based on similarity predicts exam achievement by finding students with comparable historical results. The second technique of this strategy is driven by an estimate of the implicit correlation between the input learning data and the underlying model. Using the input datasets' distributional features, the third approach is probabilistic. Student "high risk" was detected utilising all three state-of-the-art techniques and representative processes, as well as for executing test performance classifications and regressions. It was believed that a student's performance on the categorization assignment would determine whether or not they passed the exam. The estimated regression coefficient was generated using the final test results of the students. The accuracy of student test performance predictions was also examined in relation to the different forms of data provided for optimisation of a specific machine learning technique. The ideal combination of input data types was determined by taking into consideration a variety of student attributes. Data input includes demographics, prior academic performance, and student participation. Different viewpoints on student test performance prediction were explored in the analysis to ensure complete examination and comparison of underpinning approaches. When it came to predicting final test scores, for example, students were asked to supply a variety of input data at various points in time leading up to the final exam. In this manner, each technique's performance patterns were analysed. Each approach was also evaluated in terms of its computing needs in terms of the amount of time it takes to forecast. Data from the Open University Learning Analytics Dataset, one of the largest and most diverse collections of learning analytics and student-related data, was mined for use in testing and evaluation (OULAD).

1.1. Motivation

Recently, predictive analysis has relied on Machine Learning to support business decision-making. Applications in finance, operations and risk management are good attestations of the relevance of Machine Learning research in various business functions. Hassan Zeineddine et al., for example, used machine learning to predict business process performance [4], and McLean et al. to spot credit-card fraud [5].

More and more, Machine Learning is used in the field of higher education management. Specifically, there has been an increased interest in adopting Machine Learning to predict student performance and identify students at risk based on initial data gathered during their years of study, as surveyed in the work of Ding L et al. [6]. Fewer work addressed the prediction of student performance using data prior to starting their academic journey [2,3].

Given the complexity of choosing an optimal prediction model for a given dataset from a wide pool of predictive methods and different hyper-parameter values per model, the automation of this process can help increase the prediction accuracy [7–9]. In relation to that, Automated Machine Learning (ML) is a technique meant to derive the best classification model and corresponding hyper-parameters for a given decision-making problem. This technique can add value if used in predicting student performance. Yet, the review of the literature in this area shows a lack of empirical work using ML. Our research work relies on ML to help increase the accuracy of predicting student performance using data available upon entering an academic program.

The rest of the paper is organized as follows. Section 2 will discuss the literature survey. Section 3 describes the dataset. Section 4 presents the Methodology and Section 5 highlights the results and discussion. Section 6 concludes the proposed work.

2. Literature Survey

There have been a number of relevant research published in the field of student test performance analytics. Exam performance analysis at educational institutions was the primary focus of these investigations, with the classification challenge of classifying individuals as either "passing" or "failing." The purpose of these research was to identify students who were "at-risk" of failing a particular class. According to a study published in 2003 [9], k-Nearest Neighbor (k-NN) and Nave Bayes were used to classify students into dropout and non-dropout categories. Dropout risk can be identified by a student's demographic data or a brief description of where they were born. In a web-based course, [10] examined many learning algorithms for predicting final test marks for students enrolled. Students' grades were categorised into two classes (pass and fail), three (high, middle, and poor), and nine (out of a total of 10) for this study's research purposes (according to the achieved grade). It was shown that a k-NN algorithm could be used to classify students attending an online touch-typing course into two groups: those who would "drop out" and those who would finish the final test. Using the regression exercise, they were able to make predictions about how students will do on the final exam. A technique known as the k-NN algorithm was used by [11] to determine the appropriate level of study material for each learner. Despite the fact that their goals are distinct, the results of performance analysis have a considerable impact on prediction studies as well. In some cases, statistical approaches may not be adequate to establish the relationship between numerous factors and performance [12]. Educators and students alike may benefit from the deployment of advanced algorithms [13]. Many scholars have been encouraged by the progress of data mining tools to examine deeper insights into the information diffusion process. In the past, some of them have used data mining techniques to accomplish this goal [14]. There were, however, relatively few of these investigations at the time. A rise in educational quality has been spurred on by the use of digital data management systems and instructional software [15], all educational research will be based on data mining and analytics. Multiple surveys on EDM studies have been undertaken in the past by the researchers. Some of them use a broader definition of educational processes to include a wide range of topics. In addition, a small number of these programmes concentrate on analysing and forecasting student performance. Let's take a quick look at what these polls are all about. More than a decade ago, [16] released a paper in which they synthesised previous studies published in the period 1995-2005 and outlined the most likely goals of EDM. Another comprehensive assessment [17] of over 300 studies from 1993 to 2009 was published in 2010. Student performance prediction is one of eleven main sub-areas it splits the EDM research area into. It was also at that time that the field of learning analytics had begun to take off. It's important to point out that the initial impetus for educational analytics research came from two research organisations: the International Educational Data Mining Society and the Society for Learning Analytics Research. According to [18, these two research communities have a lot in common when it comes to their areas of interest. A study by [19] in the same year describes the motivations for and difficulties associated with studying learning analytics. They conducted an in-depth investigation on student modelling methodologies in 2013. Possibly, this is the first of its kind to focus on a specific facet of electronic dance music. In [20] analysed 240 EDM trials between 2010 and the first quarter of 2013 and issued yet another thorough analysis in 2014, which was published in 2014. Student performance modelling has seen a steady increase in papers published since 2010, according to this research. Additionally, researchers performed an EDM survey on the psychology of learning and the usage of clustering methods [21]. Educators and administrators may profit greatly from the prediction of students' performance, according to [22], the most recent appraisal of EDM research.

2.1. Techniques

Students' behaviour may be predicted using several sorts of data, such as demographics and grades from previous assignments, using methods like machine learning (ML) and supervised learning (SL). The Hellenic Open University's work on machine-supervised learning methods applied to a dataset provided a solid beginning point for this investigation. Findings from this research show a correlation between the Nave Bayes (NB) algorithm and the likelihood of student dropout [23]. As a result, several strategies may be used to anticipate students' behaviour depending on the nature and characteristics of each case study. As a result of this effort, the various approaches have been organised into four broad categories: ML with supervision, unsupervised ML, CF, and ANN. In order to incorporate those works with comparable goals but utilised alternative DM approaches, a new category has been formed. Figure 1 indicates how many problems and instances each of these categories of approaches is better suited to, as shown by the amount of weight they each have in the literature. An overwhelming majority of instances are handled by supervised ML, followed by CF, which accounts for less than a quarter. However, unsupervised ML has been used in a very small number of situations.

2.1.1. Machine Learning

Machine Learning is a set of techniques that enables computers to learn without the need for human intervention [24]. Predictive analysis, medical diagnostics, stock market research and DNA sequencing are just some of the many uses for ML. In particular, we are interested in predictive analysis, where ML may be used to create sophisticated models that can be used to forecast future behaviour. By supplying consumers with appropriate data, these models may be of considerable benefit. ML algorithms may be divided into two primary categories: supervised and unsupervised.

2.1.2. Logistic regression

Students' performance may be predicted using regression techniques, which make use of a finite set of relationships between the dependent and independent variables to generate an inferential function. There are a variety of different ways to characterise the relationships between independent variables in a logistic regression model, and they include binary, categorical, and continuous [25, 26]. According to the logistic regression, the degree of prediction accuracy is about 70% when utilising factors such as professional goals, CGPA, psychological scores, and personal interests as predictors of future success.

2.1.3. Decision tree

There have been several studies that have made use of the Decision Tree prediction approach, due to its simplicity and convenience of use in analysing both small and big data sets and anticipating their worth. If-then statements can be used to simplify the logic of decision tree approaches, making this method easier to grasp. Students' grades in specific courses and their current CGPA have been utilised in various articles to forecast their performance using this strategy [27]. It is possible to predict a student's success in an academic programme using this technique with a level of accuracy of roughly 70 % when utilising data collected prior to the student's enrollment in the programme [28].

2.1.4. Artificial neural network

An Artificial Neural Network (ANN) is capable of detecting all of the relationships between the variables that it is trained on. In educational data mining, it is a commonly utilised approach. The ANN is an effective tool for forecasting student performance because of its capacity to discover complicated relationships between independent and dependent factors with high confidence [29]. Many factors go into predicting student achievement with a neural network, including the student's attitude toward learning, the applicant's CGPA, and their grades in individual courses. To forecast student performance using data collected after students began their academic journey, this method had an accuracy of up to 98%, and had an accuracy of about 70% [30].

2.1.5. Naive Bayes

Another approach used to forecast student achievement called naive Bayes. In order to demonstrate the relevance and influence of each of these predictors, it does comparisons among independent variables using all of the qualities included in the data. For the most part, studies that employed this strategy relied on data from sources other than test scores and standardised test scores. According to research conducted with the help of Nave Bayes, which relied mostly on data acquired after students had begun their academic journeys, the model had a maximum accuracy of 76% [16].

2.1.6. K-nearest neighbors

The K-Nearest Neighbors methodology is a simple way to classify data points based on the dominating class of their K-Nearest Neighbors. The K-Nearest Neighbors methodology [13,21,23] is a fast method for predicting student success based on a variety of multivariate criteria (slow, medium, good, and outstanding). If data from internal evaluations, CGPA, and extracurricular activities were used, the accuracy rate increased to 83% [16].

2.1.7. Support vector machine

An SVM is a supervised learning approach that uses an N-dimensional hyperplane to classify data points. N is the number of characteristics that characterize a data point. When working with small samples, this strategy has been useful for researchers [6,12,13,21,23,25] in forecasting student performance. Overlapped data can also be effectively handled by the SVM. Student performance was predicted with an accuracy of roughly 80 percent using CGPA, extracurricular activities, psychomotor tests, and internal assessments in previous study [19].

3. Dataset Description

This data is based on the performance of students in secondary education at two schools in Portugal. It was gathered through school reports and surveys that included student grades, demographics, social and school-related aspects. Mathematics (mat) and Portuguese language performance are examined in two separate datasets. A binary/five-level classification and regression task were used to model the two datasets in [31]. G3's target property G2 and G1 have a high association with each other. Final-year grades G3 (given at 3rd period) are different from grades G1 and G2, which are awarded at the beginning and end of the semester, respectively. Predicting G3 without G2 and G1 is more difficult, but the benefits of such a forecast are far greater.

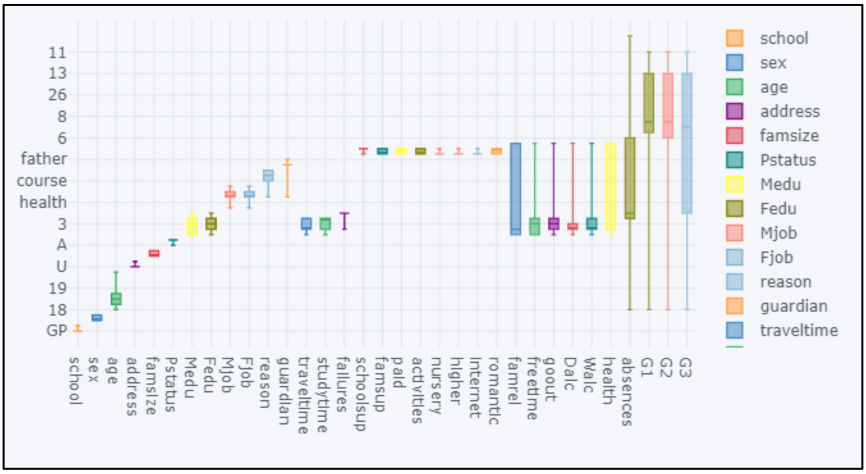

Figure 2. Box Plot to view all attributes

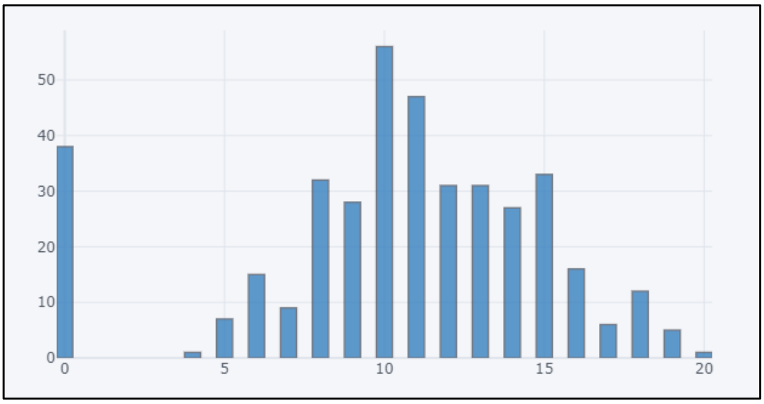

Figure 3. Histogram Plot for G3 (Final Grade) using cufflinks

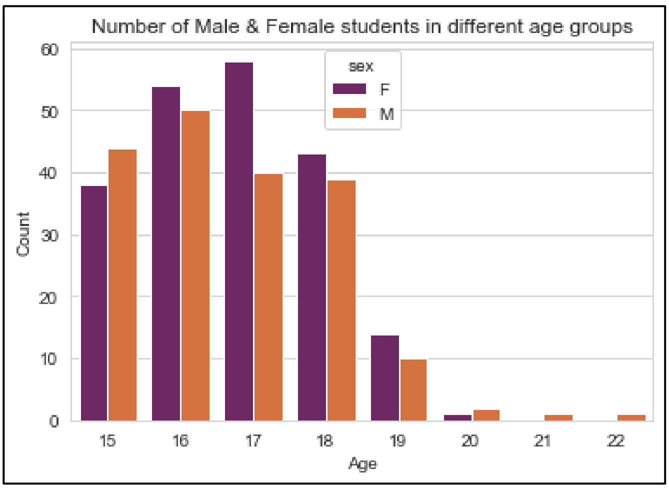

Figure 4. Male and Female with different age groups

4. Methodology

As distinguished institutions of higher learning, universities place a great value on student retention. Many students drop out of college during their first year because they lack enough help in their undergraduate courses. Consequently, many students refer to their freshman year as their "make or break" year. In the absence of any assistance, a student may get demotivated and decide to drop out of the course. There is a tremendous need to find a way to keep college students in their programmed longer. As a result of early grade prediction, the University's degree courses will be monitored more closely and the students' learning process will be improved based on their expected grades. Students' learning outcomes may be enhanced by the application of machine learning and Educational Data Mining. Students' grades in the courses they've enrolled in may be predicted using a variety of models, which can aid in the retention of those students. Using this data, a system can propose that teachers give extra attention to kids who are at danger of falling behind in class. Students' grades in various courses may be predicted with the use of this data, and the universities' retention rates can be improved as a result. Automated machine learning used a set of prediction approaches and their associated hyper-parameter values to find the most accurate model, as shown in Figure 5.

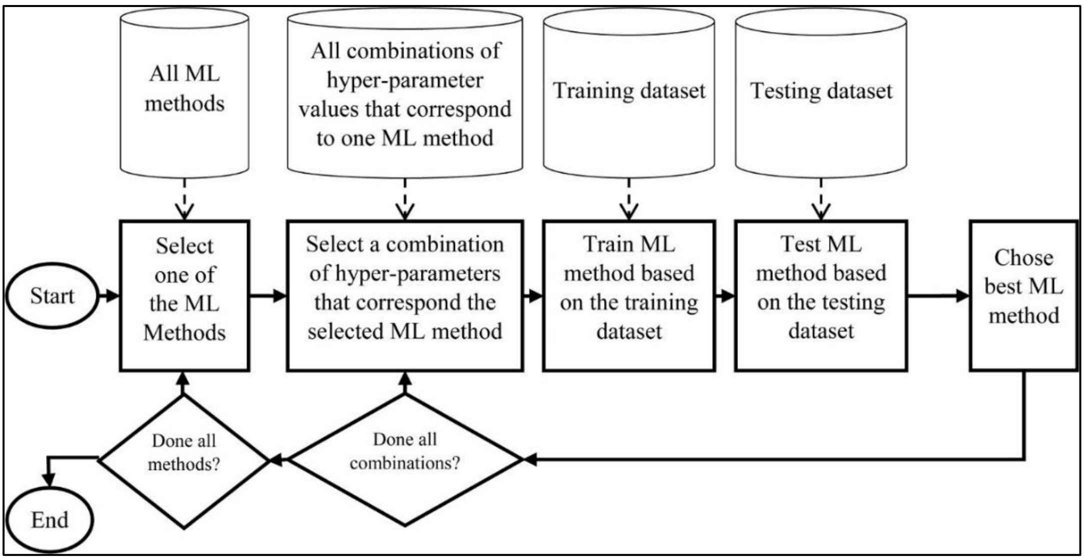

Figure 5. Proposed algorithm architecture

4.1. Artificial neural network

An artificial neural network may imitate the connections and interactions between neurons in the human brain (ANN). Neurons in the ANN are connected by nesting functions based on a network model. The argument x of the function is a vector of length n, with the values $x = [x_1, x_2, \dots x_n]$. This function can be shown as.

$$F(x) = S(\sum_i^n \omega_i F(x_i)) \tag{1}$$

If x is a scalar, then F(x) is equal to x. When training the network using historical data, the factor will be used as a weight. It's possible to standardise the output by using a transfer function called S. The sigmoid function, which modulates values between 0 and 1, was chosen as the study's transfer function:

$$S(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The ANN is a hierarchical model with several layers. Nodes (neurons) in each layer are linked in a single way to all nodes in the layer below them through unidirectional linkages. There is no way to communicate with other nodes in the same layer or upstream. Fig. 6 depicts a typical data structure with three levels: an input layer, a collection of intermediate layers, and an output layer. The ANN design used in this work consists of an input layer that represents the various category values of the adopted data characteristics, two intermediate layers with 12 and 7 neurons each, and an output layer with one neuron representing the binary result.

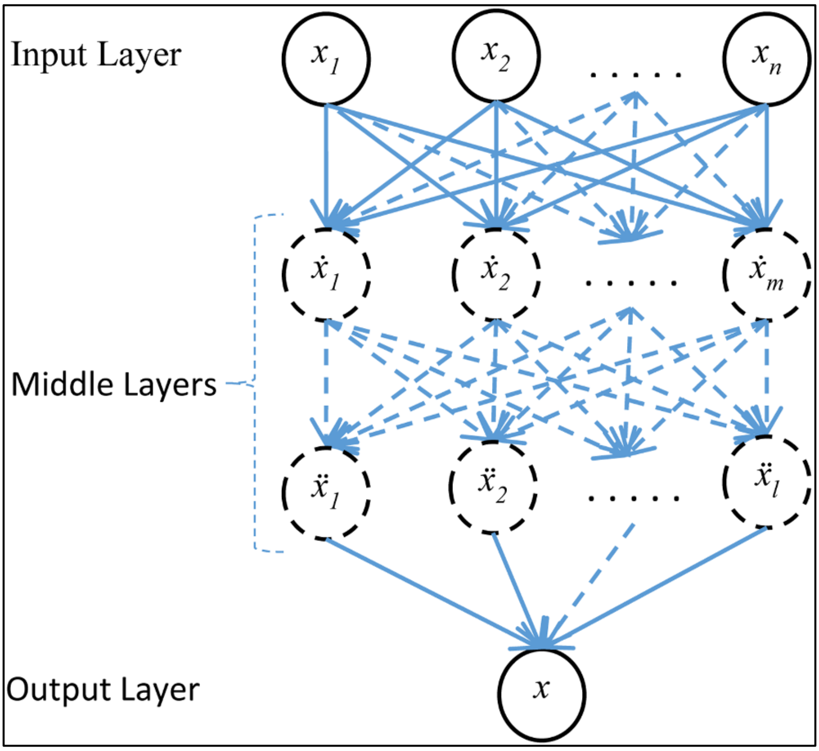

Figure 6. ANN architecture.

4.2. Support Vector Machine

The SVM classifier determines the boundaries between sets of data points. In general, points that fall within a given range are considered part of the same class. Data points belonging to various classes should be easily separated by a straight line, as this is the ideal situation. Figure 7 shows that in most circumstances, this is not practicable because of data overlaps. This new higher-dimensional space allows the data points to be linearly separated by a hyperplane, which is how SVM does it. Non-linearly separable points are more likely to be separated by hyperplanes in a higher-dimensional space when projected by a non-linear transformation, according to Cover's Theorem. The bordering data points, referred known as support vectors, will be used to reference the boundary hyperplane. A certain distance should separate the support vectors from the border. As a result of this kernel function, distances may be computed more quickly by taking the dot product of two points (x and y). Polynomial kernel F of degree d [30] was employed in this study:

$$F(x, y) = \left(\sum_{i=1}^{n} x_i \cdot y_i + c\right)^d \quad (3)$$

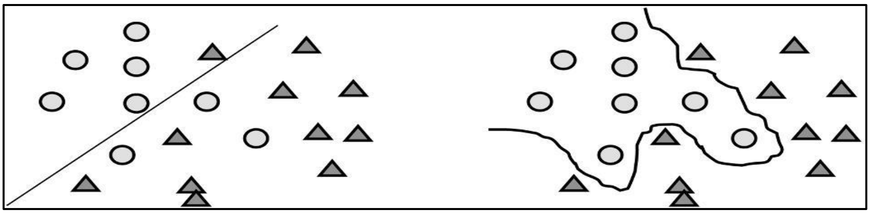

Figure 7. overlapping data sets that aren't linearly separable

4.3. K-nearest neighbors

The K-Nearest Neighbors approach uses the dominating class of its K-next nearby points to classify a data point. Euclidean, Manhattan, and Chebychev functions [31] may be used to calculate the distance between two points on a graph. Euclidean distance function was used in our investigation, with K set to 1. To measure the distance between two points on a graph, we can use the Euclidean distance:

$$E(x, y) = \sqrt{\sum_{i=0}^{n} (x_i - y_i)^2} \quad (4)$$

4.4. K-means clustering

An individual data point is assigned to one of K possible clusters in the K-Means Clustering algorithm. An algorithm for clustering data first divides a training set into K groups, each of which represents one of the classes to be classified. Due to the fact that we have two classes, Pass and Fail, K was set at 2. Data points are assigned to clusters depending on their distance from the cluster centroid. An average data point in a cluster is called a centroid. The Euclidean Distance [32] is used as the distance function in this approach.

It is possible to properly anticipate the outcome of a new data point by placing it in the cluster with the closest centroid following a training phase in which prior data points were assigned to two independent clusters. This is the case in our experiment.

4.5. Logistic regression

As explained in the function below [33], the logistic function L is used to turn the result of a linear regression function f(x) into a number ranging from 0 to 1. It represents the probability of a particular characteristic occurring in a certain class.

$$L_{(f(x))} = \frac{1}{1+e^{-f(x)}} \quad (5)$$

4.6. Decision tree

Data points from the past are used to train a Decision Tree classifier, which develops a tree-like structure in response. The characteristics and their associated values are organised in a tree-like topology, making it easier to answer queries by traversing the tree from root to branch. Two or more downstream nodes, including the root node, are connected to each decision node (all representing answers to decision questions). As the last response to a sequence of questions collected by the preceding nodes, a leaf node serves as the final node.

5. Results and Discussion

The Machine learning Model's accuracy was evaluated using a cross-validation of 10 folds. Over a period of ten runs, the model is trained on 75% of the data and evaluated on 25%. As part of the250% split, it is vital to notice that the data points allocated for testing are different each time. Fig. 8 depicts the Weka cross-validation technique used in this research. Using our data set, we can see in Table 1 which categorization algorithms have the highest accuracy. There are separate columns for estimating whether a student will fail and pass. It is crucial to distinguish between high-risk and low-risk children when trying to gauge the effectiveness of these approaches. Further, table 1 highlights the kappa coefficient (κ), which is a statistic representing the level of agreement between two different classifiers. It factors in the possibility of accidental agreements. In our case, the agreement is measured between the modeled classifier and the observed process.

$$k = \frac{P_0 - P_e}{1 - P_e} \tag{6}$$

Accuracy may be measured by calculating the probability of making the correct forecast (Po). A classifier pair's chance of accidentally agreeing on a classification is called the probability of agreement (Pe). The chance that classifier I would correctly forecast class n in a binary system with two predictors is given by the formula Pe = P1(a) • P2(a) + P1(b) • P2(b). According to Fleiss' Scale, a kappa value of between 0.4 and 0.75 is excellent. A kappa of less than 0.4 is considered bad, while a kappa of more than 0.75 is considered good. Kapa of 0.5 for our Machine learning Model is roughly two-thirds greater than the Kapa for any individual prediction model (using the same data). As a consequence, our machine learning Model derived from the automated search has a lower possibility of exhibiting the observed process and random guessing errors.

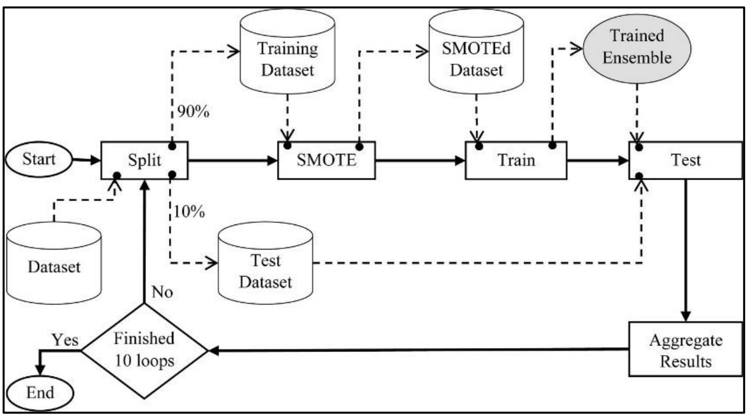

Figure 8. Model accuracy with 10 folds cross validation

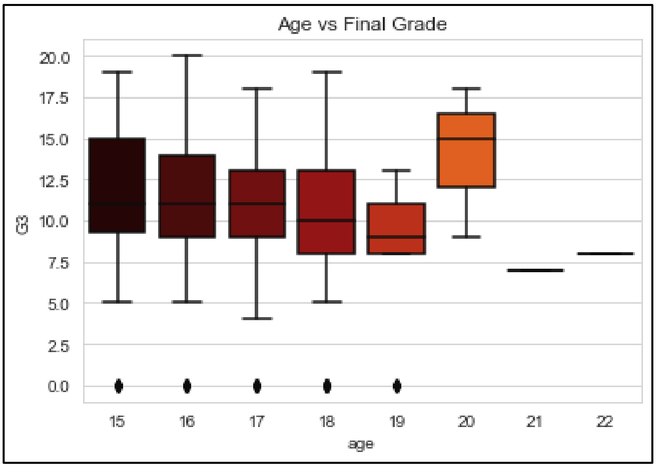

Figure 9. Students age vs Final grade

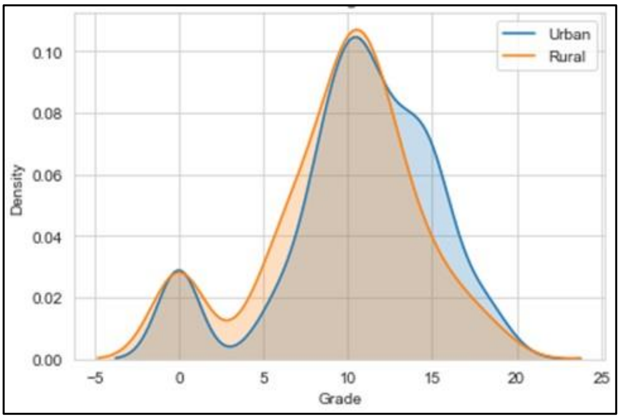

Figure 10. Urban vs Rural students grade score.

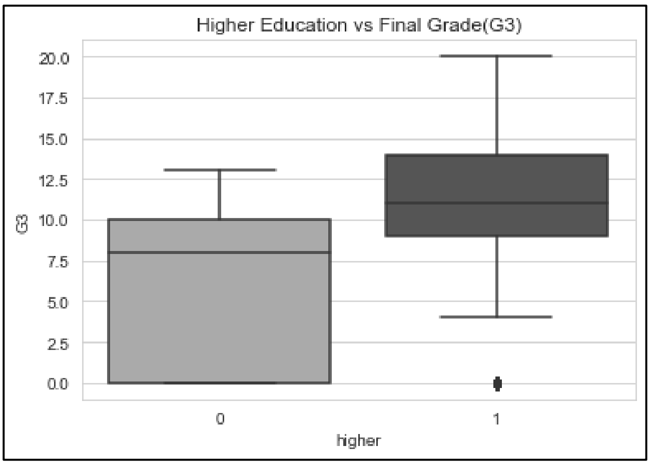

Figure 11. Final grade vs Higher Education (HE)

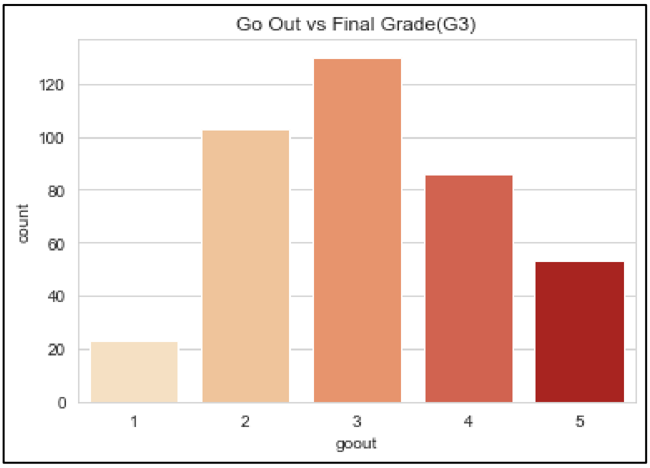

Figure 12. Go Out vs Final Grade of the students

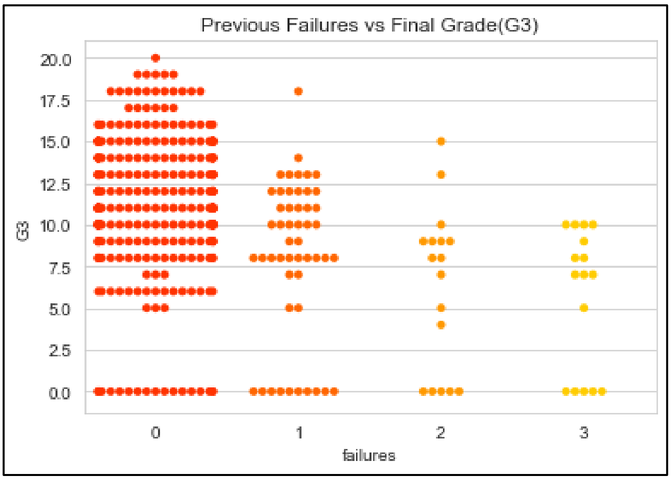

Figure 13. Previous failures vs Final Grade (G3)

Table 1. Methods comparison

Classification Method	Accuracy Rate of predicting Fail Students	Accuracy Rate of predicting Pass Students	Overall Accuracy Rate	Kappa Statistics
ANN	83.6%	89.8%	86.0%	0.39
K-NN	87.4%	85.4%	86.2%	0.37
K-Means Clustering	84.2%	86.4%	85.5%	0.08
Naïve Bayes	86.7%	89.8%	87.0%	0.42
SVM	86.0%	82.2%	83.8%	0.38
Logistic Regression	92.0%	98.8%	96.8%	0.38
Decision Tree	86.7%	85.7%	85.2%	0.37

6. Conclusion and Future scope

The research discussed in this paper contributes to the body of knowledge on the area of predicting student academic progress. Data that is available before students begin their new academic Programme can be used to increase the accuracy of student performance projections using pre-start data. Predicting student achievement using pre-start data has never had an accuracy higher than 83%, according to existing research. With the use of machine learning, we were able to achieve an overall accuracy of 96%, with a Kapa of 0.3. If you're looking for an optimal student performance prediction model, you're advised to employ machine learning (ML). Students who are at risk of failing and need early help from academic institutions' specialized departments must be identified more accurately. There is a maximum accuracy of 80% in the literature on new-start student failure predictions. An accuracy of 96% was achieved after employing the machine learning model.

Students at risk may now be identified with greater precision, which saves time and money for educational institutions. In future, descriptive statistics may be utilized to analyses the role and effect of various psychographic elements on the prediction model. In the future, it is possible that autogenerated ensemble models will be examined to determine if academic and psychographic data can predict student performance in the workplace.

References

1. Sannyuya Liu, Shiqi Liu, Zhi Liu, Xian Peng, Zongkai Yang, Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement, Computers & Education, Volume 181, 2022, 104461.
2. Puranam Revanth Kumar, Rajesh Kumar Jha, P Akhendra Kumar, and B Deevena Raju "Improved neurological diagnoses and treatment strategies via automated human brain tissue segmentation from clinical magnetic resonance imaging", Intelligent Medicine, vol. 4, Issue 4, pp. 1-21, 2024.
3. Bahareh Javadizadeh, Matthew Aplin-Houtz, Maureen Casile, Using SCARF as a motivational tool to enhance students′ class performance, The International Journal of Management Education, Volume 20, Issue 1, 2022, 100594.
4. Hassan Zeineddine, Udo Braendle, Assaad Farah, Enhancing prediction of student success: Automated machine learning approach, Computers & Electrical Engineering, Volume 89, 2021, 106903.
5. Puranam Revanth Kumar, Rajesh Kumar Jha, and P Akhendra Kumar "BrainHyperintensities: Automatic Segmentation of White Matter Hyperintensities in Clinical Brain MRI Images using Improved Deep Neural Network", The Journal of Supercomputing, vol. 80, pp. 15545–15581, 2024.
6. Ding, L., Er, E., & Orey, M. (2018). An exploratory study of student engagement in gamified online discussions. Computers & education, Vol. 120, Elsevier213–226.
7. Dobson, A. J., & Barnett, A. G. (2008). An introduction to generalized linear models. Chapman and Hall/CRC. Taylor & Francis Group.
8. Dringus, L. P. (2012). Learning analytics considered harmful. Journal of Asynchronous Learning Networks, 16(3), 87–100.
9. Puranam Revanth Kumar, B Shilpa, Rajesh Kumar Jha, B Deevena Raju, and Thayyaba Khatoon Mohammed, "Inpainting Non-Anatomical Objects in Brain Imaging using Enhanced Deep Convolutional Autoencoder Network", Sadhana, vol. 49, article number 181, pp. 1-13, 2024.
10. Advances in neural information processing systems (pp. 155–161). Cambridge, MA: MIT Press.
11. Dudani, S. A. (1976). The distance-weighted k-nearest neighbour rule. IEEE Transactions on Systems, Man and Cybernetics, 6(4), 325–327.
12. van Gerven, M. A. J., & Bohte, S. M. (2017). Editorial: Artificial neural networks as models of

neural information processing. Frontiers in Computational Neuroscience, 11(2017) article 114.
13. Iyanda, A.; D. Ninan, O.; Ajayi, A.; G. Anyabolu, O. Predicting Student Academic Performance in Computer Science Courses: A Comparison of Neural Network Models. Int. J. Mod. Educ. Comput. Sci. 2018, 10, 1–9.
14. Puranam Revanth Kumar, B Shilpa, and Rajesh Kumar Jha “Brain disorders: Impact of mild SARS-CoV-2 may shrink several parts of the brain”, Neuroscience & Biobehavioral Reviews, vol. 149, p.105150, 2023.
15. Musso, M.; Kyndt, E.; Cascallar, E.; Dochy, F. Predicting general academic performance and identifying the differential contribution of participating variables using artificial neural networks. Frontline Learn. Res. 2013, 1, 42–71.
16. Puranam Revanth Kumar, Rajesh Kumar Jha, and Amogh Katti “Brain Tissues Segmentation in Neurosurgery: A Systematic Analysis for Quantitative Tractography Approaches” Acta Neurologica Belgica, vol. 124, pp. 1-15, 2023.
17. Villegas-Ch, W.; Lujan-Mora, S.; Buenano-Fernandez, D.; Roman-Canizares, M. Analysis of web-based learning systems by data mining. In Proceedings of the 2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM), Guayas, Ecuador, 16 October 2018; pp. 1–5.
18. B Shilpa, Puranam Revanth Kumar, and Rajesh Kumar Jha, “LoRa DL: a deep learning model for enhancing the data transmission over LoRa using autoencoder”, The Journal of Supercomputing, vol. 79, pp. 17079 –17097, 2023.
19. Masci, C.; Johnes, G.; Agasisti, T. Student and school performance across countries: A machine learning approach. Eur. J. Oper. Res. 2018, 269, 1072–1085.
20. Kórösi, G.; Esztelecki, P.; Farkas, R.; Tóth, K. Clickstream-based outcome prediction in short video MOOCs. In Proceedings of the 2018 International Conference on Computer, Information and Telecommunication Systems (CITS), Colmar, France, 11–13 July 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.
21. Puranam Revanth Kumar, B Shilpa, Rajesh Kumar Jha, and Sachi Nandan Mohanty, “A novel end-to-end approach for epileptic seizure classification from scalp EEG data using deep learning technique”, International Journal of Information Technology, vol. 15, pp. 4223–4231, 2023.
22. Mantzicopoulos, P.; Patrick, H.; Strati, A.;Watson, J.S. Predicting kindergarteners’ achievement and motivation from observational measures of teaching effectiveness. J. Exp. Educ. 2018, 86, 214–232.
23. Aelterman, N.; Vansteenkiste, M.; Haerens, L. Correlates of students’ internalization and defiance of classroom rules: A selfdetermination theory perspective. Br. J. Educ. Psychol. 2019, 89, 22–40.
24. Simjanoska, M.; Gusev, M.; Ristov, S.; Bogdanova, A.M. Intelligent student profiling for predicting e-assessment outcomes. In Proceedings of the 2014 IEEE Global Engineering Education Conference (EDUCON), Istanbul, Turkey, 3–5 April 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 616–622.
25. N. Arivazhagan, K. Somasundaram, Gouse Baig Mohammad, Puranam Revanth Kumar et al., “Cloud-Internet of Health Things (IOHT) Task Scheduling Using Hybrid Moth Flame Optimization with Deep Neural Network Algorithm for E Healthcare Systems”, Scientific Programming, Volume 2022, Article ID 4100352, pp. 1-12, 2022.
26. Liu, K.F.R.; Chen, J.S. Prediction and assessment of student learning outcomes in calculus a decision support of integrating data mining and Bayesian belief networks. In Proceedings of the 2011 3rd International Conference on Computer Research and Development, Shanghai, China, 11–13 March 2011; IEEE: Piscataway, NJ, USA, 2011; pp. 299–303.
27. Puranam Revanth Kumar, Gouse Baig Mohammad, and P Dileep, “Real-Time Heart Rate Monitoring System using Least Square Method”, Annals of the Romanian Society for Cell Biology, vol. 25, Issue. 6, pp. 16302 – 16308, May 2021.
28. Pavani, M.; Teja, A.R.; Neelima, A.; Bhavishya, G.; Sukrutha, D.S. Prediction of student

outcome in educational sector by using decision tree. Int. J. Technol. Res. Eng. 2017, 4, 2347–4718.
29. Gouse Baig Mohammad, Shitharth, and Puranam Revanth Kumar, “Integrated Machine Learning Model for an URL Phishing Detection”, International Journal of Grid and Distributed Computing, vol. 14, Issue 1, pp: 513-529, 2021.
30. Gray, C.C.; Perkins, D. Utilizing early engagement and machine learning to predict student outcomes. Comput. Educ. 2019, 131, 22–32.
31. Iatrellis, O.; Savvas, I.K.; Fitsilis, P.; Gerogiannis, V.C. A two-phase machine learning approach for predicting student outcomes. Educ. Inf. Technol. 2020, 1–20.
32. Kuzilek, J.; Vaclavek, J.; Zdrahal, Z.; Fuglik, V. Analysing Student VLE Behaviour Intensity and Performance. In Proceedings of the European Conference on Technology Enhanced Learning, Delft, The Netherlands, 16–19 September 2019; Springer: Cham, Switzerland, 2019; pp. 587–590.
33. Puranam Revanth Kumar, and T Ananthan “Machine Vision using LabVIEW for Label Inspection”, Journal of Innovation in Computer Science and Engineering (JICSE), Vol.9, Issue 1, pp: 58 - 62, 2019.