PREDICTIVE ANALYSIS OF STUDENT NON-COGNITIVE SKILLS

[1]M AArul Rozario,
Research Scholar, Department of Computer Science Karpagam Academy of Higher Education Coimbatore 641021

[2]Dr.R.GunaSundari
Professor and Head, Department of Computer Applicatios.Karpagam Academy of Higher Education Coimbatore 641021

Abstract-Educational performance plays an important role in classifying the quality of students in higher education institutions. It allows students in university, college and other educational institutions to predict their academic success. Factors Affecting Students' Academic Performance Class Quizzes, Tasks, Lab Exams, Middle and Final Exams.Informing the class teacher in advance about the student's academic performance will reduce the dropout rate of students and increase performance. According to this research, students' cognitive abilities are mapped using a predictive model against their class performance.As a result of early data collection, our predictive analysis model revealed non-cognitive abilities that predict incoming students 'class performance. Built on the basis of forecast analysis results, the mandatory class for Undergraduate Business students provides targeted instruction to improve students' cognitive skills.In this work, we proposed a feature selection process to develop a student's performance prediction model using Multiple Linear Regressions (MLR).
Keywords: Predicting Student Performance, Feature Selection, Multiple Linear Regression (MLR).

1. INTRODUCTION

The number of higher education universities / institutions has exploded in the last decade.Every year, they produce a large number of graduates and postgraduates. Although universities / institutions use better teaching, suspended, underperforming and unemployed students are still a problem.To maximize students 'academic and professional success, the university curriculum must be current and include the right courses in the right order. Recently, educators have focused more on improving students' non-cognitive abilities to enhance their performance.Attitudes, personalities, and techniques for achieving a goal that contribute to students' academic achievement are classified as non-cognitive skills in education. [1,2]. Developing non-cognitive skills during college graduation will help students achieve better results such as job search and retention. [3].

Instructors should evaluate students 'learning style and needs related to the subject being taught, and examine how the development of non-cognitive skills is related to students' performance.However, to date, little information is available to college teachers on how to evaluate and improve students' non-cognitive abilities and maintain long-term positive student outcomes.Predictive analysis is a subset of advanced analytics that uses a cause and effect database to train and construct models that can predict target variables while providing insights into key patterns and signals of the data set.The results of forecast analyzes have action knowledge to help companies make better decisions.Our research suggested that even after teachers get a job, they can use a predictive analysis model to help teachers effectively increase student performance in the classroom and retain positive results in successive semesters..Since the introduction of forex analysis in the last decade, there has been a tremendous demand for its applications in various fields to provide valuable information to shareholders in various businesses to enable them to make better decisions. [4,5]. Higher education is one of the areas where forensic analysis has a lot of room for development, especially how students can use student and academic data to extract insights that help students, professors and administrators. [6].

These techniques also provide the ability to predict future outcomes, such as student performance measures, based on a set of assumptions, until strong training data are available to develop a predictive model.In addition, techniques can map input (independent) variables as target (dependent) variables, determine which input variables are significant for the target variable, compare multiple predictive models to determine the best model for a given data, and find value addition correlation between inputs and targets, as well as accurate prediction of the target variable.

The long-term predictive analysis modeling technique that identifies students' learning style and cognitive abilities at the beginning of the semester will help instructors change the teaching materials and atmosphere to get more effort and performance from their students. We expected that the use of pre-analysis in the semester would give students higher scores than those learned in the non-analytical environment.

Furthermore, we expect students who benefit from semester-long student-level personalized education to have a long-term positive outcome.During the first week of the semester, we collected self-report information about students ' non-cognitive abilities within the analysis model to predict students' final course scores using a predictive analysis approach.The non-cognitive skills reported by the students included: student's school, student's sex, student's age, student's home address type, family size ,parent's cohabitation status ,mother's education, father's education, mother's job , father's job, purpose to select this school, student's guardian, home to school travel time, weekly study time, number of past class failures, extra educational support ,family educational support, extra paid classes within the course subject, extra-curricular activities, attended nursery school , wants to take higher education, Internet access at home , with a romantic relationship , quality of family relationships , free time after school, going out with friends, workday alcohol consumption ,weekend alcohol consumption, current health status, number of school absences.

This paper is prepared as follows. Section 2 provides the related information and relatedwork of predictive analytics and its application to student performance.and Section 3 explains the data anddetails the methodology behind the predictive analytics approach. Section 5 deliberates the presentationand results from the predictive analytics analysis. Some finalobservations and future researchdirection are accessible in the final segment.

II.RELATED WORK

Several studies have tried to predict academic performance by associating academic success with various criteria. Numerous researches have provided useful information on how to expand student performance. With changing degrees of success, both cognitive and cognitive ability ratings are used to predict student achievement.

HinaGullvet at el. [2020] used logistic regression, linear regression analysis, K-nearest neighbours, classification and regression trees, and gaussian distributions in her research. On historical data on student scores in one of the student courses, Naive Bayes and support vector machines were used to develop a model to predict the grades of students taking the same course the following term. They discovered that linear discrimination analysis is the most effective method for accurately predicting students' final exam results. Out of a total of 54 records, the model properly predicted 49, resulting in an accuracy of 90.74%.

For forecasting student performance in mathematics, PhaukSokkheyv[2020] presented a comparison study of statistical analytic methodologies, machine learning (ML) algorithms, and one of deep learning architecture. The results of a statistical technique called structural equation modelling (SEM), five classes of machine learning algorithms, and a deep learning framework called Deep Belief Network (DBN) were compared. We employed two datasets, DS1 and DS2, with the same properties but different sizes. Random Forest (RF) outdone other models in predicting student performance across all three datasets.

BoddetiSravani [2020] proposed that the use of machine learning has a significant impact on teaching and learning, and that this has the potential to improve the learning environment in higher education. Students' interest in online and digital courses grew significantly, and websites like Course Era, Udemy, and others became increasingly important. They used innovative machine learning applications in teaching and learning while taking into account the students' background, previous academic performance, and other factors.

UtomoPujianto [2020] proposed the performance of two classifiers, C4.5 and k-Nearest Neighbor (KNN), in the classification of student academic performance, and used the SMOTE preprocessing approach. Experiments utilizing the Rapid Miner application revealed that the C4.5 Decision Tree technique performed better in terms of accuracy, recall, and precision, with values of 71.09 %, 71.63 %, and 71.54 %, respectively, when compared to the K-Nearest Neighbor algorithm.

V. Uday Kumar [2020] advocated using K-means and Hierarchical clustering for unsupervised learning and Naive Bayes and Decision Trees for supervised learning. In today's world, analysing a company's student performance is critical to training its employees. All of the above algorithms were merged and used in the recruitment process to evaluate students. All of the following algorithms are used to assess the presentation of K L University students.

This study aims to examine the reliability of using a predictive analysis strategy to improve and retain students' non-cognitive abilities and good student outcomes.

III.METHODOLOGY

Figure 1 depicts the predictive analysis and personalized teaching model used in this work. The initial stage is to collect data to determine which of the students' non-cognitive abilities can benefit from instruction appropriate to the instructor.

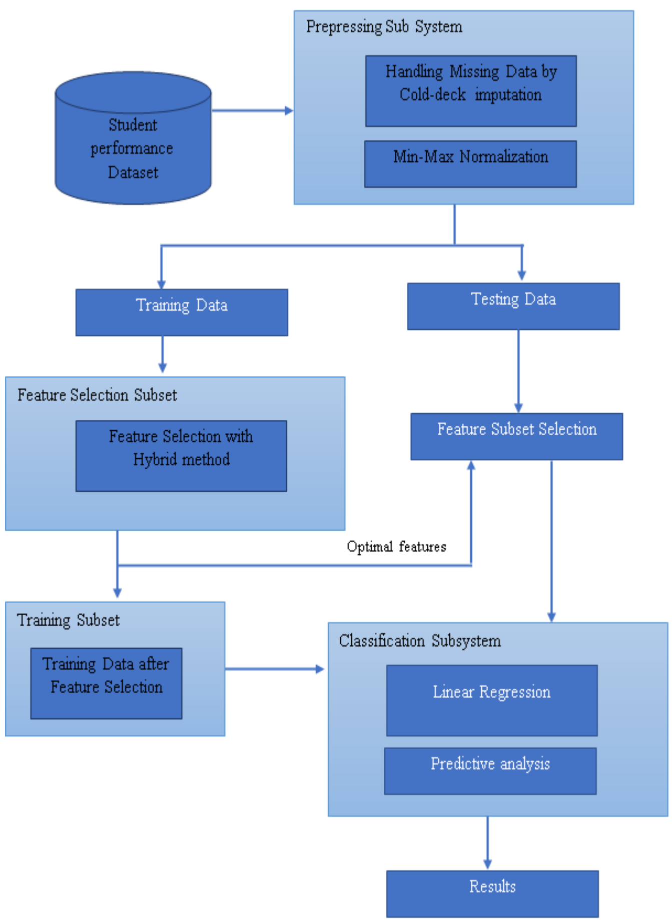

Fig 1. Proposed model

A) Data collection

The UCI Machine Learning Repository provided a set of student performance data for this investigation. The information was gathered for the academic year 2005-2006 at two schools in Portugal's Alentejo region. It contains 1044 instances, each with 33 properties, such as student grades, demographic, social, and school-related characteristics.

B) Data preprocessing

In data mining, pre-processing is important. Its purpose is to convert raw data into a format that mining algorithms can understand. During this phase, the following jobs are finished.

Data integration: The process of combining data from multiple sources into a single repository is known as Data integration.. When it comes to data integration, redundancy is a regular issue. The dataset is made up of two comma-separated values files downloaded from the UCI Machine Learning repository. These files contained performance data from two courses taken by Portuguese students (Portugal Language has 395 cases and Mathematics has 649 instances). Multiple files are combined into a single file in this stage. Consolidation is accomplished by adding an attribute (Course) that describes the course, such as (P for Portugal or M for Mathematics).

Data cleaning: Missing and noisy data are handled in this step to ensure data stability. There are no missing data or outliers in the database used in this investigation.

Cold deck Imputation: This technique involves using an external source to convert the missing value to a constant, the value of the previous perception of the same survey. This approach is similar to the alternative, except that a fixed value is used in this case and, alternatively, multiple values can be used to fill in the gaps.

Normalization :When dealing with properties at multiple levels, normalization is generally necessary; Otherwise, the (low level) performance of a significant, equally important characteristic may be largely diluted due to the values of other properties.

Min-Max Normalization**:** In the process of normalizing this data the original data undergoes a linear transformation. The minimum and maximum values of the data are retrieved, and each value is changed.

C) Feature selection

Many attributes in the student performance database may be misleading for classification purposes. When numerous student features such as educational background, social, demographic, family and socioeconomic status are combined, the problem of high dimension of data arises. This problematic can be resolved by identifying key features in the database.

The objective of the feature selection is to excellent a subset of the feature that can accurately define the input data, though minimizing the problem of feature location and eliminating extraneous data. Wrapper -based and filter-based approaches are two common types of feature selection methods.Filter method is searching for the minimum set of relevant features thoughdisregarding the rest. It uses variable ranking techniques to rank the features where the highly ranked features are selected and applied to the learning algorithm.

This work applied filter method using hybrid feature selection algorithm to evaluate the feature ranks. It's checking which features are most important to build students' performance model. During feature selection, a rank value is allocated to every feature according to their influence on data classification.

Artificial Fish Swarm-Cuckoo Search Optimization Based Feature Selection:

Our method presents a novel feature or attributes selection technique known as a mix of Artificial Fish Swarm and Cuckoo Search Optimization. Our proposed technique, which incorporates the two coupled components of irrelevant and redundant feature reduction, improves the effectiveness of feature selection. In our current strategy, NMFC removes useless characteristics using Symmetric Uncertainty (SU).

Mutual information and entropy should be maintained by the SU. To overcome this constraint, Artificial Fish Swarm-Cuckoo Search Optimization is used in this paper to remove unnecessary features or obtain relevant features quickly.

We must then locate the redundant features that are given in the relevant features after picking the relevant features. We use an unique Non-negative Matrix Factorization based Clustering approach to remove redundant features.

D) Linear Regression

The next step after feature is linear regression.Linear regression is the next step up after correlation. When we want to predict the value of one variable based on another value, we use it..The dependent variable is the variable we want to predict (or sometimes, the outcome variable).The independent variable is the one we use to predict the value of the other variable (or sometimes, the predictor variable).

Simple linear regression is the simplest instance of a single scalar predictor x and a single scalar responder y. Multiple linear regression, also known as multivariable linear regression, is the extension of linear regression to multiple and/or vector-valued predictor variables (denoted with a capital X).

A generalization of basic linear regression for more than one independent variable, multiple linear regression is also a special instance of generic linear models, restricted to one dependent variable. The following model is based on multiple linear regression.

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i \qquad (1)$$

for each observation $i = 1, \ldots, n$.

We consider n observations of one dependent variable and p independent variables in the calculation above.Thus, $Y_i$is the ith remark of the dependent variable, X_{ij} is ith observation of the jth independent variable, $j = 1, 2, \ldots, p$. The values $\beta_j$signifylimits to be projected, and ϵ_i is the ith independent identically distributed normal error.

Each dependent variable of $m > 1$ has the same explanatory variables, hence they are estimated simultaneously in the more general multivariate linear regression.

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{i1} + \beta_{2j} X_{i2} + \cdots + \beta_{pj} X_{ip} + \epsilon_i \qquad (2)$$

or all explanations indexed as $i = 1, \ldots, n$ and for all dependent variables indexed as $j = 1, \ldots, m$.

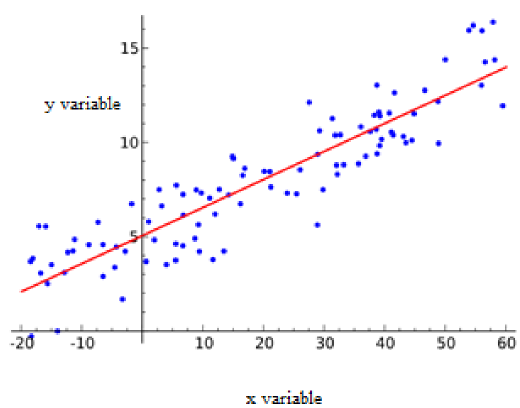

Fig 2.Simple linear regression, which has one independent variable

Multiple predictors are used in closely all real-world regression models, and fundamental presentations of linear regression are generally couched in terms of the multiple regression model Be aware, however, that in these circumstances, y is a scalar. In multivariate linear regression, ya vector, i.e., general linear regression, is used instead of ya vector.

F) Dataset Description

This information is related to the high school student achievement in two Portuguese schools. The data were foundover school reports and surveys and included student standards, demographics, community and school-related characteristics. There are two datasets for performance in two different subjects: Mathematics (mat) and Portuguese Language (por).Both datasets [Cortes and Silva, 2008] are designed using binary / five level classification and regression functions. Note that the target attribute is most closely related to the G2 and G1 properties. This is because G3 is the final year grade (given in the third period), while G1 and G2 are the first and second term grades, respectively. Although it is very problematic to calculate G3 without G2 and G1, it is very valuable (see paper basis for more particulars).

TABLE 1. DATASET DESCRIPTION

Variable	Question Description	Measurement (Scale)
school	student's school	binary: 'GP' - Gabriel Pereira or 'MS' - Mousinho da Silveira
sex	student's sex	binary: 'F' - female or 'M' - male
age	student's age	numeric: from 15 to 22
address	student's home address type	binary: 'U' - urban or 'R' - rural)
famsize	family size	(binary: 'LE3' - less or equal to 3 or 'GT3' - greater than 3
Pstatus	parent's cohabitation status	binary: 'T' - living together or 'A' - apart
Medu	mother's education	numeric: 0 - none, 1 - primary education (4th grade), 2 â€“ 5th to 9th grade, 3 â€“ secondary education or 4 â€“ higher education
Fedu	father's education	numeric: 0 - none, 1 - primary education (4th grade), 2 â€“ 5th to 9th grade, 3 â€“ secondary education or 4 â€“ higher education
Mjob	mother's job	nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at_home' or 'other')
Fjob	father's job	nominal: 'teacher', 'health' care related, civil 'services' (e.g. administrative or police), 'at_home' or 'other')
reason	reason to choose this school	nominal: close to 'home', school 'reputation', 'course' preference or 'other'
guardian	student's guardian	nominal: 'mother', 'father' or 'other'
traveltime	home to school travel time	numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour

studytime	weekly study time	(numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours
failures	number of past class failures	numeric: n if 1<=n<3, else 4
schoolsup	extra educational support	binary: yes or no
famsup	family educational support	binary: yes or no
paid	extra paid classes within the course subject	binary: yes or no
activities	extra-curricular activities	binary: yes or no
nursery	attended nursery school	binary: yes or no
higher	wants to take higher education	binary: yes or no
internet	Internet access at home	binary: yes or no
romantic	with a romantic relationship	binary: yes or no
famrel	quality of family relationships	numeric: from 1 - very bad to 5 - excellent
Freetime	free time after school	numeric: from 1 - very low to 5 - very high
goout	going out with friends	numeric: from 1 - very low to 5 - very high
Dalc	workday alcohol consumption	numeric: from 1 - very low to 5 - very high
Walc	weekend alcohol consumption	numeric: from 1 - very low to 5 - very high
Health	current health status	numeric: from 1 - very bad to 5 - very good
absences	number of school absences	numeric: from 0 to 93
G1	first period grade	numeric: from 0 to 20
G2	second period grade	numeric: from 0 to 20
G3	final grade	numeric: from 0 to 20, output target)

IV.RESULTS AND DISCUSSION

Here recommend a method aimed at removing or selecting a very small number of attributes from all attributes in the same direction. The minimum attribute set was obtained using Artificial Fish Swarm-Cuckoo Search Optimization Based Feature Selection and its simplification in following table 2.

TABLE 2 FEATURE SELECTION RESULTS

Datatype	**features**
Numeric	Medu, failures, absences, G1, G2
Binary	Schoolsup, famsup
Nominal	reason

Since all designs are performed automatically, backing up in Excel is easy in this program. The results are very difficult to interpret because essential to recognize what each count is. The breakdown of the regression analysis output is given below.

The independent variable (predictor) is a list of Grade 3 students, whereas the dependent variables are Medu, failures, health, absences, G1 and G2. It's true that there are many additional variables that can effect G3, but for now we focus only on these variables.

a) ***Regression analysis***

TABLE 3 REGRESSION ANALYSIS FOR DATA

Regression Statistics	
Multiple R	0.922327
R Square	0.850687
Adjusted R Square	0.849292
Standard Error	1.254177
Observations	649

Here's what each piece of information means:

Multiple R: In a linear connectionamong two variables, the Correlation Coefficient reflects the asset of the linear link. Coefficients of correlation have a range of values from -1 to 1, with a higher absolute value de Relationship strength increases with increasing absolute value:

1 means a strong positive relationship

-1 means a strong negative relationship

0 means no relationship at all

R Square: Coefficient of Determination is employed as a measure of the goodness-of fit. In this graph, the number of points that fall on the regression As a result of the sum of squares, the R^2 value is generated. More specifically, it is calculated by adding the squared deviations of original data from the mean

In our experiment, $R^2$is 0.85 (rounded to 2 digits), which is good. It means that 85% of our values fit theregression analysis model. In other words, 85% of the dependent variables (CF values) are described by theindependent variables (Actual coupling and Maximum possible couplings). GenerallyIt's deemed an excellent fit if R Squared is 95 %.

Adjusted R Square: There are a number of independent variables in this model, thus will need to modify R For multiple regression analysis, this value should be used instead of R square.

Standard Error: One further way of measuring the accuracy and precision of regression analysis is to look at the advantage/compatibility ratio. The smaller the value, the more confident we may be in R^2 model's dependent variables express variance as a percentage, but Standard Error (SE) measures the average distance from the regression line that data points fall.

It divides the sum of squares into separateworks that provide data about the stages of variability in your regression model.

TABLE 4 ANOVA FOR DATA

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	5753.426	958.9043	609.6173	2.9E-261
Residual	642	1009.841	1.572961		
Total	648	6763.267			

dfis the number of the degrees of freedom related with the sources of variance.
SSis the sum of squares. The lower the Residual SS is in comparison to the Total SS isthe better the data model.
MSis the mean square.
The F statistic, often known as the F-test, is used to test the null hypothesis. It is used to determine the model's overall importance. The P-value of F is the significance F. For a simple linear regression study in Excel, the ANOVA section is rarely used, but the last component is definitely worth paying attention to. The F value for Significance indicates how dependable (statistically significant) our findings are. Our model is acceptable if Import F is less than 0.05 (5 percent). If it's more than 0.05, you should probably pick a different independent variable.

a) Regression analysis output: coefficients

This section provides specific information about the components of our analysis:

TABLE 5 REGRESSION ANALYSIS

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.213837	0.288712	0.740657	0.459172	-0.3531	0.78077	-0.3531	0.78077
Medu	-0.02901	0.045288	-0.64064	0.521986	-0.11794	0.059917	-0.11794	0.059917
failures	-0.22726	0.091071	-2.49548	0.012829	-0.4061	-0.04843	-0.4061	-0.04843
health	-0.05427	0.034247	-1.58472	0.113523	-0.12152	0.012978	-0.12152	0.012978
absences	0.021594	0.010778	2.003468	0.045547	0.000429	0.042759	0.000429	0.042759
G1	0.148469	0.036158	4.106088	4.54E-05	0.077466	0.219471	0.077466	0.219471
G2	0.884698	0.034108	25.93802	5.1E-102	0.817721	0.951675	0.817721	0.951675

The most useful component in this section isCoefficients. It enables you to build alinear regression equation(4) inExcel:

$y = bx + a$ (4)

Where Y is an observed score on the dependent variable, a is the intercept, b is the slope, X is the observed score on the independent variable, and e is an error or residual.
We can extend this to any number of independent variables:

$y = bx + a + b_1x_1 + b_2x_2 \ldots \ldots b_kx_k$ (5)

$$Y = (Medu * x) + (failure * x) + (health * x) + (absences * x) + (G1 * x) + G2 * x) + Intercept \quad (6)$$

Y=(1*-0.02901)+(0*-0.22726)+(3*-0.05427)+(2*0.021594)+(9*0.148469)+(11*0.884698)+0.213837 =11.133104

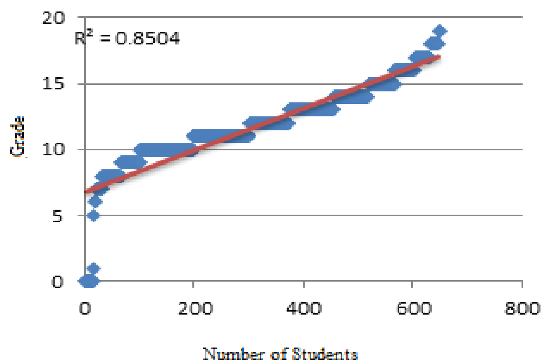

Fig 3. Multiple Linear Regressions Model

If can be seen, Medu, failures and health variables exhibit negative correlation coefficients, with the exception of the absences attribute, implying that as age and health factors grow, the final grade would fall. The outcome variable also falls when the two categorical variables romantic and schoolsup are both yes.While when the value of mother-education attribute increases the outcome valueincreases too.

V.CONCLUSION

Identifying the elements that influence students' academic performance at academic institutions is an exciting undertaking because it will assist educators in improving their learning and teaching processes.In this regard, we have introduced Artificial Fish Swarm-Cuckoo Search Optimization; a new feature selection approach that thoroughly investigates the students' attributes and selects the most essential among them to build a prediction model.Our approach involves employing several methods for identifying the most essential variables, which are then used to implement multiple multiples linear regression models.This research establishes a solid foundation for the use of predictive analytics in higher education to better prepare our students for the real world, as well as demonstrating the value of teaching non-cognitive skills in enhancing student performance.We would like to evaluate the performance of the multiple regression technique to that of other regression and classification techniques in future research.

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