A Hybrid Machine Learning Model for Grade Prediction in Online Engineering Education

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Abstract—Imposed and exclusively online learning, caused by COVID-19, revealed research challenges, e.g. curricula reformation and data collection. With this pool of data, this research explores grade prediction in an engineering module. A hybrid model was constructed, based on 35 variables, filtered out of statistical analysis and shown to be strongly correlated to students' academic performance. The hybrid model initially involves a Generalized Linear Model. Its errors are used as an extra dependent variable, incorporated to an artificial neural network. The architecture of the neural network can be described by the sizes of the: input layer (36), hidden layer (1), output layer (1). Since new factors are revealed to affect students' academic achievements, the model was trained in the 70% of participants to forecast the grade of the remaining 30%. The model has therefore been divided into three subsets, with a training set of 70% of the sample and one hidden layer predicting the test set (15%) and the validation set (15%). Finally, the model has yielded an R^2 of one. This suggests that the modeling framework effectively links the predictors with the grade (dependent variable) with absolute fitting success.

Keywords—machine learning, artificial neural network, AI, grade predictive modelling, CAD, COVID-19, online learning, hybrid model

1 Introduction

In recent decades, the use of online and electronic tools made the field of education flourish [1]. Learners can access online instructional materials, submit assignments or reports from a distance, and practice assessment tests during or after class [1]. Nevertheless, since educational software is provided to a diverse community of students with varying needs and interests, the need for individualization is highlighted [1, 2]. One of the most important aspects of providing education through online methods is to analyse students' performance and evaluation learners' results in final examination [3].

The motivation of this paper emerged during the global outbreak of the COVID-19 virus which has created challenging circumstances for researchers. The imposed online learning in higher education facilitated the accumulation of electronic data screening students' performance from different backgrounds and geographical locations. In these conditions, it was very interesting to explore the important issue of learners' performance and specifically grade prediction in fully online learning environments [1,2,3].

One of the most difficult tasks that higher education institutions need to confront is to develop a strategy for future development and actions, when it comes to support students' achievements. If student performance can be predicted beforehand, weaker students can be assisted and learning support mechanisms can be planned in order to improve their performance [3, 4].

Although grade prediction through function approximation techniques have been researched in classic learning environments [3], this new reality of merely virtual classrooms and its impact on students' performance in engineering CAD courses has not been analysed adequately yet in terms of grading of engineering students.

The present study describes a Generalized Linear Model (GLM or GLAR-Generalized Linear Regression) that has been created using the 35 most important variables, such as "Succeed in similar future tasks", "Conceive the planes on 3-Dimensional objects", "MS Teams insights" and other. After a data filtering process that will be discussed below, in order to predict students' final exam grades. Its performance is analyzed in two examples of operation, using the errors that derived from the differences between the fitted model and the actual observations. A neural network has been constructed by using the resultant errors of the GLAR model, as an additional predictor (36^{th}).

2 Related work

In [4] ensuring learning continuity, providing asynchronous support, limiting dropouts and avoiding disruption in the educational procedure have been the primary goals of a learning methodology in engineering education during pandemic. Monitoring students' progress in engineering and informatics courses through grade prediction has been extensively researched when referring to traditional and online teaching environments, in order to prevent knowledge loss and eliminating quitting students' rates [3, 4].

Corresponding software has been developed using sophisticated techniques, modelling tools and diagnostic mechanisms to offer a customized learning experience for students, taking into consideration their learning requirements and special interests. Student modelling, can store knowledge about students and then use it to ameliorate the learning procedure [5, 6]. Additional data regarding students may include exam grades, learning attitudes, progress and achievements, perception methods, and other factors. In physical classrooms, educators produce the final grade of the students based on the evaluation of individual tasks and other factors such as the complexity of the activities or their performance on the final exam. Nevertheless, in the area of e-learning this has not been generally and extensively researched [7].

One of the research initiatives on which tutoring systems should focus, is the early detection of students with lower academic achievements that could potentially fail on a specific module [8]. Many researchers that estimate a learners' performance in terms of progress in a future module use neighbourhood-based collaborative filtering method

[9, 10, 11, 12]. A group of students with similar performances, who have already attended the module, are assessed to each learner whose performance needs to be forecasted. The historical grades of peers are then utilized to estimate the ultimate mark that a single student would receive in a future module attendance using some similarity-weighted aggregation algorithm [12]. In [12 13, 14] the application of sparse linear models and low-rank matrix factorization is suggested for developing a number of approaches for predicting future modules' grades. These approaches are entirely based on the students' previous module results [15]. In the matrix set up for factorization, the rows represent the students while the columns represent the modules. Each one of the cells contains the grade that the specific learner received for each module. Missing values indicate that a student has not yet succeeded in the specific module. Various approaches for filling in missing values with expected predictions in order to measure an approximation of a potential future grade have been stated in the researches mentioned above. The field of predicting students' grades before the final exams take place have been widely researched [15, 16, 17], while most of those researches apply a variety of data mining algorithms. Among them, Decision Trees, Clustering, Naïve Bayes Classifier and association Rules are included [12]. These algorithms use academic performance indicators, such as assignments grades and quizzes marks, instructors' identity in order to perform a grade prediction. Predicting students' nest term performance has also been researched in [16, 17] using SVD and SVD-kNN and Factoring Machine.

Forecasting grades in online educations systems represent a new challenge in the academic field, especially during pandemic circumstances [18, 19], where in [20] an alternative term has been proposed "Emergency Remote Teaching"[1] and Remote Knowledge acquisition [21]. Researches have indicated specific factors that strongly affect students' academic performance under pandemic circumstances. Those factors, are grouped under constructs of online surveys, and can be applied as variables in a statistical analysis, in order to be filtered out, estimate their level of significance, as well as their reliability [22]. In [23] high rates of enjoyability, organisation and overall evaluation of the CAD module have shown to correlate with the performance of students in their weekly assignments.

The retention of students until they graduate is a persistent problem in higher education. The majority of students drop out during their first year of college [24]. Concerning the curricula of Mechanical Engineering education, and most specifically regarding first year students, [25, 4] has stated the importance of developing spatial skills. Visualising 3-Dimensional objects enables first year students to develop engineering specific skills. Other researchers [4, 19, 26] stated the link of Engineering education with the society, implementing assignments related to real world tasks and similar to students' future enrolment in their after-graduate employment. By exploring the topic of linking students' personal satisfaction and their level of academic achievements in CAD engineering courses during pandemic, researchers [19] revealed new parameters (variables) that affect students' achievements during lockdown periods. Some of those parameters mentioned in [19] are: enjoyability of the module, organization, overall

[1] ERT

evaluation, classroom fatigue, sustainability of the teaching content, presentation of the supporting videos and class notes evaluation.

3 Research methodology

This research has been conducted during the first semester of 2020-2021 (from October to February) in Athens, Greece, at the University of West Attica, School of Engineering, Department of Mechanical Engineering [19]. The module selected is a first semester laboratory course, named "Computer Aided Mechanical Design CAD I". The online module has been attended by 216 learners. They were divided in 11 groups, performing synchronous online lectures by MS Teams platform. Students were assisted by a teaching team of 5 instructors (N=216) [19]. The research sample is referring to first year students in order to focus the research on their transition from high school, entrance exams, and first semester in the university.158 students' survey answers have been validated for the purpose of this research (n=158).

3.1 Students' performance measuring methods

Data concerning first year students in mechanical engineering and their interaction with the learning environment were collected. Valuable information has been mined out of two web-based surveys[2], and additional students' related data including attendance reports from MS Teams' platform insights, as shown in Figure 1. Weekly assignments included minds-on tasks: quizzes, sketches [4, 18] (freehand drawings of object views), CAD drawings object views (top views, side views and sectional views) [19]. Minds-on tasks were aiming to increase students' spatial perception, by introducing innovative methods in task representation (presence of cutting planes in section tasks). Specific tasks were focused on a metallic building (15th assignment), situated inside the university campus, aiming to estimate the level of students' conception and its relation to real world tasks in mechanical design and discipline, as well as their importance for future employment [4, 19, 23, 27, 28].

Fig. 1. The measuring methods

After processing the collected data, a 129X158 matrix was generated, where the dimension 129 expresses the number of the examined variables and 158 the population. A statistical analysis has been performed in SPSSv20, including a correlation analysis (Spearman's rank correlation coefficient) [19] for pointing out the significant

[2] 1. pre-course, 2. post-course

correlations between all the ordinal variables, a factor analysis (PCA, and via a Varimax type of rotation) and clustering. A reliability analysis has been performed as well and ANOVA has been applied on clusters. The analysis mentioned above filtered out 35 variables that affect students' performance during the disorientated educational process due to COVID-19 pandemic. These 35 variables are highly related to the students' final grade in the CAD I module. The methodology that has been followed is depicted in the diagram presented in Figure 2:

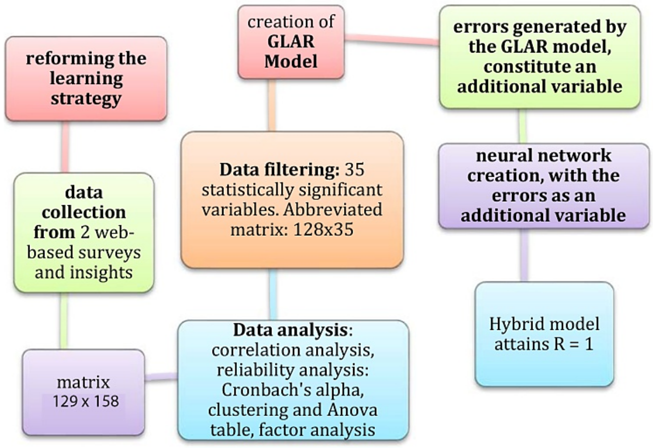

Fig. 2. Research methodology

In this study, the suggested method aims to combine the benefits of the GLAR method in fitting transformed predictors with a linear logic [19]. The effectiveness of neural networks in non-linear data fitting application should be noted. In general, neural networks are highly competent in non-linear problems. A machine learning technique for defining the function that relates a set of inputs to a set of outputs is an artificial neural network (ANN). [29, 30]. Therefore, a Generalized Linear Model produces a linear combination of transformed predictors [19] (via the response of a link function) as described below. The current method was selected over others because the main objective of the study is to maximize the efficacy of the prediction (expressed via the coefficient of determination, or the mean error of a predictive model), with a regression-based logic. Nevertheless, all the previously mentioned techniques can generate interesting insights but are specialized in serving other purposes. Decision trees and the Naive-Bayes method are more efficient for classification purposes, and not for regression purposes. SVD is used for dimensionality reduction objectives. Association rule mining relies on identifying latent rules. Clustering can improve the degree of a prediction (implemented either for classification, or for regression purposes), by dividing a large group into more homogeneous subgroups and applying regression or classification functions on them.

4 Metamodel (hybrid model) for students' grade prediction: Use of generalized linear model & neural network

The variables that were selected through the filtering process are isolated with the aim of building a function to link the students' performance with the database's most essential dependent variables. The function that will be constructed will look like this:

$$y = f(x_1, x_2, x_3, x_4 \dots x_n)$$

In the formula above, y represents the grade of the students. Moreover, x1, x2, x3, … are the predictors that concern the variables that were found to have a statistically notable association with the grade of the students.

The features of a linear regression model are generalized in a generalized linear regression model. With parameters such as the mean response, the response variable follows a regular, binomial, Poisson, gamma, or inverse Gaussian distribution. The relationship between a dependent variable and the linear combination of altered predictors is defined by a set of link functions that transform each independent variable.

Therefore, a Generalized Linear Model produces a linear combination of transformed predictors (via the response of a link function) with the following form:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \text{intercept}$$

In general, neural networks are highly competent in non-linear problems. An artificial neural network (ANN) is an artificial intelligence technique for shaping a mathematical relation that links a group of inputs to a group of outputs. This is accomplished by creating mathematical connections of an input layer, with an intermediate hidden layer (or a group of hidden layers), and then with the output layer. The nodes (or neurons) that make up each layer, pass transformed data on to the nodes that follow. ANNs has been utilized in several research efforts according to related literature [29, 30, 31].

The suggested method, as presented in Figure 3, attempts to integrate the benefits of the GLAR method in matching modified predictors with linear logic with the efficacy of neural networks in non-linear data fitting situations.

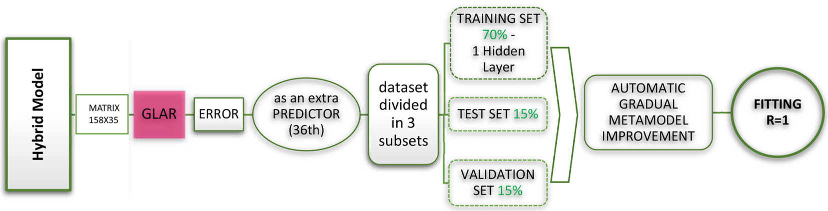

Fig. 3. Metamodel neural network's architecture

A 158x36 matrix is isolated containing the answers and related data of the 158 students in 35 statistically significant variables which display a p-values lower than 5% and whose Spearman rho coefficient is equal to absolute 0.15 or more. The last column (36^{th}) of the table concerns the exam grade of the students.

The followed approach addresses the problem of the lack of tools to deal with ordinal and nominal variables, in multivariate regressions. This is something that does not occur when modelling continuous variables. A hybrid model will be used that combines error prediction resulting from a Generalized Linear Model. Those results are entered as inputs along with a 36^{th} prediction variable (beyond the aforementioned 35 variables), into a neural network for predicting the students' exam grade. All simulations of the present study regarding the GLAR method were performed in MATLAB R2020b.

A depiction of the data processing that takes place via the use of the GLAR method is shown in Figure 4. The GLAR model is defined and the corresponding parameters are evaluated. In the examined case, the scores on the 35 variables (e.g.: Evaluation vs other courses, familiarized to MS Teams vs other courses, Conceive the meaning of planes etc.) are considered as independent variables and the students' exam grade is the dependent variable. Thus, the response (y) of the model is presented as follows:

$$y = f(x1, x2, x3, x4, x5, x6 \dots x35)$$

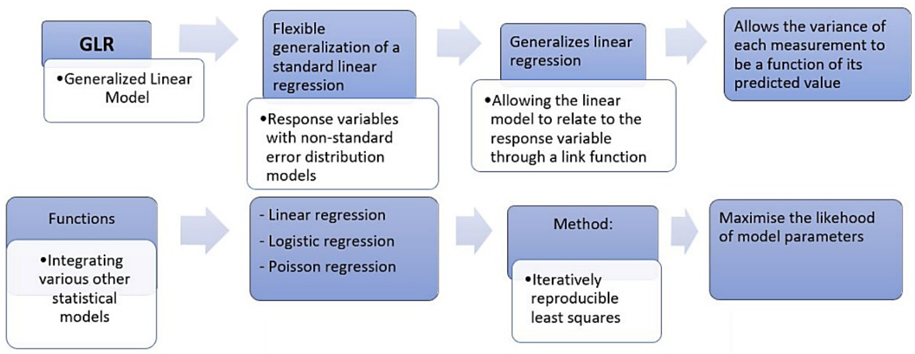

Fig. 4. Illustrated diagram of the GLAR method

The GLAR model processes the linear data. The students' exam grade minus the prediction of the GLAR mode, is considered as a non-linear element. Therefore, what does not result from the GLAR model is considered a non-linear element. That is:

$$error = actualgrade - predictedgrade$$

Therefore, the errors deriving from the aforementioned model are shown in the histogram in Figure 5:

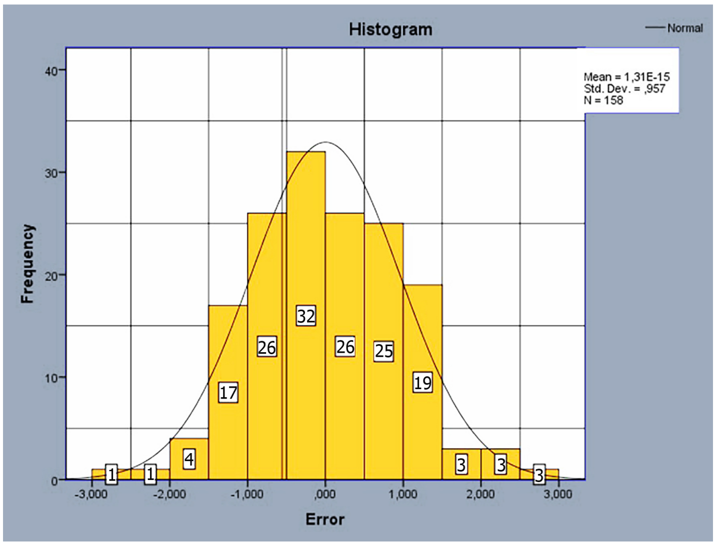

Fig. 5. Histogram of errors resulting from modelling with GLAR

The bin size in the histogram as shown in Figure 5 was selected to be equal to 0.5. It can be observed that the errors in the forecast are relatively small. Therefore, the integration of the error as 36 variable and the creation of a neural network is performed in order to increase the efficiency of the prediction. In Figure 4 and Table 1, an analysis the errors along with critical parameters, such as range, mean, median deviation is given.

Table 1. Mean error

Statistics		
Error		
N	Valid	158
	Missing	0
Mean		.00000
Median		-.04560
Std. Deviation		.957086
Range		5.349

It can also be seen in Figure 5 and Table 1 that the mean error is almost equal to zero. The majority of the errors as shown in Table 2, in 109 cases out of 158 in total (68.99% of cases), fall into the range between -1 and 1. In 91.77% of cases, the errors fall into the range between -1.5 and 1.5. It is meaningful to note that the range of the grades given to students is between 0 and 10. In Table 2, the table that resulted from the calculation of the coefficient estimates is presented, for the GLAR model that was produced. The coefficient estimates are represented in a relationship that has the following form[3]:

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \cdots + \beta nxn + intercept$$

Where: β_0, β_1, β_2 …, are the coefficient estimates from the GLAR model that also denote the significance of each variable.

Table 2. Coefficients, mean standard error, t-test, p-values derived from the correlation analysis for the examined independent 35 variables

ID	Variable	coefficient	Standard error	t-Stat	p-Value
Intercept	Intersection point with the beginning of the axis	3.99	12.810	0.311	75.6%
x1	Enjoyable vs other labs	0.13	0.19008	0.674	50.15%
x2	Familiarized to MS Teams	0.09	0.12503	0.732	46.54%
x3	Evaluation vs other modules	-0.17	0.097172	-1.793	7.54%
x4	Insecure about CAD I	0.07	0.10606	0.670	50.42%
x5	Comfortable for the finals on CAD I module	0.00	0.10388	0.042	96.65%
x6	How often technical difficulties	0.09	0.075999	1.127	26.18%
x7	Assignments graded and returned after	-0.23	0.4594	-0.506	61.34%
x8	Study time / week/ hours	-0.01	0.085646	-0.109	91.38%
x9	Study time During weekday	0.26	0.117	2.260	2.57%
x10	How well tasks are assessed	0.32	0.20158	1.597	11.29%
x11	Evaluate class notes	-0.10	0.13195	-0.746	45.68%
x12	How did the quizzes help on conceiving the theory	0.10	0.14723	0.663	50.87%
x13	Necessity of sketching for understanding the object	-0.07	0.05912	-1.231	22.05%
x14	Conceive the meaning of planes	0.05	0.13144	0.405	68.64%
x15	Helpful the presence of cutting planes 3-dimentional views	0.00	0.15607	-0.011	99.13%
x16	Enjoyable CAD I compared to theoretical courses	-0.04	0.1746	-0.220	82.63%
x17	Dealing with knowledge deficiencies	0.05	0.089314	0.510	61.12%
x18	Classroom fatigue CAD I	0.05	0.089286	0.512	60.96%
x19	Hours per day on pc for educational purposes including homework	0.11	0.12427	0.847	39.85%
x20	Hours per day on pc attend modules	-0.18	0.17757	-1.017	31.10%
x21	Resent instructor's late assignment gradings	-0.28	0.10915	-2.607	1.03%
x22	Noticing weaknesses during CAD I online lectures	0.16	0.13245	1.193	23.53%
x23	Basic computer skills (MS Word, Excel, PowerPoint	-0.04	0.1177	-0.337	73.70%

[3] Mathworks site: https://www.mathworks.com/

ID	Variable	coefficient	Standard error	t-Stat	p-Value
x24	Assignments relevant to future work	0.08	0.062739	1.315	19.11%
x25	Likely succeed in a similar future task	0.38	0.15466	2.466	1.51%
x26	Sustainability of the learning process when return to normality	-0.13	0.1209	-1.063	28.98%
x27	CAD I preferred than other courses	0.02	0.16331	0.140	88.89%
x28	Physics grades in entrance exams	0.08	0.36989	2.138	3.45%
x29	Number of active students (end)	-0.14	0.21164	-0.683	49.56%
x30	Number of quitting students	-0.06	0.33658	-0.166	86.88%
x31	Number of Lectures	0.17	0.63535	0.267	78.98%
x32	Activity MS Teams (insights)	0.02	0.011321	1.751	8.25%
x33	Class group	-0.15	0.11763	-1.269	20.68%
x34	High school type	-0.25	0.22524	-1.122	26.40%
x35	Instructor's id	-0.45	0.41376	-1.086	27.97%
x36	Grade Finals CAD I				

The t-test can be applied in samples whose size is less than 30 (smaller samples). If this limit is exceeded, the t-test distribution and the normal distribution will be indistinguishable; however, a t-test does not have to assume normality in larger samples with non-normal distributions [32, 33]. By using a t-test for merely one sample, as in the present case, the underlying assumption is that the population variance is unknown, hence this offers versatility in comparison with other statistical tests.

In Table 2, the coefficient estimates, (in the column of coefficients) of the 35 examined variables are presented with a colour scale, while those that show statistical significance (p-value <5%) are highlighted. The Table 2 also displays the mean standard error and statistical t-test of these specific weights (coefficient estimates).

- A neural network model is developed for modelling nonlinear elements, as follows:

$$ynew = f(x1, x2, x3, x4, \dots, x35, error)$$

- The results of the combined forecasts will then be obtained.

By sequential tests that were done while running the neural network training process in MATLAB, the number of hidden layers was selected as equal to 1. From the relevant literature [31], the number of hidden layers is recommended to be between the number of input variables (in this case: 36) and the number of output variables (in this case: 1) [34]. This is done to avoid any overfitting of the neural network. Hence, the created neural network can be seen in the following diagram.

The other network hyperparameters (namely: solution algorithm, percentages of the subsets into which the data is divided) as defined in MATLAB, have the following properties: The solution algorithm used was Levenberg-Marquardt, the subset ratio network training was 70%, the validation ratio was 15%, and the network test was 15% [31, 35].

In order for MATLAB to enhance the generalization capabilities of a neural network, the 128 observations are automatically divided into 3 subsets (training, validation and test subset), and the model is trained to fit the main subset (training set). After that, its effectiveness is checked in the other subsets.

The following diagrams are produced: R (coefficient of determination in this case; R = 1), error histogram (grouping the errors of each characteristic subset) and neural network performance during the training process, which is based on a number of user-defined epochs [31, 35]. The term "epoch" as shown in Figure 8 refers to the number of loops the machine learning algorithm has made over the entire dataset.

The method of breaking down the observations into smaller sets, aids the neural network's generalization capability, as illustrated in Figure 8. A large sequence of observations (training set) is isolated. After that, the fitted neural network model that applies on it, performs predictions on the other data subsets.

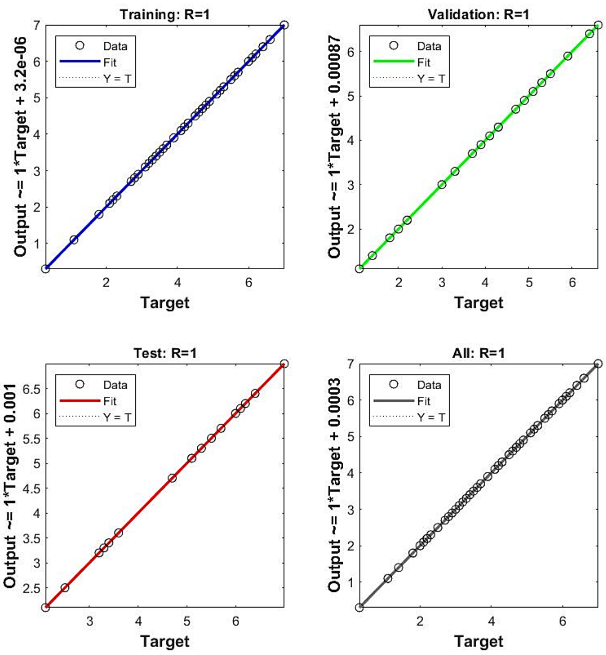

Fig. 6. 1 (R) in each subset (training, validation and test set), but also in the sample as a whole

The R^2 is equal to 1, and this is true both for the total dataset, and for all of its subsets.

The trained model that has been constructed, can be used for prediction purposes of the performance of students that will attend the CAD module in the future. It is evident that by using the trained GLAR model and the 35 variables as predictors, an estimation for the students' performance can take place. If the error (as a 36th variable) is to be predicted by associating it with other highly correlated and statistically significant variables, the trained hybrid model can be utilized with a similar logic.

In Figure 7, the histogram of errors it can be observed that all errors are close to zero and the distribution of errors below zero and above zero is shown in equally distanced bins.

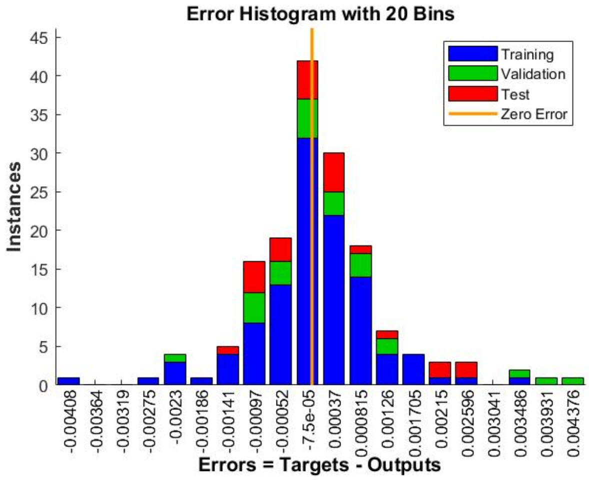

Fig. 7. Error histogram

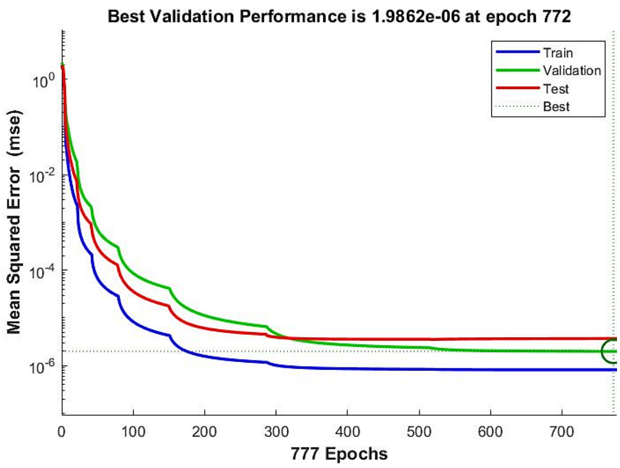

Fig. 8. Neural network performance by epoch and by subgroup of observations.

4.1 Qualitative analysis and discussion

In the correlation analysis as detailed in Table 2, the variables applied in the model have shown to have a signifiable statistical correlation with students' grade in the final exam. When referring to MS Teams activity a number is extruded for each student deriving from the attendance and activity report [4], not only during e- lectures, but when being active on MS Teams in order to follow homework tasks, or even just pressing the link for viewing supportive videos that have been attached as links to each assignment. [4, 23]. The variable of number of students, is associated with each group: As shown in Table 3, student 2017 has been attending the module in an online "Team" or class group where 26 students remained active until the end of the e-lectures, and all of them participated in the final exams. On the contrary, student 2137 has been attending the module in an online "Team" where 24 students remained active until the end of the e-lectures, but two of them did not attend the final exams. A new issue is revealed which is the impact of teachers' id and the number of quitting students in each class group. It needs to be mentioned that all instructs have been highly evaluated from the students under the university's internal teachers' evaluation as to their skills.

Regarding the result of the generalized linear model, the basic threshold that was used to filter the most important variables, corresponded to a degree of correlation above +0.15 and below -0.15 (Spearman's rho coefficient of the examined variable correlated with the final grade of the student), ensuring also that the p-value of the important variables is below 0.05. This approach has isolated the variables that have a substantial level of statistical significance and at least a moderate-to-weak level of correlation with the grade, maintaining only 27.13% (35 out of 129 variables in total) of them to be used in the final metamodel. This was considered to be a balanced approach between opting for a metamodel with very few dimensions that ignores the impact of variables with moderate or weak (albeit statistically significant) value, and a metamodel with too many dimensions that would be prone to statistical noise and overfitting.

In order to interpret the results of the grade prediction process, students with similar predictions and larger differences have been isolated from the sample and evaluated back to the original matrix of the 129 variables (85 ordinal and 44 nominal), out of which 40 of them have shown significant homogeneities and differences among the 6 students. In the following passage, two examples of operations will be presented.

The first example of operation refers to students with higher prediction accuracy, and the data used is presented in Table 3.

Table 3. Students with higher prediction accuracy

Student's id	2017	2094	2110	2137	2095	2108	2128
Enjoyable vs other labs	3	3	4	5	4	4	4
Familiarized to MS TEAMS	3	3	5	4	3	4	4
Evaluation vs other modules	6	5	10	8	8	9	7
Insecure about CAD I	4	3	4	4	5	3	4
Comfortable for the finals CAD I	4	3	1	4	4	4	3
Technical difficulties	3	1	1	5	1	3	3
Assignments graded & returned after	5	5	5	5	2	2	2
Study time week	7	4	6	4	4	5	3
Study time during weekday	6	6	6	6	6	5	6
How well tasks are assessed	4	3	5	4	3	3	4
Evaluate class notes	3	3	3	3	3	3	4

Student's id	2017	2094	2110	2137	2095	2108	2128
Quizzes contribute understanding theory	4	3	5	4	4	4	4
Necessity of Sketch	7	7	3	5	4	7	5
Meaning of planes	4	4	5	3	5	4	4
Helpful the presence of cutting planes	5	4	5	4	5	4	4
Enjoyable CAD I vs other modules	4	3	4	5	3	4	4
Knowledge deficiencies	6	5	5	3	3	5	5
Classroom fatigue	2	1	5	2	3	3	3
Hours/ day pc FOR educational purposes	4	3	4	3	3	5	4
Hours / day pc attend modules	3	3	3	2	2	3	3
Resent late Assignments gradings	3	2	5	5	4	3	4
Sense Weaknesses during CAD I	3	5	5	5	5	5	5
Basic software skills	3	3	3	3	3	3	3
Tasks relevant to future work	8	7	7	7	8	9	9
Succeed in a similar future task	3	3	5	4	4	3	4
Sustainability of the framework	4	3	3	3	4	5	3
CAD I vs other modules	2	3	5	5	5	5	4
Physics grades	12	15	18	14	12	10	10
Number of active students at the end	26	26	26	22	24	24	24
Number of quitting students	0	0	0	2	2	2	2
Number of lectures	10	10	10	10	12	12	12
Activity MS Teams	44	41	43	34	41	30	47
Class group	3	3	3	4	6	7	7
Highschool Type	4	4	4	4	4	4	4
Instructors' id	1	1	1	1	3	3	3
Grade in CAD I	4.1	4.5	6.1	5.5	4.7	3.7	4.7
Predicted grade (round of 0.0)	4	4.6	6	5.6	4.7	3.6	4.8
Error	0.15	-0.06	0.09	-0.1	-0.02	0.13	-0.12

In the 7 students presented on Table 3, the prediction error varies from -0.12 to +0.15.

The second example of operation as shown in Figure 9, discusses students with high differences in grade prediction. Student 2080 seem to have a negative attitude towards the learning module due to his resent to distance learning in general. An age difference can be noticed, as of being older than his classmates. His low ratings to most aspects of the online module shows being highly affected by the lack of social distancing (1: extremely discomfortable), as shown in Figure 9. He is also negatively affected by technical issues.

The student considers that the majority of tasks assigned are not relevant to his future work, but understands that the 15^{th} assignment is highly relevant. It can be assumed that since the 15^{th} assignment represents a Computer Aided Design drawing of a metallic building structure, which is represented by video, it establishes a direct relation to real world constructions.

It can be assumed at this point that for the specific student with aversive attitude towards distance learning and being negatively affected by social distancing, certain module's features related to real world tasks, increased his learning abilities and improved his academic performance. It can be seen in Figure 8, that all of the five students expected to acquire higher grades did not download the module's notes syllabus, but rated highly the CAD I module when compared with other laboratory courses. They expressed being covered by the YouTube MCAD I UNIWA channel videos. They all do not need to perform freehand drawings (sketches). They were only sketching during the first lectures, when it was assigned under their weekly tasks. It seems that those students managed to develop their 3-Dimensional conception.

The critical deviations in errors have an important significance when it comes on deciding if the student will pass the module or not. By taking into consideration that the excellent grade on this exam is 7, the actual grade's range from 3.4 to 7 have been isolated, since an error larger than 1.00 grade is subjected to fail the module.

Students' id	2071	2080	2187	2002	2013	2203
Age	18-21	22-25	18-21	18-21	18-21	18-21
Gender	male	male	male	male	male	male
Enjoyable vs other labs	4	2	4	4	5	4
Why like online CAD module	don't like it for all courses	don't like it for all courses	like it, new methods	like it, use of pc	like it, attend from home	like it, attend from home
Evaluation vs other modules	10	5	9	8	8	6
Reason for choosing the faculty	1rst choice	1rst choice	1rst choice	wanted other faculty	1rst choice	wanted other faculty
Discomfort of social distancing	2	1	2	1	3	2
Insecure about CAD	not insecure, only for the finals	very insecure to all modules	not insecure at all	not insecure, only for the finals	not insecure at all	not insecure, only for the finals
Meeting new classmates during lectures	no	no	no	yes	no	no
Affected by technical issues	not at all	a lot	not at all	not at all	somewhat	fairly
Assignments' load	normal	normal	normal	normal	not so heavy	not so heavy
Well organised	8	7	9	7	10	8
how well tasks are assigned	very well	very well	very well	very well	extremely well	very well
Times reviewed the theoretical ppt.	read all 1, rarely go through it	read all until the 5th OL lecture	never read them beside OL class	read all 1, often go through it	read all 1, often go through it	read all 1
Download the class notes	no	no	no	no	yes	no
Review CAD notes	not aware of their existence	no	not related to lecture content	no	yes, few times,	covered by lecture & video
necessity of sketching	only for complicated parts	during the first 4 lectures	extremely necessary	only for sectional views	extremely necessary	only for sectional views
part fully perceived in tasks	very well	enough	very well	very well	very well	enough
enjoyable vs other theoretical modules	4	4	4	4	4	4
still sketching during the last lectures	no	no	no	no	no	no
if quit sketching when?	quit sketching on the 6th lecture	quit sketching on the 5th lecture	no, only during the 1st task	quit sketching on the 5th lecture	no, only during the 1st task	quit sketching on the 5th lecture
familiarised to MS Teams	during the first month	still having difficulties	during the first month	immediately	during the first month	during the first 2 weeks
Social Media app skills	5	4	3	5	5	4
Tasks relevant to future work	3	8	7	8	8	7
15th task: presentation and clarity	4	3	3	5	5	4
15th task relevant to real world	2	4	5	5	5	4
assignments related to real world tasks	2	3	5	4	5	4
likely succeed in a similar future task	somewhat likely	unlikely	extremely likely	very likely	somewhat likely	somewhat likely
Sustainability of the framework	somewhat likely	unlikely	extremely likely	somewhat likely	very likely	somewhat likely
Overall evaluation CAD I	8	4	9	8	8	7
High school type	general lyceum	vocational lyceum	athlete	general lyceum	general lyceum	general lyceum
Activity MS Teams	30	28	3	34	29	15
Assignment grades	1.6	1.4	0.9	2.6	2.4	0.6
Finals' grade	1.1	6.0	5.7	6.6	7.0	5.9
Predicted grade (round of 0.0)	3.4	2.9	3.3	4.0	4.6	2.3
Error	**-2.30**	**3.14**	**2.44**	**2.63**	**2.37**	**3.59**

Fig. 9. Students with lower prediction accuracy

In Figure 10, a boxplot has been created indicating the mean for the actual grade equal to 5.1 with three outliers, and the mean of the predicted grade at 4.6 which leads to a mean of 0.66 in the error. The heatmap in Figure 10, represents the deviations in the errors found. Since the representation is almost uniform between the actual grade and the predicted grade (shades of red mostly), it can be deducted that the errors of the methodology presented are quite small.

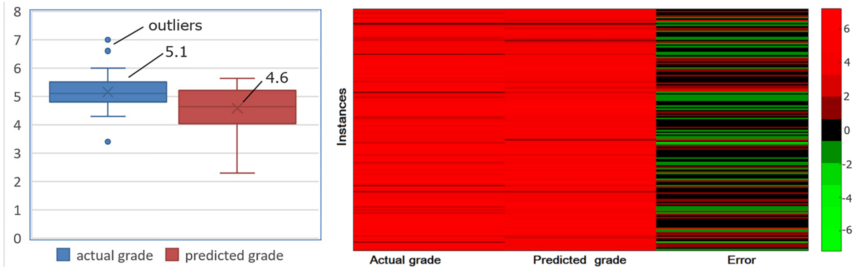

Fig. 10. Boxplot with mean values and heatmap of errors

5 Conclusions

It can be concluded that grade prediction is studied in a variety of ways in literature, and that it can become a valuable component in the process of developing a course recommendation tool, in order to improve students' satisfaction with their own modules' choices. It can also be used as a forecasting tool of potential progress in mandatory modules, as well as a tool to identify modules in which the student is likely to receive poor or even failing grades. Students can even benefit from a pre-course planning of their extracurricular activities during a specific semester where the selected high-risk module will be attended.

Based on the results of this research, critical variables have been revealed concerning factors that affect student's performance in an online first semester engineering Computer Aided Mechanical Design (CAD I) Module, during imposed distance learning circumstances. Even though students have been isolated from their physical learning environment, the applied teaching strategy has managed to relate curricula assignments to real world tasks.

The hybrid model that has been created, used the aforementioned 35 critical variables as predictors. Since imposed distance learning through COVID-19 pandemic started on the second semester of 2020-2021 academic year, the current research has been centred on a forecasting students performance of the same period of attendance: The hybrid model has been divided in three subsets, where a training set of 70% of the sample with one hidden layer predicted the test set (15%) and the validation set (15%) applying an automatic grade prediction improvement which led to a fitting of R=1.

Future work could consist in testing the performance of model to next year first semester students, for the same academic module and examine the level of prediction, in an online or a blended learning environment. A confusion matrix can be created in order to determine the percentage of prediction. In the meanwhile, those variables can be tested at the same population in order to predict their grades on the second semester Computer Aided Design (CAD II) module, whose context is a sequence of CAD I and takes place during the second academic semester 2020-2021. A survey with the same variables can be launched in a previous stage, after the sixth or seventh lecture, in order to identify low performers and provide them with the adequate support and avoid failing on the final exam.

An interesting research field should be testing the model in a face-to-face learning environment, since pandemic circumstances are gradually improving worldwide. The same learning approach used can be applied in a classic learning environment, as a parallel asynchronous support mechanism. Since this prediction model has been applied in a minds-on module, another future work could consist on testing the statistical significance of those variables on a hands-on engineering course, and test the model's accuracy.

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