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Ai Based Structural Equation Modelling to Classify the Students' Performance in Higher Education Institutions

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Abstract: When conducting classification tests, one of the most difficult challenges that can occur is ensuring that a high degree of accuracy is maintained in spite of the presence of unbalanced data sets. Achieving a high accuracy result in a classification study in which a class with a large number of samples can be better learned does not, however, provide information about the efficiency of the results of the other classes, and the accuracy provides conclusions that are misleading due to the fact that the results are so accurate. Using this strategy, it is possible to classify the great majority of students into a range of different categories (pass/fail, risky/not hazardous, etc.). When dealing with data that is not evenly distributed, the F1-score and the ROC AUC score are more accurate evaluations of the overall performance of the model compared to the other metrics. On the other hand, certain measurements, such as recall and precision, represent the level of achievement for lessons and provide direction for understanding the material covered in those classes. If the findings of the study solely depend on the accuracy metric, then it is possible that it will be challenging to integrate these findings into reality.

Keywords: *Structural Modelling, Classification, Student Performance, Education*

1. Introduction

It might be challenging to live up to the expectations of one consumers in the fast-paced corporate climate that exists in the modern world. As a result of the SARS-CoV-2 pandemic and its variants [1] many businesses have been compelled to adapt by applying new technologies and strategies in order to build a foothold in the digital market and better prepare themselves for the new standard of living. A quantity of information the likes of which has never been seen before as a direct result of the pandemic effects on business has been compiled. The analysis of this data can yield insights that are capable of assisting organizations in making more informed decisions [2]-[4].

Knowledge is a vital resource that helps contribute to greater organizational performance in today society, which is characterized by the generation of a substantial volume of information through digital means [5]. Since the turn of the millennium, new approaches to education and research have emerged. These approaches, such as big data analytics (BDA), have an impact on the traditional processes of knowledge management (KM).

Business data analysis, often known as BDA, is the process of reviewing massive amounts of information with the goal of getting actionable insights by the application of mathematical and statistical approaches. BDA is employed in a broad number of sectors, and one of those fields is education. Higher education institutions (HEIs) may acquire a profusion of data about their students and instructors during teaching [6], and they may employ big data analysis (BDA) to combat the challenges posed by increasing worldwide competition.

This is of utmost significance when viewed against the backdrop of the quickening pace of change that is occurring all across the world. Through the utilization of BDA, they are able to simulate not only the behavior of the market but also the learning patterns of specific students. BDA could pave the way for academic and learning analytics to, for example, enhance educational quality, optimize curricula, and pinpoint students who are at risk of failing a course so that they can receive individualized counseling to keep them enrolled and on track to graduate from high school or college. BDA has the potential to pave the way for academic and learning

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analytics to perform the objectives because it helps facilitate data-driven decision making [7].

In circumstances in which the goal of an organization is to respond strategically and competently [8], but doing so involves the development of dynamic capabilities, activities related to knowledge management (KM), in addition to business planning and analysis, become vital. Additionally, higher education institutions (HEIs) have a responsibility to manage the information that is gained through the utilization of the new educational methodology in order to produce value, provide crucial services, and prepare themselves for the new normal.

However, there are still gaps in the implementation of the BDA as a result of a lack of understanding of the components required for its success. This is the primary source of the gaps in the implementation. BDA is a crucially important disruptive technology that is now in the preliminary stages of its development [9].

This is evident from the fact that there are only a few references to these types of studies. The fact that only a limited number of research have been conducted to investigate the factors that play a role in the dissemination of BDA has led to the discovery of this particular finding. There have been a number of studies that have attempted to quantify BDA adoption by employing the technology, organization, and environment (TOE) paradigm, however they have all arrived at incongruent findings [10].

More empirical studies about its application are required, but it is more vital to examine the factors that influence BDA adoption in HEIs. According to the findings of a recent study on the acceptance of BDA technology in the education sector, educational institutions only utilise 3% of the available analytical data [11]. Due to the fact that this was the situation, it is even more crucial to do study into the factors that influence BDA acceptance at HEIs.

Although research on BDA has been conducted in a variety of industries, the vast majority of this study has been conducted in underdeveloped nations, where it is unknown how widespread the adoption of BDA is [11]. Although research on BDA has been conducted in a variety of industries, most of this study has been conducted in underdeveloped nations. This is because the factors that effect adoption are different for each firm due to the distinctive qualities of each industry. Therefore the factors that affect adoption are different for each business. Although a number of studies [12]-[14] conducted across a variety of industries have found that BDA has a positive impact on organizational performance, other studies have found that the relationship between BDA and performance is more ambiguous. Higher education institutions have not spent a significant amount of attention on the subject of BDA, despite the growing number of studies investigating BDA and its effect on performance. A widespread misunderstanding of the ways in which BDA might improve both operations and strategy in this industry is another factor that contributes to people reluctance to invest in the usage of BDA [15]. This lack of awareness leads to the resistance that is developed.

Even though it is important for HEIs given the complexity and enormous availability of information, only a small number of these studies have been conducted. Although research has been conducted, it is not possible to derive any general conclusions from it due to the utilization of a wide diversity of various cultures and institutions in the study [15]. In a similar vein, while some research presents more critical views and provides empirical evidence for the relationship between business development activity (BDA) and knowledge management (KM) processes, little attention has been paid to their application within higher education institutions. This is since most of the research that has been conducted on the topic has focused on other topics. This is due to the fact that certain studies give empirical evidence for the connection between BDA and KM processes. According to the findings of several studies, investments made in BDA information systems have not always resulted in a return on the money spent. This phenomenon, which has been dubbed the productivity paradox of IT, was brought about as a result. According to one school of thinking, the relationship between BDA and organizational performance is murky, and knowledge management systems only partially mediate the connection. Additionally, this school of thought maintains that BDA is a poor predictor of organizational performance. On the other hand, there are some schools of thought that argue that the connection is really obvious. On the other hand, other study has shown that there are positive correlations between them, while others have suggested investigating the mediating function that KM processes can have in relation to performance and innovation, specifically BDA.

2. Related Works

The resource-based theory is the conceptual underpinning of BDA since the extent to which an organization possesses valuable, limited, imperfectly imitable, and appropriately organized resources is a significant factor in determining the level of that organization performance. This is the inspiration behind the formation of the BDA [16]. According to RBT, BDA is a strategic asset because of its high value and unique skill sets, both of which lead to increased productivity within an organization. Additionally, RBT states that BDA is a strategic asset due to the fact that it was developed by BDA. Because of this, RBT holds the belief that BDA is extremely significant. The links that exist between the various components of the BDA are very important given that they enhance performance and make it more challenging to replicate the business model. Other researchers, such as those cited in [17]-[19], have also made use of the methodology that is based on resources.

It has been demonstrated [20] that the information-gathering, -preparation, and -analysis capabilities of an organization have a positive effect on performance indicators like profitability or return on investment, and it has been demonstrated that having such BDA capabilities gives an organization an advantage over its competitors because they are difficult to imitate. Similarly, it has been demonstrated that having such BDA capabilities gives an organization a positive effect on performance indicators like profitability or return on investment, in corresponding order. If higher education institutions (HEIs) embraced business decision analysis (BDA) and used it to make decisions based on in-depth analyses of data to increase business performance, they could potentially transform into data-driven enterprises, which would have implications for the generation of value . This would be the case if HEIs used BDA to make decisions to increase business performance based on in-depth analyses of data.

There has been an increase in both performance and reputation as a result of the utilization of BDA by a number of highly regarded educational institutions, such as Purdue, Nottingham Trent, and Cambridge, with the goals of bettering the overall student experience and lowering the dropout rate, respectively [21]. The dropout rates at these educational institutions needed to be reduced, and the entire student experience needed to be improved.

The higher education sector in India is well aware of the fact that the capacity to evaluate and utilize data will be a crucial aspect in establishing a competitive edge in the twenty-first century. One of the many applications of analytics in higher education that has been identified through previous research [22] is the ability to predict student performance and make pedagogical adjustments to increase the satisfaction indicator. This is just one of the many uses of analytics in higher education. Compiling data such as student profiles, participation rates, and pertinent historical data from past semesters is one way to achieve this goal. Additional applications of analytics in higher education include the following:

As a result of this, the implementation of BDA has the potential to improve major educational performance indicators such as student retention and achievement. Although there is an increasing body of research looking at the effects of BDA on performance, the studies that are currently accessible are limited and scattered, notably in the social sciences [90], and higher education institutions have paid little attention. Studies carried out in a diverse selection of sectors have vouched for its efficacy, but others have arrived at the conclusion that its effect on corporate performance is indirect [20]-[22], and that money invested in BDA technology has not resulted in any observable dividends or improved outcomes.

3. Proposed Method

We chose a random sample of one thousand undergraduate students from University to participate in our survey; there were 500 females and 500 males among those participants. The findings of the investigation revealed that there are three unique undergraduate majors, each of which is offered through a different department at a different university for incoming students in 2020-2022. The educational experience of each new class of students ran a total of four years.

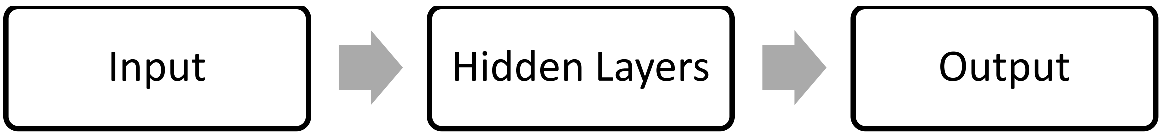

Fig. 1: ANN

The level of knowledge in these five fundamental topic areas determined how well you did on the entrance examination. The cumulative grade point average (CGPA) was the metric that was applied to each student academic performance to standardize it throughout the course of their four years in school. This was done to ensure that there was consistency in the evaluation of each student academic performance. A person cumulative grade point average (CGPA) is determined by multiplying each grade point by the number of credit hours that are linked with each course that they have taken. The formula for determining a person CGPA is as follows:

$$CGPA=\sum g_i c_i,$$

where

c_i - credit per course i and

g_i - grade point per course i.

Statistical hypothesis testing

Before any kind of ANN modeling can get underway, there needs to first be a research into the ways in which student socioeconomic, family, and educational backgrounds influence their academic performance. This can be accomplished by interviewing students and analyzing their academic records. In this investigation, we start by carrying out some elementary statistical tests and analyses, such as t-tests, correlations between one and two samples, and one- and two-way analyses of variance. These tests and analyses are used to determine whether there is a significant relationship between the variables of interest (single factor).

The cumulative grade point average of an individual is determined by utilizing five standard subjects from admission examinations, and the Pearson correlation coefficient is utilized to quantify the linear correlations between these subjects and the GPA. In addition to this, the grade point average of a person is taken into consideration when deciding whether they will be permitted to attend a particular school.

When using an ANN to model something, the associated variables are what are referred to as input neurons in the modeling process. The significance level of $p = 0.05$ was selected for both the t-test and the ANOVA to evaluate the difference that exists between two or more groups, specifically the difference in mean CGPA that exists between the groups. This was done to determine whether there is a significant relationship between the two or more groups.

In this context, the testing of hypotheses is done with the intention of determining whether factors such as gender, location, parental participation, and student background have a significant impact on the mean grade point average (GPA). Specifically, the goal of this investigation is to determine whether GPA is significantly affected by factors such as gender, location, parental participation, and student background

Neural network modelling

Within the framework of this application, artificial neural networks (ANN) are utilized both for the classification of data on the basis of the input observations as well as for the development of neural predictions regarding the grade point averages of students. Both of these strategies rely significantly on supervised machine learning as their primary method of data analysis. This is true for both of the approaches. The ANN that is utilized in this work is based on ones that were utilized in previous studies. The purpose of this investigation is not to evaluate the effectiveness of ANNs in relation to the performance of other machine learning methodologies.

It is common practice to write the ANN model in the form of a straightforward mathematical function, such as:

$$Y{\sim}=f(X^{'},W^{'}), \quad (2)$$

where

Y' – output vector and

X' - input vectors.

W' - weight parameters.

Within an artificial neural network, connection is denoted by a scalar value denoted by *W*, which is a vector of weight parameters (ANN).

The input layer is in charge of gathering the input values by making use of feature sets, and the hidden layer is in charge of processing the data in accordance with the input values. We use the following equation to determine the values of y_j that are produced by the j^{th} neuron in vector Y' of elements *x* and *w*:

$$y_j = \theta(\sum w_{ij}x_i).$$

where,

xi is the value that was transmitted back by the ith neuron in the layer below it. N_i is the total number of connection lines that extend from the ith neuron to the jth neuron (transfer function).

The value of the weighted sum of inputs is communicated to the output layer by means of the utilization of the hyperbolic tangent activation function θ. The node x_j is going to be the one that is activated in the succeeding input layer:

$$xj=\theta(yj).xj=\theta(yj).$$

Principal component analysis, or PCA for short, is a method of statistical analysis that lowers the number of dimensions that comprise the predictor space and avoids the risk of overfitting. Principal component analysis, often known as PCA, is a method for reducing enormous amounts of data. This method involves applying a linear transformation to predictors, deleting unneeded dimensions, and producing new sets of variables. Principal component analysis can also be abbreviated as PCA.

In this particular situation, the ANN model is educated using a supervised learning process that is BP-based. Within the framework of this methodology, parameters are provided for both the inputs and the outputs. Backpropagation, often known as BP, is the learning rule that is implemented in the ANN model.

To achieve the objectives that have been specified, this rule makes adjustments to the neuron weights wij based on the mistakes that have been determined. We are able to determine how far off the computed BP-based ANN is from the outputs that were desired by using the formula that is presented here:

$$E=0.5\sum Nj(yj-tj)^2,$$

where

tj - target *i* neuron value in output and

Nj - the total output neurons.

Iterative adjustments are made to the weights of neural networks that are run automatically. In order to ensure that the ANN learning process is as successful as possible, an optimization strategy based on the Levenberg-Marquardt algorithm is applied. When it comes to the process of training a model, the Levenberg-Marquardt approach takes advantage of both the steepest descent and the Gauss-Newton method. The steepest descent is also known as the gradient descent. When it comes to the resolution of non-linear issues, it beats other training algorithms because of the accelerated convergence to the optimal solution that it offers. The following algorithm demonstrates a new method for approximating the Hessian matrix that is analogous to the Gauss-Netwon approach:

$$wij+1=wij-[J'J+\zeta I]-1J'e^{k}$$

where

J - Jacobian matrix,

ek - network error,

wij - updated weight,

wij - current weight and

ζ - damping factor.

The Levenberg-Marquardt training methodology is based on the Gauss-Newton method for solving small issues ζ and the gradient descent algorithm for solving large problems. In order to direct the optimization process and move back and forth between the two methods, we need to make adjustments at each cycle.

The amount of neurons present in the output layer [4] will serve as the basis for the judgment that will be made on this matter. In the output layer of the model, the predicted CGPAs are stored as a collection of vectors denoted by Y. These vectors represent the model output. criterion for evaluation

Evaluation Criteria

The purpose of this work is to evaluate the performance of ANN in the final data analysis and to prevent challenges related to over-fitting from arising in the future. As part of this evaluation, a number of novel perspectives have been presented in this work. In order to carry out the assessment, we employed a number of distinct methods of measurement, such as the mean square error (MSE), regression analysis, error histogram, and confusion matrix. The model predicted outputs (tij) should closely match the model intended outputs, hence a well-trained ANN should have a mean square error (MSE) that is close to zero or very close to zero. This suggests that the model has been properly trained (tij). The formula for determining the mean squared error is as follows:

$$MSE = \sum_{Nj}\sum_{i=1}(yij-tij)^{2}.$$

As was discussed earlier, there is a chance that the training network will become overfit if the MSE value that is obtained is too low. This was indicated in the introduction. This is more evidence that the ANN is only beneficial during the training phase of the process and not at any other time. In order to handle this issue, a regression is first carried out, and then the R-value, which represents the degree to which the expected and actual outputs match one another, is computed. This step is followed by the resolution of the issue. You will be able to judge the efficiency of the fitting with the assistance of the plot. When training results in a low R-value, it is necessary to make necessary adjustments to the hidden layers as well as the neurons.

As was previously indicated, the error histogram can also be applied as a performance statistic for artificial neural networks (ANNs). The error histogram reveals that the vast majority of errors have a propensity to congregate around the value zero. The notation illustrates the disparity between the outcomes that were desired and those that were anticipated to take place in the scenario.

The usage of a confusion matrix, which is sometimes referred to as an error matrix, is required in order to verify the performance of an ANN with regard to classifications. In the context of binary classification, a table known as the confusion matrix is typically utilized. trix is a table that is employed in the context of binary classification.

The utilization of the confusion matrix, which is a component of this study endeavor, enables one to gain measurements of rates such as prediction accuracy, error rate, sensitivity, specificity, and precision. These are all examples of measures that may be achieved. The area under a receiver operating characteristic curve, also known as a ROC, can also be used to identify the best balance between the true-positive and false-positive rates. This can be done by using the ROC (AUC). In the realm of machine learning, ROC is a method that is widely used for testing and evaluating the performance of classifications. ROC stands for receiver operating characteristic.

4. Results and Discussions

The tasks of regression and classification each use their own distinct set of indicators in order to evaluate the level of performance they have achieved. Even though the vast majority of the studies that classified anything employed the same criteria, there were still some noteworthy variations from the norm. Despite the fact that the vast majority of the studies that classified anything employed the same criteria, there were still some significant variations. This variance may have arisen as a result of the asymmetry or symmetry of the datasets or the characteristics of the tasks themselves, which may have included binary classification, multi-classification, and other activities of a similar nature. Alternatively, it may have been a result of the characteristics of the datasets themselves. The primary evaluation criteria that were provided by the authors of these research were used as the basis for the establishment of the rates. The key assessment criteria were utilized to calculate rates in a manner that was analogous to that of the model selection process, during which a range of evaluation metrics were investigated.

Because each data point in a regression investigation represents an independent output, there is no room for debate regarding the balance or unbalance of the data in these types of investigations. Researchers have the opportunity to get insight into the capabilities of the models with regard to the multiple elements that they take into consideration since they use a wide variety of evaluation criteria. The RMSE (used 33% of the time; 22/67 total times) and the MAE (used 27% of the time; 18/67 total times) were the evaluation metrics that were used the majority of the time in regression investigations. The score was one of the metrics that was used the least in the studies that predicted student success (only 7%, or 5/67), despite the fact that it is an important factor in establishing the general regression capacity of a model. This was due to the fact that the score was one of the metrics that were utilized the least in the studies that predicted student success.

While final studies employ datasets that do not include this kind of information, midterm studies use datasets that do include information about student online activity (assignments, quizzes, exams, logins, and so on) at specified points in the semester. This is the most important distinction that can be made between the two kinds of studies. Because of this, we are able to make an accurate prediction on the performance of the students in the subsequent class. These databases are also employed in longitudinal research, and the additional information that they provide could potentially lead to more accurate findings. Both of these research methods are referred to as database research.

Fig. 2: Accuracy

Fig. 3: Precision

Fig. 4: Recall

Fig. 5: F-Measure

Table 1: Training/Testing

Classes	Training	Testing
10	0.99	0.99
20	0.97	0.98
30	0.99	0.99
40	0.91	0.91
50	0.67	0.72
60	0.99	0.97
70	0.89	0.89
80	0.88	0.88
90	1	1
100	1	1
110	0.93	0.87
120	0.75	0.77
130	0.96	0.92

In these investigations, the datasets and problem domains that were explored had a significant impact on the machine learning models that were applied. When machine learning models are taken into account, it becomes abundantly clear that the capability of neural-based models to process and learn a large amount of data and deliver accurate findings is an essential component in the majority of research that aims to predict the performance of students. This becomes abundantly clear because when machine learning models are considered. By recalling previous experiences while simultaneously learning data, has seen a surge in the processing of time-series data, such as that which is seen in online datasets. Recurrent neural networks are able to learn by recalling previous experiences while simultaneously learning data.

Despite the fact that SVM and SVR models were investigated quite frequently throughout the course of this research, it is important to point out that one of the most important aspects of these models is the optimization of the classification and regression processes. Because of this, in order to get the most out of the SVM and SVR classification and regression capabilities, we culled and picked the data that was entered into them.

Because there was a lack of clarity on the interpretability set out to develop models that would generate results that were both accurate and easy to comprehend. The DT and RF variations are currently the ones receiving the most attention, and this trend is expected to continue. However, the sensitive data processing of the DT and the possibility of mediocre outcomes brought into focus the RF, which maximizes the output of the DT by creating a predefined number of DTs. This brought the DT into focus. The meticulous way in which the DT handled the data brought into emphasis, in addition, the danger of substandard results. The purpose of this study was for the researchers to come up with noteworthy findings and to zero in on the aspects that are most responsible for the academic success of students.

5. Conclusions

As a result of the difficulty in predicting which model will result in greater outcomes in applications of AI and ML. This makes it impossible to select a model that would lead to research in the future. Because of this, it is impossible to choose a model that would pave the way for further investigation. However, as a result of the rising amount of data collected as a result of the development of computer and data storage technology, artificial neural networks and deep learning approaches will become increasingly popular for regression and classification problems. These methods can process and comprehend enormous amounts of data, and as a result, they will become increasingly frequent given their capabilities. When conducting research that is relevant to the evaluation of student performance, it is possible that there is room for improvement in the data analysis and data selection phases of the research process by taking into consideration other conventional and tree-based models. This could be the case if there is room for improvement in the data analysis and data selection phases of the research process.

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