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Leveraging Cognitive and Academic Models for Predicting Campus Placement Success

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ABSTRACT

Industrial organizations select the students for placement by conducting tests based on the academic content and targeting students' cognitive levels, such as the problem-solving ability. Educational institutes are mostly dependent on the students' academic performance to judge the likelihood of Employing the students. Cognitive and academic-based models are required to accurately predict the students' employment and assess the areas of improvement required. The interrelationships must be established to achieve coherence between the models. In this paper, three predictive models have been presented, which are based on: cognitive factors, Academic factors with and without anomaly correction. The models will help the educational institutions prepare the students for the highest number of placements. The models provide the basis for prediction on the individual subject/factor basis and the overall prediction considering all the subjects/cognitive factors. 98% accuracy in predicting the placement of the students has been achieved considering both the cognitive and Academic models with a built-in anomaly correction mechanism. The anomaly correction mechanism presented in the paper improved the accuracy of prediction from 92% to 98%. The positive correlation between the cognitive and Academic model helps inferencing one model from the other.

1. INTRODUCTION

The demands for the programs offered by the educational institutions are dependent on the % of the students placed who are admitted. Industrial organizations conduct several tests, the questions of which are based on the students' academic excellence and cognitive levels. Some students, while getting placed, are not placed. The Academic institutions must be able to predict the students who will not be placed based on their performance in the academic subjects and their cognitive levels so that the gap is found, and the academic institutions take corrective actions to ensure that the students improve their performance and get placed in the next attempt. The subject predictability will help to recognize weakness in a specific subject, and the overall predictability will help to predict the placement on the overall performance basis. These models will help the institutions raise the students' overall capability so that all the students admitted are placed. The academic institutions must find the reasons why some students are not placed based on the performance of the students in different subjects.

Every educational organization is fully busy undertaking activities directed towards the students' employment as it has a lot of bearing on the performance of the institutions. The demand for getting admitted into an institution largely depends on the institutions' Employment percentages. Educational institutions offer as many as 45 courses to qualify the students to graduate. Only a few of the subjects designed for the program concerned are directly related to employment.

Industrial organizations conduct a series of tests related to the students' cognitive levels and select those students who have crossed the threshold levels required for doing a specific job. The tests conducted by the organizations differ a lot from industrial organization to organization. Training the students to different requirements of the industrial organization is complex. The educational institutions need to focus on the training of the students such that the training is sufficient to meet the requirements of any industrial organization. There is a need to scientifically assess and select the subjects directly related to employment.

Every student has some psychology that has a bearing on employment. The students learn different courses, and some directly relate to the placement. A students' performance in the courses related to the placement depends on the students' cognitive levels. Improvement of the cognitive levels of the students improves the placement chances. The educational organization should be thriving to improve the students' performance in subjects directly related to improvement in the students' cognitive levels.

The placement prediction of the students has never been attempted based on academic performance. Many models have been presented [1]–[6], which are based on the cognitive factors in the past for predicting the placement of the students. The prediction using these models goes wrong and deviates much compared to the students' academic performance.

Many expert systems have also been presented for predicting the placement of the students [7]–[11]. These models have failed as they could not relate the requirements of various Jobs vis a vis the students' cognitive level. Converting quantitative scores to qualitative factors based on the prediction through expert systems has been a serious bottleneck.

Predicting the placement of the students is not sufficient. The reasons for the non-placement of the students must be known so that corrective actions are taken to improve the student's performance so that they stand to get selected eventually. Prediction based on academics involves many anomalies which must be corrected before using the same for prediction. Prediction based on cognitive factors alone or academic performance alone may lead to improper conclusions. Predicting the placements considering both academics and cognitive levels will help accurately predict the students.

The problem is to develop expert models that help predict the placement of the students most accurately and find the weak areas of the students considering both academic and cognitive levels so that educational institutions could work on those weak areas and improve the students so that they become employable. The solution proposed in this paper constitutes the following components:

- An expert model based on student academic performance that can predict student employability.
- A predictive model based on the cognitive factors of the students, which are assessed based on the tests conducted by the industrial organizations
- The method to inferencing the cognitive model from the Academic model and vice versa
- A Predictive model that allows prediction considering a single-subject and also considering all the subjects, and also considering several anomalies existing in the performance of the students

2. RELATED WORK

Many have investigated the issue of prediction for assessing driving capability [12] development of human robots [13] ability to carry military command and control [14] based on the cognitive factors of the persons involved in doing such activity. Cognitive models also have been used to assess the learning ability of the persons involved in doing different jobs. Zhao *et al.* [15] proposed the fuzzy cognitive model to predict student performance. Their method used the cognitive diagnosis model with the theoretical examination and experimental scores to get prediction scores in both the theoretical and experimental examinations.

Papinczak *et al.* [16] proposed a cognitive model based on personality traits and social cognition. The model explains the Rash Impulsiveness behaviors of persons addicted to cannabis. Davis and Lorimer [17] proposed a method to create a cognitive model based on an action theory-based error categorization scheme that categorizes errors as either mistakes or logical errors. Weingard *et al.* [18] proposed a cognitive model-based approach to evaluate neuro-psychological declines during tobacco abstinence.

Long *et al.* [19] demonstrated a model of emotions and temperaments in cognitive mobile robots. Bosse *et al.* [20] presented a visual attention cognitive model used to develop a software agent that assists a naval warfare officer in compiling a tactical picture of the situation on the field. Ekiz *et al.* [21] proposed a cognitive model which is helpful to treat patients with Behavioral and Psychological Symptoms of Dementia. Basu *et al.* [22] proposed a cognitive model of the bio-inspired approach used to find the optimal task scheduling solution for internet of things (IoT) applications in a heterogeneous multiprocessor cloud environment. Envick [23] proposed a cognitive model for developing entrepreneurial intelligence.

Bindu *et al.* [24] proposed a 3D cognitive model to classify emotions' uncertainty, contradiction, and cognitive nature. The model can classify 22 emotions subject to a facial expression database. Adhikari *et al.* [25] proposed an artificial intelligence-based cognitive model for emotion awareness in industrial chatbots. The model can extract emotions from talks, recognize transitions over time, anticipate real-time emotions, and intelligently profile human participants based on their unique emotional traits.

Faizal *et al.* [26] have classified students based on the ability of academics using Profile and Linear Interpolation Weighting. Pal and Pal [27] proposed a classification model of Prediction for Placement of Students. Khatoon *et al.* [28] have presented a neural network-based career prediction system that is not entirely related to predicting the student's placement. Elayidom *et al.* [29] proposed a framework to predict the chances of placement for a student. Seng and Zeki [30] designed career guidance and employment management System to provide job opportunities for students.

Gera and Goel [31] developed a model using a decision tree algorithm to predict the eligibility for placement of students in a company. Prathipa and Sekaran [32] predicted the placement results of the students using Bayesian classification. Naik and Purohit [33] predicted the result of the students along with the placement of the students with the help of classification algorithms. Tripti Mishra *et al.* [34] predicted students' employability using data mining techniques.

2.1. In-sufficiency of the existing models to solve the problem-gap

Most of the literature focused on career prediction but not on employability. The issue of uncertainty has not been considered. Predictability is computed using different techniques based on the qualitative factors derived from the quantitative factors. There was no mention of placement predictability based on the students' academic performance. None have attempted to trace the relationship between cognitive factors and students' academic performance. None have evolved an inference model that can be used to relate the cognitive and academic factors.

3. RESEARCH METHOD

3.1. Establishing data set for experimentation

Data relating to 3,000 students who are graduated during the last five years have been collected from a deemed university. Placement details include industrial organization tests, student performance in those tests, test connectivity to cognitive factors, and subjects used to derive the tests used to examine students. Academic performance in 8 subjects and overall cumulative grade point average (CGPA) are collected. It includes scores in eight subjects (data structure, design, analysis of algorithms, problem-solving through programming, Java programming, operating system, database management system, software engineering, English, and communication) and the overall CGPA. These nine scores are considered directly related to the placement in the IT industry, which is the focus domain of this research.

The placement particulars collected from the placement cell of the University include the number of companies the student attempted, the number of companies selected the students, average salary offered by the industrial organizations. All the recruiting organizations have been classified into four categories based on the salary offered. Only category-1 IT organizations that offer more than 4 Lakhs have been selected for this research. The students' placement particulars regarding category-I companies have only been collected and updated into the database.

The details regarding the tests/interviews/group discussions conducted by the placement organizations include Logic, Reasoning, and Learning ability. Each test is mapped to 11 different cognitive factors based on the types of questions included in the tests. Problem-solving, knowledge base, and communication, have been collected and stored in a database. The 11 cognitive factors include logical thinking and reasoning (LTR), problem-solving ability (PSA), learning ability (LA), patience and perseverance (PAP), memory power (MP), attention and concentration (AAC), overall level of knowledge in computer science (OKC), ability to communicate (ACO), level of knowledge on different platforms for the development of software (LKDS), level of knowledge on information retrieval (LKIR), and level of knowledge in designing and implementing software (LKDIS).

The scores obtained by the students in the tests conducted by the industrial organizations have been collected and stored in the database. The development of tests derived from the different academic courses has also been collected under discussions with industry persons and academic experts. Now that the cognitive factors and academic courses are linked, the academic courses are used for prediction. Predicting based on the academic course is the same as predicting based on cognitive factors.

3.2. Establishment of mapping between selection tests, cognitive factors, and academic courses

The score obtained by the student in a test is attributed to the score achieved by a student concerning cognitive factors. The data set is processed to find the relationship between the psychological factors and the academic courses. The score obtained in the tests is related to the average score obtained in the related subjects. Table 1 shows the mapping between the scores obtained in the tests conducted by the industrial organization, psychological factors, and the related academic subjects.

Table 1. Relationship between the psychological factors score secured in tests and the related academic subjects

S. No.	Psychological factor(s)	Type of test conducted by the industrial organization	Subjects from which the questions have been derived
1	Logical thinking & reasoning	Objective Examination on Logic handling using Java/C	Data structures Design & Analysis of Algorithms
2	Problem Solving Ability	Code development for a small application that involves DA, Algorithms, and JAVA	Problem-Solving through Programming Java Programming Data Structures Design & Analysis of Algorithms
3	Learning Ability	Given two questions and answers and the student to answer the third question, Solving puzzles	CGPA
4	Patience & Perseverance	Answering Huge Comprehension based questions	
5	Memory power	Questioning and answering using a series of questions wherein some questions contradict the other	
6	Attention & Concentration	Answering questions intermixed text and data	
7	The overall level of knowledge in Computer Science	Question and answering and through objective-based teats	
8	Ability to communicate	Interviewing	English & Communication
9	Level of knowledge on different platforms (Windows and UNIX) for developing software	Question and answering related to the operating system	Operating System
10	Level of knowledge on Information retrieval	Question and answering related database management system	Database Management System
11	Level of knowledge in designing and implementing software	Based on the approaches followed in the development of the application	Software Engineering

3.3. Expert model for prediction based on academic excellence

The scores achieved by each student in each course (8 Courses) and the overall CGPA (9^{th} course) have been collected and recorded in the example set database. The scores obtained by a student have been classified into 5 Classes (6, 7, 8, 9, 10). The classification is done as per Table 2. If a students get < 6 marks, no classification is done. The probability of being selected based on a subject's score is computed. The probability of getting placed can be computed using (1).

P = probability of getting Placed given the score achieved by the student in a specific subject
NC = Number students included in a specific class
NP = Number of students in the class who are placed

$$P = \left(\frac{NC}{NP}\right) * 100 \tag{1}$$

Table 2. Classification of marks obtained by a student in XYZ Subject

Class number	Minimum Marks	Maximum Marks	Number of students in the class	Number of students in the class who have been placed	Probability of getting selected based on the score obtained by a student in a specific subject
6	>=6	<7	O	A	(O/A)*100
7	>=7	<8	P	B	(P/B)*100
8	>=8	<9	Q	C	(Q/C)*100
9	>=9	<10	X	D	(X/D)*100
10	10	10	Y	E	(Y/E)*100

The overall probability of getting placed considering all the classes is computed as per (2)

$$\square\, \boldsymbol{i}\,(\mathbf{1}..\mathbf{5})\ \boldsymbol{Overal}(\boldsymbol{Ci}) = \sum_{j=1}^{9} \boldsymbol{Sj}[\boldsymbol{Ci}\}/\mathbf{9} \qquad (2)$$

where
Overall(Ci) = probability of class considering all the subjects
Sj[Ci} = probability of class i of subject j

The algorithm shown in Table 3 is used to compute the probability of placement of a student. The algorithm computes the probability of placement considering the students' performance (scores) in all the subjects. The score obtained in each subject is used to find the class it belongs to. Each class has two counters that count the number of students and the number of placed students relating to a specific class. The probability of the placement is computed based on these two counters. The overall probability of placement is also computed considering the aggregate performance of the students.

Table 3. Algorithm

Variables used	int tns #total no. of students int nsp #no. of students placed. int score #score obtained by the student in the current course. pps #pps (probability per score) contains five items; each represents the computed probability of students getting placed with the score. The scores range from 6 to 10 int ipps=0 # index to list pps
step 1:	initialize tns, nsp to zero
step 2:	initialize pps
step 3:	ipps=0
step 4:	for the score in range (6,11):
step 5:	extract all the records with a given score into a list
step 6:	tns=len(list)
step 7:	nsp=0
step 8:	for index in range(tns):
step 9:	if(list.placed==1):
step 10:	increment nsp
step 11:	end for
step 12:	probability=(nsp/tns)*100
step 13:	pps[ipps]=probability
step 14:	increment ipps
step 15:	end for

3.4. Handling non-linearity in the academic performance

Considering all the classes most of the time, the probability of prediction is linear, which means as the class increases, the probability of placement also increases. Sometimes, the linearity does not hold well in some cases, too, in a few subjects. The anomaly is resolved through the use of an interpolation method.

3.4.1. Interpolation method

Interpolation is a type of estimation, a method of constructing new data points within the range of two data points. Let (x_1, y_1) be the first data point coordinates and (x_2, y_2) be the second. Let x be the point where interpolation is undertaken using (3), and y will be the interpolated value.

$$\boldsymbol{y} = \boldsymbol{y1} + (\boldsymbol{y2} - \boldsymbol{y1}) * \left(\frac{-x1}{x2-x1}\right) \qquad (3)$$

3.4. Expert model for prediction based on cognitive factors

In Table 1, the mapping between the cognitive factors and the academic subjects as recommended by industrial organizations has been explained. The scores obtained in the subjects related to cognitive factors are added and averaged. The average scores obtained for each cognitive factor have been classified as done in the case of academic performance in the individual subjects. The prediction probabilities are computed considering the number of students in a class and classified students.

3.5. Predicting the placement

The expert system collects a student's academic performance considering eight courses and the Overall CGPA, which are employment-related, and computes the probability of getting placed for that student. The prediction is done for each subject, considering all the subjects (overall prediction). The prediction is done directly using the class tables related to a subject or the overall prediction table provided; the score secured/overall score computed is equal to one of the class intervals. If the score secured/computed falls between two class intervals, then the interpolation method is used to compute the probability of the employed student.

3.6. Comparing the coherence through cognitive and academic factors

The coherence between the Academic and cognitive models can be computed by computing the correlation between the models using (4). If the calculated correlation coefficient is positive, it can be construed that one can infer cognitive predictions from Academic prediction and vice versa. The correlation between both the models is computed by considering difference of the individual prediction from the mean of the predictions and using the standard deviations of the predictions.

$$\text{Correlation}(X, Y) = \frac{1}{(n-1)}\sum\frac{(X-\mu_X)(Y-\mu_Y)}{\sigma_X\sigma_Y} \tag{4}$$

where

X is a vector of probability percentages relating to 5 different classes considering Academic subjects
Y is a vector of probability percentages relating to 5 different classes considering cognitive Factors
μ_X = mean of probabilities relating to 5 classes of academic subjects
μ_y = mean of probabilities relating to 5 classes of cognitive factors
σ_X = Standard deviation of X, which can be computed through e (5)
σ_y = Standard Deviation of Y, which can be computed through (6)

$$\sigma_X = \sqrt{\frac{\sum(X-\bar{X})^2}{n-1}} \tag{5}$$

$$\sigma_Y = \sqrt{\frac{\sum(Y-\bar{Y})^2}{n-1}} \tag{6}$$

3.7. Accuracy estimation

Accuracy of cognitive model/Academic model without the anomaly correction and the Academic model with anomaly corrections is computed using the (7). The accuracy of the models is computed based on true positives (TP) (The students placed are predicted as placed students), true negatives (TN) (Students not placed are predicted as not placed), false positive (FP) (Students not placed are predicted as placed), false negatives (FN) (Students placed are predicted as not placed. It can be construed that higher the accuracy, the more is the dependability of the model.

$$Accuracy = (TP + TN)/(TP + FP + FN + TN) \tag{7}$$

Where
TP = True Positives (Students who are placed are predicted as placed)
TN= True Negatives (Students who are not placed are predicted as not placed)
FP= False positives (Students who are not placed are predicted as placed)
FN=False Negatives (Students who are predicted as not placed but are placed)

4. RESULTS AND DISCUSSIONS

4.1 Computing the probability of placement based on a single subject

The number of placed students of a class divided by the number of students in the class gives the probability of placement. If a student gets marks in the subject-data structures (DS), which falls into a specific class, then the probability of placement related to that class applies to the student. The score obtained by a student is used to find the class, and therefore, the student's placement is predicted. Sample probability calculation considering DS subject is shown in Table 4.

Table 4. Placement prediction based on DS subject

Class	Class Name	Number of students placed (nsp)	Total number of students (tns)	Probability for placement (%)
6	E	14	133	11
7	D	25	144	17
8	C	748	1870	40
9	B	367	706	52
10	A	177	305	58

Figure 1 shows the relationship between the scores obtained and the probability of selection considering the DS subject. The X-Axis shows the score, and the y axis shows the probability of placement. One can observe from the figure that as the class number increases, the probability of getting placed is also increasing. Thus, the hypothesis that the probability of placement increases as the student's performance in DS subject is high holds good. The classification method, in a way, places the students into a class as per the predictability of the students. The lesser the predictability based on the student's academic performance exposes the student's weaknesses.

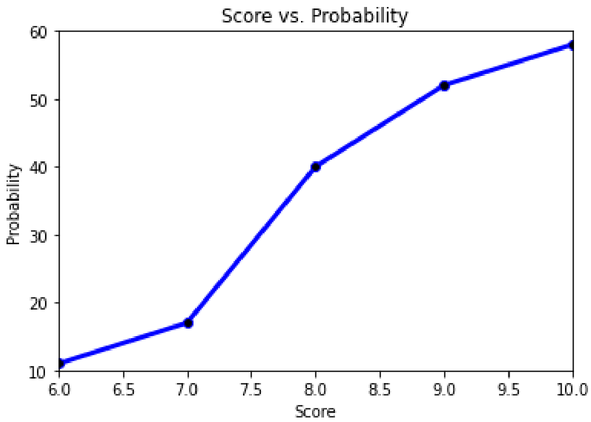

Figure 1. Score vs. probability w.r.t. DS

4.2. Anomaly corrections

In some subjects, such as SE, the linear relationship between classes and prediction probability does not hold due to non-linearities that must be adjusted. Table 5 shows the calculated probability w.r.t. the course SE. One can see a minor anomaly existing with class D. The anomaly is indicated as *. As shown in the table, the probability of class D is 45, which is more than class C (=42). A non-linearity in the predictability can be noticed when linear progression in the % prediction as the class intervals increase has not been witnessed. The interpolation method has been employed to correct the existence of such non- linearity.

Table 5. Probability of placement w.r.t. SE containing the minor anomaly

Class	Class Name	Number of students placed (nsp)	Total number of students (tns)	Probability for placement (%)
6	E	226	632	36
7	D	273	610	*45
8	C	671	1599	42
9	B	98	213	46
10	A	63	101	62

As explained in (3), the interpolation method removes the anomalies. The corrected prediction probabilities for the subject SE are shown in Table 6. Figure 2 shows the Score on X-Axis and the corresponding probability on the Y-Axis w.r.t. SE subject. From Figure 2, it can be seen that the non-linearity is removed, and smooth progression in predictability is maintained as the class interval increases. The graph is re-plotted after resolving the anomaly using the interpolation method and shown in Figure 3, from which one can see that the non-linearity is smoothened out.

Table 6. Probability for each score w.r.t. SE after the anomaly is corrected

Class	Class name	Number of students placed (nsp)	Total number of students (tns)	Probability for placement (%)
6	E	226	632	36
7	D	273	610	39
8	C	671	1599	42
9	B	98	213	46
10	A	63	101	62

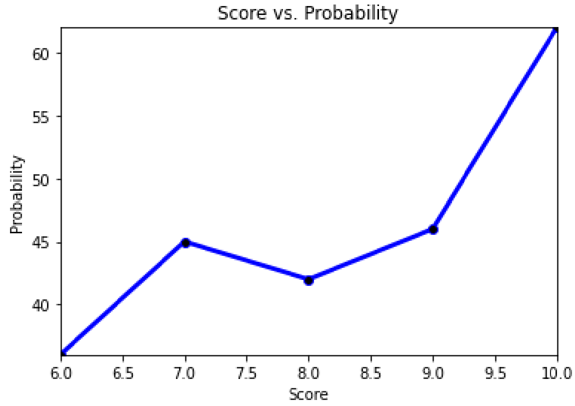

Figure 2. Score vs. Probability w.r.t SE containing the minor anomaly

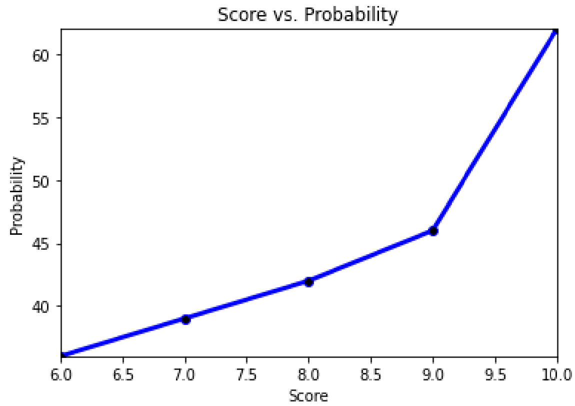

Figure 3. Score vs. Probability w.r.t SE after resolving the anomaly

4.3. Computing the probability of placement considering all the subjects

The placement prediction considering all the subjects is done by adding the marks obtained in all the subjects and taking an average. The classification of these average marks is done as in the case of individual subjects. The overall predictability is shown in Figure 4, a smooth graph that holds good the hypothesis that as the score increases, the probability of placement increases. Table 7 shows the overall predictability, and Table 8 shows the predictability considering each subject and different classes separately. The combined predictability is the overall predictability considering all the subjects. It does not reflect the true predictability based on a single subject. Single subject-based predictability should only be seen for finding the weakness of the students in that subject. From Table 8, it can be seen the predictability based on different subjects varies a lot. The lower classes' predictability is much weaker than, the higher classes. The combined predictability evens out the students' performance in different subjects.

Table 7. Placement prediction based on all the subjects

Class	Class name	Number of students placed (nsp)	Total number of students (tns)	Probability for placement (%)
6	E	2	18	11
7	D	146	697	21
8	C	626	1470	43
9	B	499	873	57
10	A	59	98	60

4.4. Placement prediction of a students

The predictability of placement considering the score obtained in a single subject or overall score is straightforward when the score matches the class interval. It is sufficient to find the class and note the probability of the placement. However, if the score falls between any two classes, then the predictability is assessed through interpolation. Table 9 shows that the prediction is done using the interpolation method when the score obtained by a student in the DS subject is 7.4, which falls between classes 7 and 8.

Table 8. Courses vs. probabilities

S.No.	Course name	Probability for score 6 (=class E)	Probability for score 7 (=class D)	Probability for score 8 (=class C)	Probability for score 9 (=class B)	Probability for score 10 (=class A)
1	DS (Data Structures	16	17	40	52	58
2	DAA (Design and Analysis and Algorithms)	16	29	42	54	59
3	JP (Java Programming)	18	21	37	50	60
4	PSP (Portable Server Pages)	16	22	43	47	56
5	SE (Software Engineering)	36	39	42	46	62
6	DBMS (Database Management System)	26	30	41	47	62
	OS (Operating System)	26	39	48	49	54
8	EC (Effective Communication)	23	34	43	44	45
9	CGPA (Cumulative Grade Point Average)	13	31	45	60	61

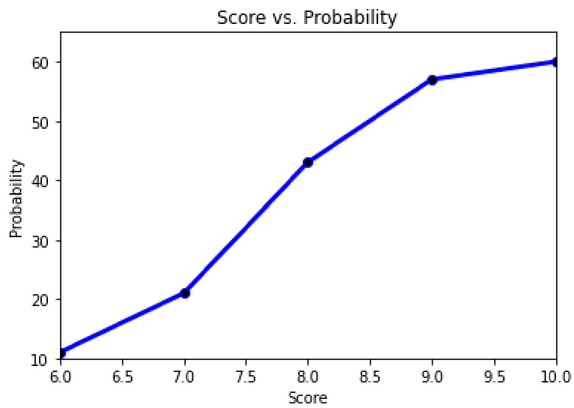

Figure 4. Overall predictability of placement

Table 9. Student vs. Probability for getting placed w.r.t. course DS

Course name	Academic score of the student	Corresponding class name	Probability of class (%)	Next higher class	Probability of next class (%)	Probability for getting placed (%)
DS	7.4	D	17	C	40	26

4.5. Predicting based on specific cognitive factors

Table 1 shows the mapping between the cognitive factors, the tests conducted by the industrial organizations, and the subjects used to derive the tests. The scores obtained by the students in the tests are directly related to the cognitive factors. If one test is derived from two subjects, then the average score obtained by the students in both the subjects is taken and assigned to the concerned cognitive factor. Table 10 shows the probability computation based on the cognitive factor, the "Level of knowledge on Information retrieval". The test related to the assessment of this cognitive factor is derived from the subject DBMS. The score obtained in the DBMS subject is directly attributable to the score obtained concerning the cognitive factor. Figure 5 shows the linearity between the classes and the probability of placement prediction of the student. It can be seen from Table 10 that the predictability of a student placement can be assessed considering a specific cognitive factor, and the predictability increase as performance falls in higher class intervals of the cognitive factor concerned.

4.5. Predicting based on all the cognitive factors

The predictability considering all the cognitive factors is shown in Table 11. The scores for each cognitive factor are computed by averaging the students' scores in the subjects related to the cognitive factor**.** The score is then categorized into one of the classes, and then counters are accumulated. The scores computed for each cognitive factor are averaged to get the overall score due to the cognitive factor. Figure 6 shows the linearity between the classes and the probability of placement prediction of the student considering all the cognitive factors. One can observe the linearity in the predictability considering all the cognitive factors. It is also observed that the predictability increases as the students' performance considering all the cognitive factors increases. It can be observed from Table 11 the variations in the performance consider all the cognitive factors and generally leads to lower predictability when compared to a single cognitive factor. However, the predictability is more accurate than the predictability done through a single cognitive factor as the variations due to all cognitive factors have been taken care of.

Table 10. Prediction table - level of knowledge on information retrieval - DBMS

Class	Class Name	Number of students placed (nsp)	Total number of students (tns)	Probability of placement (%)
6	E	79	312	26
7	D	103	344	30
8	C	633	1550	41
9	B	218	460	47
10	A	291	466	62

Table 11. Overall placement prediction considering all cognitive factors

Class	Class name	Number of students placed (nsp)	Total number of students (tns)	Probability for placement (%)
6	E	405	1882	22
7	D	743	2507	30
8	C	3058	6935	44
9	B	2139	4123	52
10	A	1682	3083	55

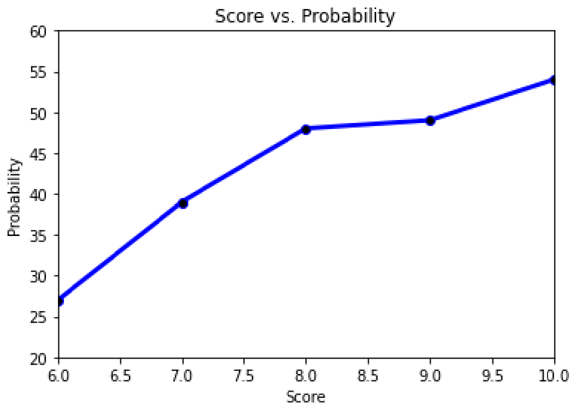

Figure 5. Predictability based on cognitive factor-level of knowledge on Information retrieval

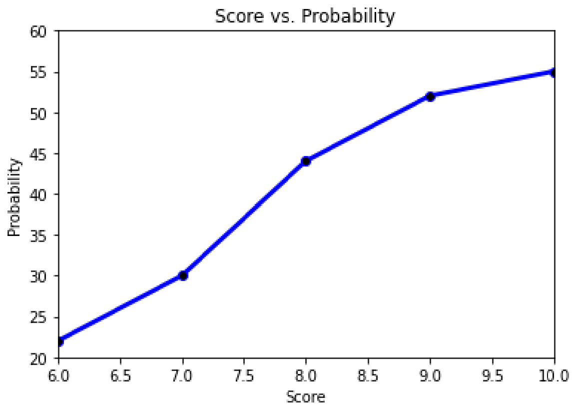

Figure 6. Predictability based on all cognitive factors

4.6. Comparing predictability based on academic and cognitive performance

A comparison of overall prediction models considering both the cognitive and Academic models is shown in Table 12. The computed standard deviation of educational prediction is computed as σ_X=21.85, and the standard deviation of cognitive predictions are computed as σ_Y=14.20, and the overall correlation is computed as 77.69, which is found to be positive, meaning the probability of cognitive factors can be inferred from the probabilities of the Academic model and vice versa.

Table 12. Comparisons of the probability of predictions – overall cognitive and academic prediction model

Class	Class name	Academic Performance Probability of placements	Cognitive Factors Probability of placements
6	E	11	22
7	D	21	30
8	C	43	44
9	B	57	52
10	A	60	55

4.7. Estimating the accuracy of the models

One thousand records have been used as a test sample to test the accuracy of the models. The tests results collected after undertaking to test using all three models are shown in Table 13. From Table 13, it is seen that the accuracy of the cognitive model is the same as the accuracy of the Academic model with anomaly correction (98%). The accuracy of the Academic model without anomaly correction is only 92%. Thus, there is an improvement of 6% prediction when anomaly corrections are applied.

Table 13. Accuracy estimation of predictive models

Serial Number	Type of results	Description of the type	Cognitive model (Count)	Academic model (without anomaly correction) (Count)	Academic model (with anomaly correction) (Count)
1	TP	True Positives	910	890	909
2	TN	True Negatives	70	30	71
3	FP	False positives	10	50	9
4	FN	False Negatives	10	30	11
	Total		1000	1000	1000
	Accuracy		98	92	98

5. CONCLUSION

Predicting the placement of the students is as important as predicting suitable careers for the students. To have realistic predictability, there is a need to assess the students' performance in each subject/cognitive factor and the overall performance considering academic/ cognitive performance. There is a need to find the gap in terms of student performance considering individual subjects and considering the overall performance of the students. The student's performance during placement-related evaluation and considering the students' cognitive levels is equally important for assessing accurate predictability of placement of the students. The relationship between the students' cognitive levels and academic performance must be explored to determine the dependency on others. Individual subject-wise predictability involves anomalies that need to be corrected to make accurate predictions. An expert predictive model has been presented, which can be used to predict the students' placement considering either academic performance or cognitive performance of the students both at an atomic or overall level. Anomaly correction models have been presented, which are used to eliminate the anomalies exiting the students' performance at the atomic level (subject/cognitive factor level). An interpolation method provides for prediction when the score obtained by the students falls within the standard class intervals. It has been inferred that a cognitive-based predictive model can be derived from academic predictive models and vice versa. The accuracy of the model presented is proved to be 98%. In the future, alternative assessment of cognitive levels can be done using game playing and assessing the levels through conducting cognitive tests. The models can be compared to find the consistency and accuracy of the students' cognitive levels assessment. The placement is also dependent on the students' knowledge base as required by the industry. Thus, modeling the placement prediction is necessary based on the students' knowledge base, academic performance, and cognitive levels. The combined effect of cognition, academic excellence, and knowledge base must be considered for developing an overall model that can be used as an expert model to predict the placement of the students. Machine learning techniques can be employed to learn each of the Models and how the models are interlaced to get deep-learned expert models, which gives a high degree of prediction accuracy.

REFERENCES

[1] V. P, “Predicting suitable careers through use of snakes and ladder game,” *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 5, pp. 2065–2073, May 2020, doi: 10.30534/ijeter/2020/96852020.

[2] S. B. J, “Career guidance through TIC-TAC-TOE game,” *Int. J. Emerg. Trends Eng. Res.*, vol. 7, no. 6, pp. 25–31, Jun. 2019, doi: 10.30534/ijeter/2019/01762019.

[3] C. P. V, “An expert system for building a cognitive and career Prediction model based on N-coin puzzle game,” *Int. J. Emerg. Trends Eng. Res.*, vol. 7, no. 11, pp. 410–416, Nov. 2019, doi: 10.30534/ijeter/2019/037112019.

[4] V. C. Prakash, S. Jammalamadaka, V. Kantharao, V. Sriharshini, G. Sriram, and C. H. V. S. Ganesh, “An expert system to assess the memory power of a student for selection of a suitable career,” *J. Adv. Res. Dyn. Control Syst.*, vol. 9, no. 6, pp. 309–321, 2017.

[5] V. Chandra Prakash, J. K. R. Sastry, V. K. Rao, T. Vineetha, V. Harika, and A. Abhishek Reddy, “A critical study on applicability of sokoban game for building cognitive model of a student for career assessment,” *Int. J. Eng. Technol.*, vol. 7, no. 1.1, pp. 260–264, Dec. 2017, doi: 10.14419/ijet.v7i1.1.9482.

[6] V. Chandra Prakash, J. K. R. Sastry, K. Anusha, P. Ashok Kumar, N. Venkatesh, and G. Ravi Teja, “Expert system for building cognitive model of a student using 8-puzzle game and for career assessment,” *Int. J. Eng. Technol.*, vol. 7, no. 2.27, pp. 113–117, Aug. 2018, doi: 10.14419/ijet.v7i2.27.12014.

[7] S. Hossain, D. Sarma, F. Tuj-Johora, J. Bushra, S. Sen, and M. Taher, “A belief rule based expert system to predict student performance under uncertainty,” in *2019 22nd International Conference on Computer and Information Technology (ICCIT)*, Dec. 2019, pp. 1–6, doi: 10.1109/ICCIT48885.2019.9038564.

[8] A. Drigas, S. Kouremenos, S. Vrettos, J. Vrettaros, and D. Kouremenos, “An expert system for job matching of the unemployed,” *Expert Syst. Appl.*, vol. 26, no. 2, pp. 217–224, Feb. 2004, doi: 10.1016/S0957-4174(03)00136-2.

[9] B. Walek, O. Pektor, and R. Farana, “Proposal of the web application for selection of suitable Job applicants using expert system,” in *Computer Science On-line Conference*, 2016, pp. 363–373.

[10] E. el Haji, A. Azmani, and M. El Harzli, “Multi-expert system design for educational and career guidance: an approach based on a multi-agent system and ontology,” *Int. J. Comput. Sci. Issues*, vol. 11, no. 5, pp. 46–52, 2014.

[11] S. Khanna, A. Kaushik, and M. Barnela, “Expert systems advances in education,” in *Proceedings of the National Conference on Computational Instrumentation NCCI-2010*, 2010, pp. 109–112.

[12] S. Chen, S. Zhang, J. Shang, B. Chen, and N. Zheng, “Brain-inspired cognitive model with attention for self-driving cars,” *IEEE Trans. Cogn. Dev. Syst.*, vol. 11, no. 1, pp. 13–25, Mar. 2019, doi: 10.1109/TCDS.2017.2717451.

[13] K. Kawamura, T. E. Rogers, and X. Ao, “Development of a cognitive model of humans in a multi-agent framework for human-robot interaction,” in *Proceedings of the first international joint conference on Autonomous agents and multiagent systems part 3 - AAMAS ’02*, 2002, pp. 1379–1386, doi: 10.1145/545056.545135.

[14] O. Juarez-Espinosa and C. Gonzalez, “Situation awareness of commanders: a cognitive model,” Carnegie Mellon University, 2004.

[15] Z. Zhao, L. Zhang, and D. Hu, “Student performance prediction method based on fuzzy cognitive model,” in *Proceedings of the 2016 International Conference on Education, E-learning and Management Technology*, 2016, pp. 483–487, doi: 10.2991/iceemt-16.2016.94.

[16] Z. E. Papinczak, J. P. Connor, P. Harnett, and M. J. Gullo, “A biosocial cognitive model of cannabis use in emerging adulthood,” *Addict. Behav.*, vol. 76, pp. 229–235, Jan. 2018, doi: 10.1016/j.addbeh.2017.08.011.

[17] J. Davis and S. Lorimer, “A cognitive model for automatic student assessment: classification of errors in engineering dynamics,” in *2014 ASEE Annual Conference & Exposition Proceedings*, 2014, pp. 24.26.1--24.26.10, doi: 10.18260/1-2--19918.

[18] A. Weigard, C. Huang-Pollock, A. Heathcote, L. Hawk, and N. J. Schlienz, “A cognitive model-based approach to testing mechanistic explanations for neuropsychological decrements during tobacco abstinence,” *Psychopharmacology (Berl).*, vol. 235, no. 11, pp. 3115–3124, Nov. 2018, doi: 10.1007/s00213-018-5008-3.

[19] L. N. Long, T. D. Kelley, and E. Avery, “An emotion and temperament model for cognitive mobile robots,” 2015.

[20] T. Bosse, P.-P. van Maanen, and J. Treur, “A cognitive model for visual attention and its application,” in *2006 IEEE/WIC/ACM International Conference on Intelligent Agent Technology*, Dec. 2006, pp. 255–262, doi: 10.1109/IAT.2006.2.

[21] E. Ekiz, A. C. Videler, and S. P. J. van Alphen, “Feasibility of the cognitive model for behavioral interventions in older adults with behavioral and psychological symptoms of dementia,” *Clin. Gerontol.*, pp. 1–12, Apr. 2020, doi: 10.1080/07317115.2020.1740904.

[22] S. Basu *et al.*, “An intelligent/cognitive model of task scheduling for IoT applications in cloud computing environment,” *Futur. Gener. Comput. Syst.*, vol. 88, pp. 254–261, Nov. 2018, doi: 10.1016/j.future.2018.05.056.

[23] B. R. Envick, “Achieving entrepreneurial success through passion, vision & courage: A cognitive model for developing entrepreneurial intelligence,” *Acad. Entrep. J.*, vol. 20, no. 1, pp. 55–74, 2014.

[24] M. H. Bindu, P. Gupta, and U. S. Tiwary, “Cognitive model - based emotion recognition from facial expressions for live human computer interaction,” in *2007 IEEE Symposium on Computational Intelligence in Image and Signal Processing*, Apr. 2007, pp. 351–356, doi: 10.1109/CIISP.2007.369194.

[25] A. Adikari, D. De Silva, D. Alahakoon, and X. Yu, “A cognitive model for emotion awareness in industrial chatbots,” in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, Jul. 2019, pp. 183–186, doi: 10.1109/INDIN41052.2019.8972196.

[26] E. Faizal, S. Sumiyatun, and S. Sudarmanto, “Classification of students based on academic ability using profile matching and linear interpolation weighting,” *Int. J. Comput.*, vol. 34, no. 1, pp. 72–94, 2019.

[27] A. K. Pal and S. Pal, “Classification model of prediction for placement of students,” *Int. J. Mod. Educ. Comput. Sci.*, vol. 5, no. 11, pp. 49–56, Nov. 2013, doi: 10.5815/ijmecs.2013.11.07.

[28] H. Khatoon, V. C. Prakash, J. K. R. Sastry, and B. T. Reddy, “An expert system to build cognitive model of an IT student using artificial neural networks for predicting placements during campus recruitments,” *Int. J. Emerg. Trends Eng. Res.*, vol. 8, no. 3, pp. 838–846, Mar. 2020, doi: 10.30534/ijeter/2020/38832020.

[29] S. Elayidom, S. Mary Idikkula, and J. Alexander, “A Generalized Data mining Framework for Placement Chance Prediction Problems,” *Int. J. Comput. Appl.*, vol. 31, no. 3, pp. 40–47, Oct. 2011, doi: 10.5120/3807-5257.

[30] K. Seng and A. M. Zeki, “Career guidance and employment management system,” in *2014 3rd International Conference on Advanced Computer Science Applications and Technologies*, Dec. 2014, pp. 73–78, doi: 10.1109/ACSAT.2014.20.

[31] M. Gera and S. Goel, “A model for predicting the eligibility for placement of students using data mining technique,” in *International Conference on Computing, Communication & Automation*, May 2015, pp. 114–117,

doi: 10.1109/CCAA.2015.7148355.

[32] J. Prathipa and S. C. Sekaran, “Predicting student placements using bayesian algorithm,” *Int. J. Pure Appl. Math.*, vol. 18, no. 22, pp. 127–132, 2018.

[33] N. Naik and S. Purohit, “Prediction of final result and placement of students using a classification algorithm,” *Int. J. Comput. Appl.*, vol. 56, no. 12, pp. 35–40, Oct. 2012, doi: 10.5120/8945-3111.

[34] T. Mishra, D. Kumar, and S. Gupta, “Students’ employability prediction model through data mining,” *Int. J. Appl. Eng. Res.*, vol. 11, no. 4, pp. 2275–2282, Jun. 2017, doi: 10.17485/ijst/2017/v10i24/110791.