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Predicting Suitable Careers Through Deep Belief Networks And Game Playing

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Abstract:

Deciding on a career path is a Major Decision in one's life. Many professionals suffer from poor performance in the career path they have chosen earlier in their lives. The industry is also suffering due to the wrong people being assigned the right jobs. Generally, there is a relationship between a person's cognitive factors, which may change from time to time, and the kind of jobs they can perform efficiently. Skills acquired by a person directly correlate with the cognitive levels and the kind of jobs that a person can undertake. The selection of a proper career that matches the skills acquired dependent on the cognitive levels is the most critical issue that must be addressed by building cognitive, expert, and learning models. Assessing the cognitive levels of a person is complex, and predicting suitable careers based on the cognitive levels is further complicated due to the lack of proper expert models which can learn from a live example set. This paper presents a method that computes the psychological levels through game playing and uses the results to determine the skills acquired. Using the skills, the method predicts suitable careers that the students and professionals can effectively pursue. The learning of the expert model required is implemented through Deep Belief Networks. 98% Accuracy in the proper prediction of the careers has been achieved using the Cognitive, Expert and Learning models presented in the paper.

Keywords: Career Prediction, Deep Belief Networks, Cognitive levels, psychological assessment,

1. Introduction

Career planning has become one of the key elements as one has to plan for nearly 40 years. Improper career options will make a person unsuccessful in life. There are millions of jobs of different types that one can pursue, especially after graduating. Each Job requires a different skill set and experience. The extent to which the skills can be acquired is dependent on the cognitive levels of a person, which are to be measured quantitatively. There is a need to MAP the skill sets to the cognitive levels of the job seekers and the skill sets required to perform a specific job [Apa.org, 2022] [1].

Thus, there is a need to implement two-stage processing to assess the cognitive levels & skillsets and predict suitable careers for the students and professionals. The use of Deep belief networks helps determine the skills based on cognitive levels and predict the suitable careers based on the skills [Google.co.in, 2022} [2].

The cognitive levels keep changing from time to time and therefore call for an adjustment to the career options. Many cognitive aspects of a person need to be considered, including intelligence, patience, perseverance, problem-solving ability, speed of solving the problems, memory, recollection, etc. Many skills of different types also are required for doing different types of jobs. A model is required to associate cognitive levels to skill sets. Similarly, different types of jobs are on offer, which requires different types of skill sets. A model is also required that associates the Skills to the Jobs. Thus the entire problem requires three-stage processing (link. springer, 2002) [3].

The game-playing technique is a frequently tried method for assessing the cognitive factors of students. Several games have been tried, which include Tic-Tac-Toe (Sasi Bhanu et al., 2019-1) [4], (Sasi Bhanu et al., 2019-2) [5], snakes and ladder (Vamsi et al., 2020) [6], 8-puzzle (Chandra Praksah et al., 2018-1) [7], n-coin puzzle (Chandra Praksah et al., 2019-1) [8], Sokoban (Chandra Praksah et al., 2018-2) [9], Chandra Praksah et al., 2018-3) Sudoku (Chandra Praksah et al., 2018-3) [10], (Chandra Praksah et al., 2019-2) [11], Crypto Arithmetic (Chandra Praksah et al., 2019-3) [12], memory power (Chandra Praksah et al., 2017-1) [13], Concentration game (Kantha Rao et al., 2018) [14], Integrated Approach (Chandra Praksah et al., 2019-4) [15], Career Prediction through Neural Networks (hameeda et al., 2020) [16]. Different and varied cognitive factors have been assessed based on the time taken to complete the game, the number of times a game is played, won, lost, etc. A score is computed for each factor that can measure the cognition concerning a psychological factor.

Most of the institutions prepare the students for placement considering the academic record and provide the training required to improve the skills concerning effective communication, problem-solving ability, verbal and nonverbal vocabulary, speed of solving the problems, group-based accomplishment, improvement in logic and reasoning, improvement in the domain knowledge, etc. No consideration is given to the students' cognitive levels and the predictions of suitable careers and then directing the effort towards preparing the students in that direction.

A few techniques such as aptitude tests, reasoning tests, IQ tests, etc., are in vogues such as reasoning and intelligence. These tests focus more on the students' general characteristics than the real cognition, which has more bearing on acquiring skill sets and choosing the most appropriate career option. The modern approach to finding the jobs that the student can pursue is based on the student's cognitive levels, which are assessed by making a student play several games.

Huge data is collected with the details related to academic performance, skills sets, cognitive levels, career details, and students' performance in those jobs undertaken. It will provide a great scientific basis to assess the career options that are most suitable to the students. Collection of data related to the cognitive factors, Mapping cognitive factors to the skill sets and the skillsets to the Career options would become the key issues.

Thus the main problem is centered around the computations of the cognitive factors and building two models that learn the Mapping of the cognitive factors to the skill sets and the skill sets to the career options

Selecting a proper career is extremely important for a student that helps their life planning. Generally, a human expert suggests career(s) options to the students based upon their academic standards. But, a human expert can also make errors in suggesting the most suitable career(s) for students. The expert system can be built using AI techniques to replace the human expert. That expert system can suggest the best suitable career(s) for the student by constructing a cognitive model. That model will be generated by assessing various psychological factors, viz., logical thinking, learning ability, decision making, patience, perseverance, etc.

Balasubramanyam, S. et al. (2018) [17] developed a rule-based expert system that suggests a suitable branch based on students' interests. Gupta et al. (2019) [18] developed an expert system that evaluates students' performance using machine learning techniques. Drigas et al. (2004) [19] developed an expert System that suggests the suitable Job (s) for an unemployed person. Walek et al. (2016) [20] developed a web-based expert system that selects the suitable applicant for a given job. El Haji et al. (2014) [21] developed a multi-expert system to predict students' performance in the introductory computer science course.

Khanna, et al. (2010) [22] developed an expert system useful in various domains of the education field, viz., educational planning, decision-making ability, and tutor training. De Alwis et al. (2008) [23] proposed a cognitive metric to measure "Programming Task Difficulty" quantitatively. Shovon et al. (2014) [24] proposed a cognitive metric useful for diagnosing a patient's cognitive impairment.

Lent et al. (2016) [25] presented two studies in which the social cognitive model for career self-management is applied to career analysis and the decision-making aspect of college students. Handayani et al. (2016) [26] designed and developed a cognitive model for Collaborative Writing online. Boyer et al.

(2018([27] designed and developed a cognitive model for folk-economic trust.

Tao Yong-hong [28] predicted the quality of college employment using the Back-Propagation Neural Network. Santoro et al. (2017) [29] developed a simple module of the neural network for assessing relative reasoning. Liang, et al. (2015) [30] explain the recognition of objects using recurrent neural networks. Alharbi et al. (2019) {31] performed the Twitter emotional analysis using the deep neural network. Bisquert et al. (2012) [32] predicted the danger of forest fire in Galicia by applying the neural networks and the logistic regression to MODIS data.

Al-Saiyd et al. (2014) [33] proposed a system for predicting the suitable IT job based on the skills, experience, and knowledge using Artificial Neural Networks (ANN). Elayidom et al. (2011) [34] proposed a framework using data mining techniques to predict the chances of student placement. Guleria et al. (2015) predicted the placement results of the students using Bayesian classification. Seng et al. (2014) [36] developed a CGEM system to provide job opportunities for students. Mishra et al. (2016) [37] predicted the student's employability using data mining techniques. Jeevalatha et al. (2014) [38] performed a detailed analysis of undergraduate students' placement selection using Decision Tree algorithms. Naik et al., (2012) [39] predicted the result of the students along with the placement of the students with the help of classification algorithms. Mangasuli et al. (2016) [40] applied Fuzzy logic and K Nearest Neighbour to the students' database to predict campus placement. Revathy et al, (2017) [41] proposed an approach to predict placement opportunities of students for a specific company using data mining techniques. Ramanathan et al., (2013) [41] applied the ID3 algorithm to predict student's campus placements.

2.0 Research Gap and Proposed Solution

Most of the contributions presented in the literature concentrated on assessing the cognitive factors and then using the same for predicting suitable careers. Data Mining techniques have been used extensively for predicting the employability of the students. Some machine learning techniques also have been used for predicting employability, but not much focused on predicting suitable careers. The issue of "skills" has not been given any focus, while it has a lot of bearing on career prediction.

An Approach to predicting suitable careers considering cognitive factors and skills using Deep Belief networks implemented through Two-stage processing solves the problem of career prediction considering both cognitive factors and skills. While in stage 1, a neural network that takes cognitive factors as input predicts the skills required, in stage 2, the predicted skills are taken as input, and suitable careers are predicted as output..

3.0 Methods and Techniques

3.1 Overall processing for career prediction

Career prediction based on the cognitive factors and skillsets requires three-stage processing, as shown in **Figure 1.** The students' cognitive levels are assessed through a game called ("Magic Squares,") "Magic Square of magic numbers" which has been proved to be assessing the cognitive factors more realistically compared to other games such as Tic-Tac-Toe, N-coin puzzle, 8 Puzzle game. Sudoku game, and Sokoban games. In the second stage, a model is to be learned that maps the cognitive factors to the skill sets and then the skill sets to the career prediction. Both Mappings are learned by modelling the neural networks and establishing a Deep Belief network connecting the networks that provide an overall assessment and prediction model.

Deep Belief Networks are composed of unsupervised networks like Restricted Boltzmann Machines (RBMs). In this, the invisible layer of each sub-network is the visible layer of the next. The neurons in each hidden layer are not connected and are conditionally independent. The probability of a joint configuration network over both visible and hidden layers depends on the joint configuration network's energy compared with the energy of all other joint configuration networks.

The first step is to train a layer of properties to obtain the input signals from a specific model. The next step is to treat the values of this layer as input data and learn the students' skills as features that are considered unsupervised output. The deep belief network with two individual neural networks is sufficient to model the cognitive and predictive networks.

The design of such a model is shown in **Figure 2**. The inputs to the first Neural network are achieved through game playing using "Magic Square," which are nothing but computed scores relating to several cognitive factors. The first neural network learns a model that maps to a skill set, given the scores related to the different cognitive factors, and the second neural network learns a model that maps a set of Skills sets to a set of different Jobs. The output generated by the first neural network is fed as input to the second neural network, which learns to produce predictable careers.

3.2 Creation of a Dataset

Information is collected, and a database is created that has the elements related to academic performance in terms of Registration Number, branch, name, CGPA, type of job being performed, list of skills possessed by the students, Kind of Job being performed by the students, salary drawn and weather the students' performance is acceptable or otherwise. The database is updated for each student with the cognitive scores computed by making the person play the "Magic Square of magic numbers" game.

The quantitative scores updated in the database are converted to Discrete qualitative values using pattern mining carried on the database created through the Example set. The qualitative values are computed based on scores, percentage of the students placed in the range, and stored in the database. The database thus becomes a perfect base for career prediction using game playing and deep belief networks.

3.3 Assessing cognitive levels of the students using Magic Square Game

A magic square is a matrix (n x n) in which each element is a distinct positive integer such that the sum of the elements in each row, column, and diagonal is equal. The sum is called the magic sum of the magic square. A sample magic square is shown in **Table 1** based on a magic sum equal to 15. The sum of numbers counted either horizontally, vertically, or diagonally is the same.

A magic number is defined as an integer number in the range from 1 to 99, which, when inverted by 180 degrees (i.e., tilted up-side-down), still represents a meaningful number. Examples of Magic numbers include (19 -- 61), (18 -- 81), (11-- 11), (88-88) etc. There are a total of 16 magic numbers viz. 11, 16, 18, 19, 61, 66, 68, 69, 81, 86, 88, 89, 91, 96, 98, and 99.

The Magic Square of magic numbers is a Magic square filled with distinct magic numbers where every column sum or row sum is equal to 264, and when the magic Square is inverted up-side-down, every column sum or row sum should be equal to 264. An example of a magic square of magic numbers is shown in **Table 2**, and an inverted version of the same is shown in **Table** 3.

The puzzle Magic square of magic numbers is one of the toughest examples of Artificial Intelligence Constraint Satisfaction Problems (CSP). The student must have sufficient intelligent visibility to recognize the inverted numbers. The Magic square problem imposes the following constraints.

(1) Each element of the magic square should be a distinct magic number.
(2) The sum of any row or column of the magic square should equal a given number, say 264.
(3) When the square is inverted (tilted upside down), still the magic square property should hold good

An expert system is a computer system that simulates the decision-making ability of a human expert. It has a knowledge base, a database, an inference engine, and an interface. Expert systems are designed to solve complex problems.

The process of evaluating the psychological factors of a student plays a crucial role in career(s) prediction. Basing on the suitable career(s) suggested by the expert system, a student may choose their career-related academic courses which will be of use in the future.

The magic square is difficult and differs in many ways from other types of games. The games help to compute the psychological behavior of the students under constraints. Other games do not consider the imposition of the constraints. The magic Square can be generated at different levels that include very easy (level 1), easy (level 2), moderate (level 3), hard (level 4), very hard (level 5). Masking operation is useful to hide some elements in the full solution of a Magic square. The expert system (ES) (component) generates a set of magic squares and masking patterns, and the same is stored in a file system or a database. A magic square and a magic pattern are selected at random, given the game's complexity. Masking operation is performed on the Magic square matrix, and thus, the puzzle with the required level of complexity is generated.

The student can play the game, (which) who fills up the numbers in the Matrix cells and commits the solution, which is then verified to find whether all the (conditions are true.) constraints are satisfied. The student receives a score based on the game's difficulty and whether the conditions are met.

Using the Magic square game, various cognitive factors can be measured, including problem-solving ability, learning ability, the ability to exhibit patience, and perseverance. These are important factors required for some typical jobs related to code development, software testing, and similar jobs.

3.3.1 Computing score - Problem-Solving Ability (PSA)

The Expert System generates Magic square puzzles of increasing complexity depending on the complexity level chosen by the player. These levels are termed as Very easy (Level 1), Easy (Level 2), Moderate (Level 3), Hard (Level 4), and Very hard (Level 5). The student must solve puzzles of all levels. A student can go to the next level if and only if they complete the present level. The PSA score is directly proportional to the total score obtained by the student while solving the puzzle at different levels.

The expert system computes the PSA score using equation 1, where S_i is the score obtained by playing the game at the i^{th} level. A Score is awarded when a student solves the magic (problem) square as per the details provided in Table 3. Increasing scores are awarded to the students as more complex games are played and solved. A student can get a Maximum score of 10 for the PSA factor.

$$PSA = \sum_{i=1}^{5} s_i \qquad (1)$$

From **Table 4**, it can be seen that increasing scores are awarded as the student could solve higher levels of complex problems. At the same time, the lowest complexity problems are awarded a score of 1.0. The students are awarded the highest score when highly complex problems are solved. The magic score has been designed to cover five levels of complexity.

The quantitative PSA scores are converted to discrete qualitative values through querying the database previously created. The quantitative scores are converted to qualitative based on the placement status in terms of "not selected", "Qualified but not selected", "Selected with mid-range salary", and selected with high-range salary. The database is mined based on the selection criteria and selection of the tuples that satisfy a range of values. **Table 5** shows the range of quantitative scores and the related qualitative scores mined from the database.

3.3.2 Assessing Learning Ability (LA)

The level up to which a student can complete indicates the Learning ability of the student. For example, the best student is expected to complete level 5. LA scores (given quantitatively) into qualitative scores using the criteria shown in **Table 6**.

3.3.3 Assessing Patience and Perseverance

A student is supposed to solve two puzzles at each level. The cognitive system assesses patience and perseverance based on the number of puzzles solved at each level. The number of levels completed by the student indicates their patience and perseverance. Since the puzzle's complexity increases with the level number, some weightage is assigned to each level, as shown in **Table 7. Table 8** is used to convert PP scores (given quantitatively) into qualitative scores. Patience and perseverance (PP) are calculated using equation 2.

$$PP = \sum_{i-1}^{5} w_{i * n_i} \qquad (2)$$

where n_i ($0 <= n_i <=2$) is the number of puzzles solved by the student at the i^{th} level and

W_i is the weightage for the i^{th} level, shown in Table 6.

3.4 Predicting Suitable Career(s) based on the Cognitive Values

The database is mined for discrete value patterns, and the Job associated with the cognitive value pattern is selected. Table 9 shows the jobs that match the patterns of cognitive scores.

3.5 Eliminating the noise existing in the database

The association between different academic and cognitive scores has been studied to find any noise in the database. The CSP-SA and CGPA of each student who played the game are shown in **Table 10**.

A graph is drawn by taking the CSP-SA score of each student on the x-axis and the corresponding CGPA on the y-axis, as shown in **Figure-3** shows the relationship between CGPA and PSA score obtained by a set of students no specific relationship can be seen. In some cases, it can be seen that even though CGPA is high, the PSA score is low, which is not expected.

We can observe that the graph in Figure 3 is zig-zag. Generally, we can expect that if a student has a high Academic track record (CGPA), they possess a very high level of intelligence and problem-solving ability. Similarly, if a student has a low CGPA, we can expect a low level of intelligence. Of course, in rare cases, it is also possible that a student may possess high intelligence but maintains a low academic track record. One of the reasons for this anomaly may be that the student does not study well. Such a student is an outlier. Such outliers are recognized and removed so that academic performance and cognitive performances are consistent. Figure 2 shows the relationship between the CGPA and PSA form, which can be seen as a linear relationship. The relationship between the CGPA and other cognitive factors is studied similarly, and the outliers are removed. **Figure 4** shows the Behaviour of PSA concerning CGPA after removing the outliers.

3.6 Learning Deep belief networks

3.6.1 Overview on Deep Belief Networks

From the above discussion, we have seen that the issue of skills has not been considered. Skills possessed by a person have a direct bearing on a career that they can pursue. The extent of skills possessed by the students is dependent on cognitive levels possessed by the students. The problem is thus a two-stage problem that deals with the Mapping between cognitive factors and skills and between the skills and the jobs. The use of a deep belief network is the clear case to solve the problem.

A deep belief network (DBN) is a sophisticated generative neural network that uses a machine learning model to produce results. Deep belief networks are a set of restricted Boltzmann machines (RBMs) stacked on one another. In general, deep belief networks are composed of various smaller unsupervised neural networks. One of the common features of a deep belief network is that although layers have connections between them, it does not include connections between units in a single layer.

Stacked RBMs provide a system that can be trained in a "greedy" manner and extract a deep hierarchical representation of training data.". Unsupervised machine learning model shows less structured, more rugged systems where there is not as much data labelling and the technology has to assemble results based on random inputs and iterative processes.

Deep Belief Networks are a graphical representation that is essentially generative, i.e., it produces all possible values generated for the case at hand. It amalgamates probability and statistics with machine learning and neural networks. Deep Belief Networks consist of multiple layers with values; wherein there is a relation between the layers but not the values. The main aim is to help the system classify the data into different categories.

Deep Belief Networks are composed of unsupervised networks like RBMs. In this, the invisible layer of each sub-network is the visible layer of the next. The hidden or invisible layers are not connected and are conditionally independent. The probability of a joint configuration network over both visible and hidden layers depends on the joint configuration network's energy compared with the energy of all other joint configuration networks.

The first step is to train a layer of properties that can directly obtain the input signals from the pixels. The next step is to treat the values of this layer as pixels and learn the features of the previously obtained features in a second hidden layer. Every time another layer of properties or features is added to the belief network, there will be an improvement in the lower bound on the log probability of the training data set.

A typical representation of a deep belief network is shown in Figure 5. It can be seen from the figures that different hypotheses are tested using different networks with outputs passed as inputs to the next layer.

3.6.2 Mathematical formulation – Deep belief networks

- Let v_i and h_j represent the states of visible node and hidden node, respectively. For binary state nodes, that is, vi and hj € {0,1}
- The state is set to 1 with probabilities.

$$ph_j = p(h_j = 1 \mid v) = \sigma(b_j + \sum_i w_{ij} v_i \quad (3)$$

- Where σ(x) is the logistic sigmoid function?

$$1/(1 + \exp(-x)), b_j \quad (4)$$

Which Is the bias of h_i, v_i are the binary state. W_{ij} is the weight between the networks. After binary states have been chosen for the hidden units, set the state of v_i to be 1 with probability. Where v_i is the visible node and h_j is the hidden node.

$$p_{vi} = p(v_i = 1 \mid h) = \sigma(b_i + \sum_i w_{ij} h_j \quad (5)$$

The regular deep belief network is modified by incorporating RBM (Restricted Boltzmann networks for undertaking stage processing. The stochastic binary units in belief networks have a state 0 or 1, and the probability of becoming 1 is determined by a bias and weighted input from other units. The probability equation can be represented as

$$P(s_j = 1) = {}^{1}/_{1 + \exp(-S_j W_{JI}} \quad (6)$$

The Boltzmann machine is a stochastic recurrent neural network with stochastic binary units and undirected edges between units. Mainly there are two layers those are visible layer and the hidden layer. Probability distributions over hidden and visible units are defined in terms of the energy function as shown in equation (7):

$$P(v, h) = {}^{1}/_{Z} \exp(-E(v, h)) \quad (7)$$

$$\text{where}, Z = \sum_{vh} \exp(-E(v, h)) \quad (8)$$

3.6.3 Algorithm for learning RBM

X is a sample drawn from the example database discussed above, containing the discrete values representing the cognitive factors.
e = learning rates
w = weight matrix of size [Number of Inputs * Number of hidden units]
b= bios vector for hidden units
c= bios vector for Input units

RBM (x, e, w, b, c)
{
for all hidden units i
{
Compute

$$Q(h[0][i] = {}^{1}/_{(1 + \exp(x[0]))} \quad (9)$$

for all Gaussian Units
{
Compute

$$\text{Sigmoid}[b[i] + (w[i][j] * x[0][j])) \quad (10)$$

$$\text{Sample } h[0][j] \text{ from } Q(h[0][i] = {}^{1}/_{(1 + \exp(x[0]))} \quad (11)$$

}
}

For all Visible Units j
{
compute

$$p(v[1][j] = {}^{1}/_{\exp[0]})) \quad (12)$$

compute

$$\text{sigmoid } [c(j) + \text{sum}(w[i][l] * h[0][j]))) \quad (13)$$

$$\text{sample } v[1][j]] \text{ from } P(v[1][j] = {}^{1}/_{(1 + \exp(h[0]))} \quad (14)$$

}

For all hidden Units i

{

compute

$Q(h[1][i] = {}^{1}/_{(1 + \exp\ h[1]}$ (15)

Compute

$\text{sigmoid}\ [b(i) + \text{sum}_j\ (w[i][j] * x[1][j]))) $ (16)

}

$W += e * (h[0] * x[0\}^T - Q(h[1][0] = {}^{1}/_{v[1] * x[1]^T}$ (17)

$b += e * (h[0] * Q[0]^T - Q(h[1][0] = {}^{1}/_{x[1]}$ (18)

$c += e * (x[0] - x[1])$ (19)

}

3.6.4 Algorithm to learn DBN

The V values are the expected careers which are code as a numerical value. The output values after having generated are dedicated back to find suitable careers. Similarly, the Visible vector is derived out of the possible skills possessed by the student, which are available in the example set

Z =	Supervised training distribution for the DBN
(x, y) =	sample (input, target),
C=	Training Criteria, which is a function that takes f(x) as network output, and y as target output and returns a differential in f(x)
Epsilon-C=	Learning Rate for stochastic gradient descent on supervised cost C
L=	number of layers = 2
n=	n(1), n(2) ….. n(L) number of hidden units in each of the layer
W(i)=	Weight Matrix for layer i
b(i)=	bios vector for layer i
v=	weight matrix for the supervised output layer of the network
c=	Bios vector of the output layer

DBN (Z, C, epsilon_C, L, n, W, b, V, c)

{

// recursively define mean-field deviation

$\text{mu}[i](x) = \text{Expectation}\ (g[i] * [g(i-1] = \text{mu}[i-1](x))$ (20)

// where mu[o]=x and Expectation (g[i] * [g(i-1)] = mu[i-1](x)) is the expected value of g(i) under RBN conditional distribution Q(g[i] * g[i-1]

// when the values of g[i-1] are replaced by mean filed value mu[i-1](x) and when g[i] are gaussian then

$\text{Expectation}\ \left(g[i] * [g(i-1)] = \text{mu}[i-1](x)\right) =$ (21)

$\text{sigmoid}\ (b[i][j] + \text{sum}_k w[i][j][k] * \text{mu}[i-1][k](x)$

Define the work output function

$f(x) = V * \text{mul}\ [L](x) + c$ (22)

Iteratively minimize the expected value C(f(x), y) for pairs (x,y), sampled from Z, by tuning the parameters W, b, V, C using specific stopping criteria on the training set

}

4.0 Results and Discussion

Career prediction thus can be done in two ways which include careers predicted diretclt based on cognitive factors through a Cognitive model and an expert system**.** 100 Test records have been selected and subjected to the above models, and the Accuracy estimation has been carried. **Table 11** shows the results obtained after completing the testing**.**

TP(Positives) are the records that match the predicted career, and the actual career is the same. TN(True negative) are the records that show not selected status are predicated as not selected. FP(False positive) selected records are predicated as not selected, and FN(false negative) selected records are predicted as not selected. The accuracy of such a model is estimated to be 94% **((TP+TN) / (TP+FP+FN+TN) = 0.94)**

The second way of predicting suitable careers is through Deep belief netwrks which predicts the skills in the first place and then the careers in the 2nd stage. The previously used 100 Test records have been selected and subjected to the above models, and the Accuracy estimation has been carried. **Table 12** shows the results obtained after completing the testing**.**

The accuracy of such a model is estimated to be 99% ((TP+TN) / (TP+FP+FN+TN) = 0.94)

Accuracy of prediction increased to 98% percent from 94% which is the maximum accuracy achievable by any type of Game based model

5. CONCLUSIONS

Even though some conventional tests like Aptitude and reasoning tests, IQ tests, etc., are used popularly to assess some of the psychological factors of a student, a clever way is to assess the psychological factors of the student. In contrast, the student plays games or solves puzzles because games or puzzles are much more interesting for every student than appearing for the routine type of tests.

Constraints imposed by Games will help in assessing the psychological behavior of the students in tested conditions. Magic square-based assessment helps in assessing the psychological behavior of the students in tested conditions.

An expert system helps assess a student's psychological factors using the Magic Square of Magic Numbers puzzle. It builds the cognitive model of the student and predicts the most suitable careers for the student. Such a system predicts suitable careers to the extent of 94%. The less accurate prediction is because the skills are not considered, which will have a greater impact on the placement.

Deep belief networks support multi-stage processing. In this paper, a two-stage model is learned to learn Skills from cognitive factors and the careers from skills in the second stage. The percentage of accuracy of prediction increased to 99% by using deep belief networks.

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Tables

Table 1 Magic square based on a magic sum of 15.

8	**1**	**6**
3	**5**	**7**
4	**9**	**2**

Table 2. Magic (squares) square of Magic (number) numbers

11	96	89	68
98	19	66	81
86	61	18	99
69	88	91	16

Table 3. Magic Square of Magic Numbers (Inversed) inverted version

91	16	88	69
66	81	19	98
18	99	61	86
89	68	96	11

Table 4. Problem-solving scores – Level of the problem solved.

S.No.	Score (Si)	Level of the game
1	1.0	Very easy
2	1.5	Easy
3	2.0	Moderate
4	2.5	Hard
5	3.0	Very hard
Total	10.0	

Table 5. CSP-SA-Quantitative to Qualitative conversion table

S.No	CSP-SA			
	Quantitative Score (max. 10)	Qualitative Score	Discrete value	Placement Status
1	<3	Low	1	Not selected
2	>=3 && <=5	Moderate	2	Qualified but not selected
3	>5 && <=7	Good	3	Selected with mid-range salary
4	>7	Very Good	4	Selected with high range salary

Table 6. Learning Ability- Quantitative to Qualitative conversion table

S.No.	LA Score	Qualitative Score	Discrete value	Placement Status
1	>=0 && <=2	Low	1	Not selected
2	3	Moderate	2	Qualified but not selected.
3	4	Good	3	Selected with mid-range salary.
4	5	Very Good	4	Selected with high range salary

Table 7. Level wise weightage Factors

Level No.	weightage Factor (w_i)
1	0.5
2	1.0
3	1.5
4	2.0
5	2.5

Table 8. The Patience and Perseverance (PP)- Quantitative to Qualitative conversion table

S.No.	PP Score	Qualitative Score	Discrete value	Placement Status
1	>=0 && <=5	Low	1	Not selected
2	>5 && <=10	Moderate	2	Qualified but not selected.

3	>10 && <=15	Good	3	Selected with mid-range salary.
4	>15	Very Good	4	Selected with high range salary

Table 9. Job Table with minimum levels of CGPA and psychological factors

S. No.	Job title	Minimum CGPA	Discrete Cognitive values		
			Minimum Problem-Solving Ability	Minimum Learning Ability	Minimum Patience and Perseverance
1	Software Developer	8.0	5	5	5
2	Software Testing	7.5	4	4	4
3	Programmer Analyst	7.0	4	3	5
4	Marketing	6.0	3	4	5

Table 10. Student's PSA and CGPA

S.No.	Student-ID	PSA Score	CGPA
1	30735	1.0	7.07
2	30456	2.5	7.20
3	30752	7/0	7.80
4	30021	2.5	8.20
5	30870	2.5	8.30
6	30651	7/0	8.90
7	31133	4.5	8.90
8	30040	7.0	9.27
9	30095	7.0	9.30
10	30673	10.0	9.54
11	31531	10.0	9.70

Table 11. Accuracy Estimation

Serial Number	Type of results	Description of the type	Count of the Type
1	TP	True Positives	92
2	TN	True Negatives	2
3	FP	False positives	3
4	FN	False Negatives	3
Total			100

Table 12. Accuracy Estimation

Serial Number	Type of results	Description of the type	Count of the Type
1	TP	True Positives	98
2	TN	True Negatives	1
3	FP	False positives	1
4	FN	False Negatives	0
Total			100

Figuers

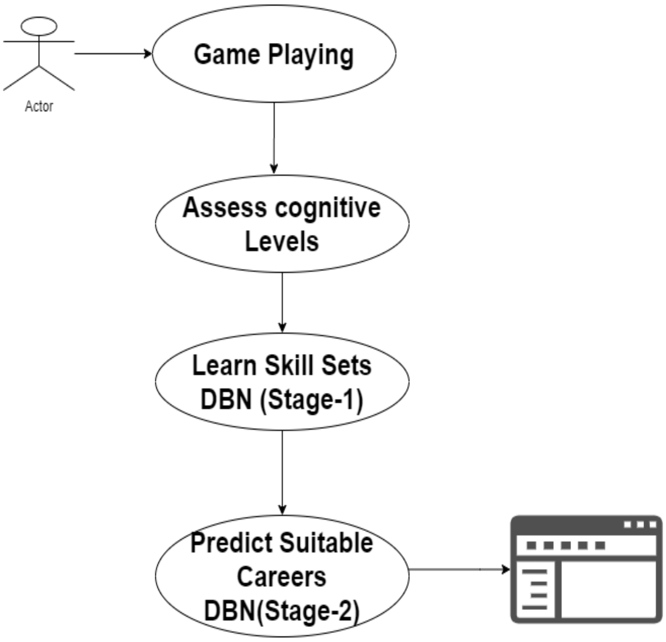

Figure 1. Multi-Stage Processing for job prediction through Deep Belief networks

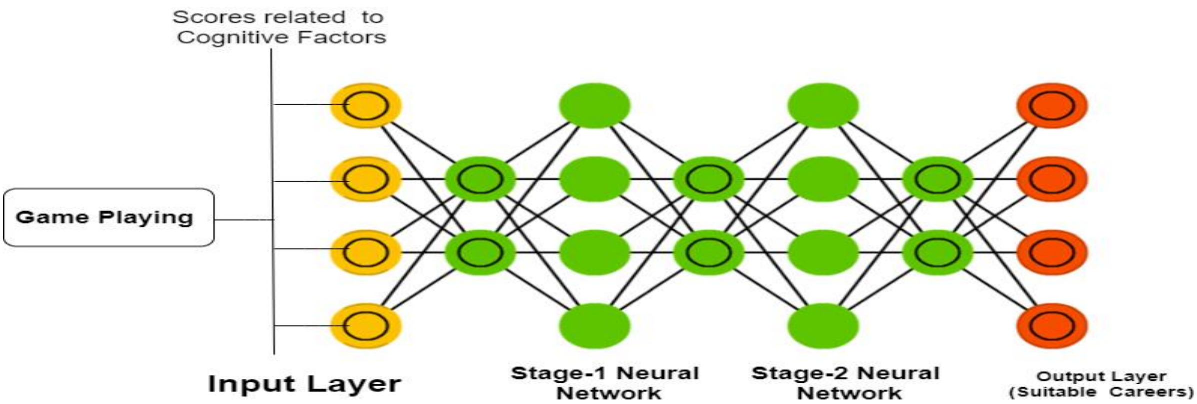

Figure 2. Example A two-stage Deep belief Network

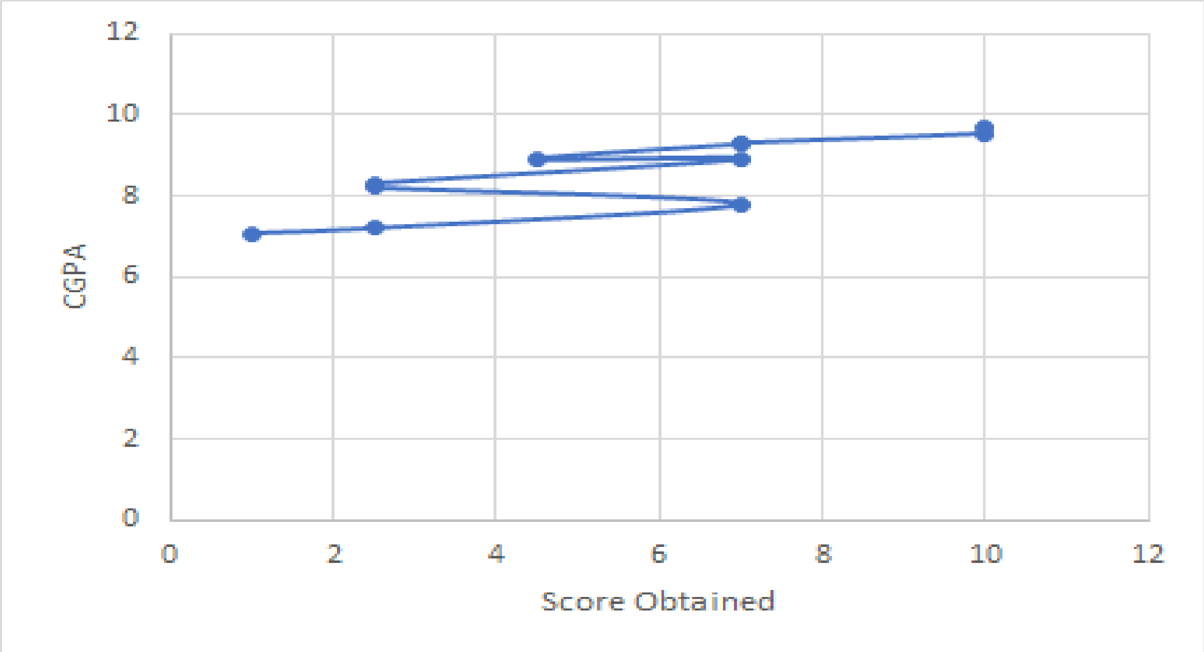

Figure 3. PSA Vs. CGPA

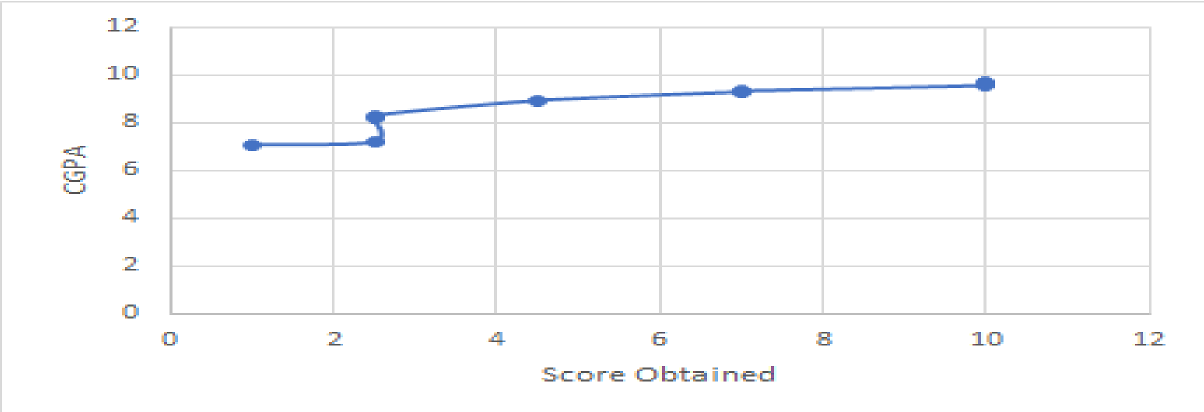

Figure 4. CGPA Vs. PSA after removal of outliers

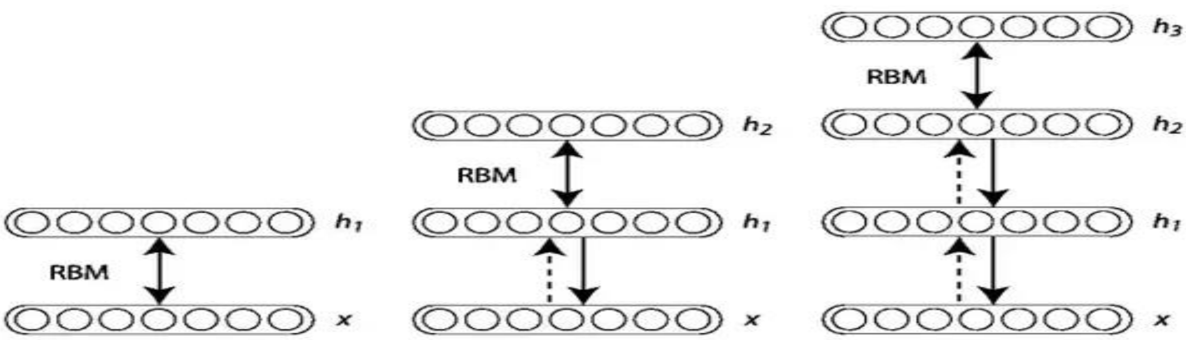

Figure 5 Representing deep belief networks.