IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-3, March 2019 E-ISSN: 2347-2693

Analyzing Cognitive Factor to Enhance Student Performance using Deep Learning Technique

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DOI: https://doi.org/10.26438/ijcse/v7i3.156160 | Available online at: www.ijcseonline.org

Accepted: 06/Mar/2019, Published: 31/Mar/2019

Abstract- Cognitive skills (CS) are the basic processing functions that enable to learn. These include attention, memory, auditory processing, visual processing, logic, and reasoning ability. It play a vital role in performance of any individual. Performance of students can be predicted by knowing the level of cognitive skill. The proposed method consists of three stages quantization, simulation and prediction. Finally, we analyzed the simulated data using deep learning algorithms. The learning algorithm Convolutional Neural Network (CNN) is used for our study. The proposed method is tested on the students' performance data sets in UCI repository. The results shows that CNN achieve higher accuracy than other the traditional approach.

***Keywords* –** Cognitive skills, Study related characteristics, quantization, Deep learning algorithms, Convolutional Neural Network.

I. INTRODUCTION

Cognitive skills is referred to as human ability to process, learn new things, or perform something intelligently. These are the mental capabilities that our students need in order to successfully learn. In order for our students to effectively read, write, think, analyze, understand, remember, and solve problems, all of these cognitive stills must come together and be able to function properly. When these skills are weak, then that is when we see our students begin to struggle. Some of most important cognitive skills are follows:

- ***Concentration:*** It is a cognitive skill that has to be taught. If someone is weak in this area, then it can impact a lot of other cognitive areas. Watch for a student's inability to stay on task for a long period of time. This is called sustained attention. Teach students how to have selective attention, where they learn to ignore distractions and stay on task.

- ***Memory:*** If information cannot be retained long enough to remember it, then learning will suffer. Students have both a working memory and a long-term memory. Their working memory allows them to retain information for short periods of time, while their long-term memory allows them to store and recall information later.

-***Processing Speed:*** The rate at which a student can process information or the time it takes them to complete a mental task is called their processing speed. In other words, it's the time between receiving information and responding to it. If a student's processing speed is slow, then the information that they have in their working memory will be lost.

- ***Logic:*** A student's ability to plan, prioritize, problem-solve, and comprehend would falter if they don't have the cognitive skills of logic and reasoning.

-***Auditory Perception:*** The ability to perceive and understand what you hear is another essential cognitive skill. In order for students to be able to read and even spell words, they have to be able to hear the difference in sounds. Students need to be able to blend sounds, separate sounds, and analyze sounds in order to read words.

- ***Visual Processing*:** The ability to think and retain information in visual images is another cognitive skill that all students need to have. In order for it to be possible to retain visual information, it requires students to remember and understand the information.

Cognitive development is one of the most essential aspects of growth in a student. It encompasses both mental and emotional growth. There are many factors that determine the progress of cognitive development. They are biological and environmental factor

Biological factors

The following are some of the main biological factors that affect both children and adults:

- ***Hereditary aspects***. Genetics play a major role in cognitive development. Children actually inherit their intelligence from their parents.

- ***Nutritional factors***. According to research, women who do not consume enough amounts of protein during their pregnancies ruin their children's chances of cognitive development.

-***Sensory organs***. Sensory organs enable children to recognize things and people around them more easily.

Environmental factors
Environmental factors are the external influences that affect cognitive development. These are mostly controllable. They include:

- ***Economic factors***. The children from well off families often have access to more learning opportunities. Their parents also have more time to teach them and interact with them hence stimulating cognitive development and growth.

-***External stimuli***. External stimuli such as books and learning toys are important in developing cognitive abilities.

-***Family and society***. Children who interact frequently with other people tend to become brighter and gain confidence as compared to those who relate with less people.

-***Play***. Playing with other children can also build social confidence which improves cognitive abilities.
Cognition is define as a process in which inputs collected by different input methods are processed, transformed, consumed, and stored. According to scientific definition, cognition is a mental process that uses working memory and inferring capabilities for speaking, reasoning, problem solving and other decision making activities. In psychology, the term cognition is referred as individual psychological function to process information. In social psychology cognition is termed as a branch to explain the group dynamics, behavior and attitude. In cognitive engineering, says that, it is a process of brain or mind used to process information that can be both natural and unnatural, doing consciously or unconsciously.

Cognitive abilities that are the combination of different brain processes [1] are analyzed differently in diverse fields. Cognitive ability is affected by the emotions such as happiness, sadness, anger, fear, disgust, surprise as well as stress. Intensity of emotions has a great impact on the behavior, attention and decision making of a human being [2]. The relationship between human and its environment is understand, then we can determine the intensity of emotion of that specific person. Emotions have a great impact on cognitive skills because performance of a person not only depends upon cognitive skills but also depends on different human emotions and motivations [3].

Cognitive Skills (CS) prediction is necessary to track the time-varying knowledge state of a student. This can be useful to identify the weaknesses of students in their performance and help them in recovering these deficiencies. The prediction of the student's CS depends on different factors, such as study schedule, family-related characteristics, and problems due to frustration [4]. Many survey has conducted relating cognitive skill with students' characteristics [5]. There are several methods to predict students' CS using grades and study-related information of the students [6].

Recent methods provided significant contributions in predicting student's cognitive skill, however, they are insufficient for the measurement of CS in different circumstances. To accurately modulate student's CS, we use quantization, modulation, and simulation of study characteristics. It consists age, study time, travel time, outing time, free time, family relationships, alcohol consumption and health. Our proposed work includes (1) quantization of study characteristics and cognitive skills of the student, (2) design a model and (3) simulation of the nonlinear relationship between CS and study characteristics. Finally deep learning technique, Convolutional Neural Network is applied to the simulated data. Therefore, the method can predict CS of the students.

In our proposed method during quantization study characteristics is divided into eight factors, and specific ranges are assigned to these factors. The CS is split into 21 intervals. These method increases the accuracy and preciseness of the student's skills prediction. After simulation the value is trained and tested using deep learning technique i.e., Convolutional Neural Network for more accurate prediction of CS. In particular, deep learning techniques provide new means for performing student modeling. There are two extraordinary advantages of the deep learning-based student models over the traditional cognitive science based student models.

First, the construction of the new type of models does not base itself on the assumption that human learning can be modeled regardless of extent. Deep learning based methods are agnostic with regard to this assumption [7]. They are simply using any reasonable machine learning techniques to understand student properties of interest.

Second, the range of objects being modeled is enriched by the use of the learning based student models. The student models based on cognitive science therefore focus on student knowledge. For the sake of deep learning techniques, it becomes possible that a variety of constructs could be well modeled, such as student performance, student affect, student robust learning, etc.

With regard to the two commonly used roles for a student model: (1) Predictive: to help determine the student's likely response to tutorial actions; (2) Evaluative: to help assess the student, deep learning-based student models can fulfill the roles naturally.

Moreover, section II presents the related work. Methodology is explained in section III while the result and discussed in section IV. The paper is concluded in section V.

II. RELATED WORK

An important goal of cognitive science is to understand human cognition. Good models of cognition can be predictive — describing how people are likely to react in different scenarios — as well as prescriptive — describing limitations in cognition and potentially ways in which the limitations might be overcome. In a sense, the benefits of having cognitive models are similar to the benefits individuals accrue in building their own internal model.

Cognitive science-based student models were introduced, developed and thrived in the 1980s and 1990s. The big assumption of adapting cognitive science in student modeling is that how humans learn can be modeled as a computational process. Therefore, traditional ways to construct student models require a significant amount of time and human labor. The common techniques include structured interviews and think-aloud protocols. Despite high construction costs, these student models are inevitably subjective. Previous studies have shown that human engineering of these models often ignores distinctions in content and learning that have important instructional implications [8].
Two common techniques are model-tracing (MT) and the constraint-based modeling (CBM). The development of model tracing is grounded in cognitive psychology based on the ACT-R (Adaptive Control of Thought – Rational) cognitive theory. The belief is that human learning processes can be modeled by some form of structures describing how a task is procedurally accomplished. The technique is closely related to domain modeling and expert systems. In the model tracing framework, student actions are atomized as encoded topics, steps and rules forming to the path through the problem space [9]. The student model uses these rules or steps to represent student knowledge. By tracing student execution of these rules, the model reasons about student knowledge, infers whether they followed the path and diagnoses the reason why an error or divergence occurs.

Xu *et al*. [10] focused on multiple base predictors and matrix factorization approach to predict students' skills for the qualification of degree requirements. They have faced three challenges such as; (1) dissimilarity in student background, (2) the selected courses, (3) the progress information of the student. Method mainly focused on evolving states of student's performance and course relevance. The main drawback is that, the method fails to achieve accurate quantization. Different machine learning technique as Naive Bayes, decision tree, and the regression analysis were used, but this method is not able to predict student's performance on the basis of quantization and simulation. Student's characteristics were not split into different layers as well as modeling [11].

Iqbal *et al*. [12] collected data in information technology university Lahore. Compared the collaborative filtering matrix factorization and restricted Boltzmann machine to predict the skills of the students that based on their grades. Student's performance is dependent on their study-related schedules. So, this method has limitations for the prediction based on Study related characteristics. A method for the childhood development is proposed. It has limitations during evaluation of the study-related, and family-related characteristics [13].

Ohye et al. [14] focused on three generation family structure to address the challenges and problems in a family system. Health care model developed at the Veteran and Family Clinic of the Home Base Program, a partnership between the Red Sox Foundation and Massachusetts General Hospital designed to improve treatment engagement of veterans with posttraumatic stress disorder (PTSD) and related conditions, and to provide care to the entire military-connected family. Fosco *et al.* [15] also concentrated on the family-related issues that are addressed by family checkup. Therefore, the most significant attribute of SRC is the family relationship of a student. Thus, the primary need is to select the correct family and study related characteristics of the students and then correctly quantize it to modulate the relationship between CS and SRC This study was conducted with 2 overarching goals: (a) replicate previous work that has implicated the Family Check-Up (FCU), a multilevel, gated intervention model embedded in public middle schools, as an effective strategy for preventing growth in adolescent depressive symptoms and (b) test whether changes in family conflict may be an explanatory mechanism for the long-term, protective effects of the FCU with respect to adolescent depression.

Livieris *et al*. [16] implemented a user-friendly software tool in student's CS prediction. The tool uses a neural network classifier to predict the performance of a student in a mathematics course of the first year of Lyceum. In student's CS measurement circumstances (during cognitive tasks), focusing only on tools can compromise the novelty of the method because an accurate and precise prediction system need proper quantization and modulation of the problem. RNN, NN, and Bayesian Inference, etc. can be used in different node. The tool was tested by a small number of teachers who were enthusiastic with its predictions as they felt they were close to their own based on their extensive teaching experience.

In another experiment Dorner and Gerdes [17] developed a model about motivation, emotion and intelligence/ cognitive functions. The author tried to show that the efficiency or performance of someone is not only depending on cognitive function but it also dependent one emotion and motivation. The author showed through experiment that there is an interaction between emotion, motivation and cognitive function. As it is a known fact that lack of motivation brings the performance considerably down so, in this research relation among emotion, cognition and motivation is investigated through experiments. The result of the paper showed that cognitive processes can be affected by the environment and can be increased through proper motivation. This paper gives us a good research direction and motivation to find association among emotions and cognitive skills.

III. PROPOSED WORK

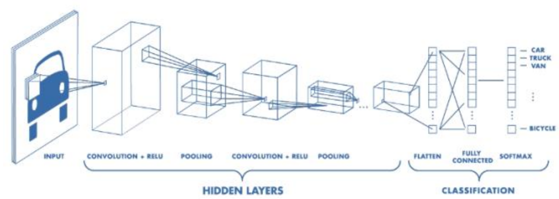
In our proposed method uses Convolutional neural network for predicting students performance though cognitive skill.

Convolutional Neural Network

A CNN, in specific, has one or more layers of ***convolution*** units. A convolution unit receives its input from multiple units from the previous layer which together create a proximity. Therefore, the input units (that form a small neighborhood) share their weights.

The convolution units (as well as pooling units) are especially beneficial as:

- They reduce the number of units in the network (since they are *many-to-one mappings*). This means, there are fewer parameters to learn which reduces the chance of overfitting as the model would be less complex than a fully connected network.
- They consider the context/shared information in the small neighborhoods. This future is very important in many applications such as image, video, text, and speech processing/mining as the neighboring inputs (eg pixels, frames, words, etc) usually carry related information.
  - A CNN accepts arrays of pixel values as input to the network. The hidden layer consists of several different layers which carry out feature extraction. There is a fully connected layer that recognizes the objects in the image.
  - Convolution operation forms the core of every convolution neural network. There are 4 layers in a CNN. These are Convolution layer, ReLU layer, Pooling layer and Fully Connected Layer.
  - The Convolution layer uses a filter matrix over the array of image pixels and performs convolution operation to obtain a convolved feature map. Below is an example which represents the convolution operation over the input array.



IV. EXPERIMENTAL RESULTS

Performance Evaluation:

A confusion matrix was generated after running the current data set on Single Layer Perceptron using WEKA tool [18]. All measures can be calculated based on four values, namely True Positive (TP, a number of correctly classified that an instances positive), False Positive (FP, a number of incorrectly classified that an instance is positive), False Negative (FN, a number of incorrectly classified that an instance is negative) and True Negative (TN, a number of correctly classified that an instance is negative).

Table 1 Performance Measure

Classi fier	Accuracy	Sensitivity	Specificity
SVM	78.76%	68.17%	83.97%.
ANN	85. 78	86.31%	88.16%
CNN	97.54%	96.33%	98.12%

For training and testing the CNN, 10-fold cross validation method is used to subset the data. The data is randomly divided into 10 parts of which one part is used for testing while the remaining parts are used as the training data. The CNN algorithm is applied for training the neural network. These values are defined in Table1.

Table 2. Confusion Matrix

		Observed	
		True	***False***
Predicted	***True***	True Positive (TP)	False Positive (FP)
	False	False Negative (FN)	True Negative (TN)

From the values of Table1 sensitivity, specificity and accuracy are calculated.

Sensitivity = TP / (TP + FN) (1)

Specificity = TP / (TP + FP) (2)

Correctly classified instances are known as sensitivity and incorrectly classified instances are known as specificity and can be calculated using Eq. 1 and Eq. 2 described above.

Accuracy is defined as the overall success rate of the classifier and computed by Eq. 3

Accuracy = (TP + TN) / (TP + FP + FN + TN) (3)

The classifiers experimental results are shown in Table2.

V. CONCLUSION AND FUTURE WORK

In the current study, we presented a cognitive Skills (CS) measurement method that depends on the quantization of student's study characteristics. The contributions of the proposed approach are threefold. The results show that the proposed multilayer CS measurement method achieved 97.54% accuracy. Future, different machine leaning technique can be applied to find more accuracy.

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