IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received May 1, 2020, accepted May 19, 2020, date of publication June 1, 2020, date of current version June 12, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2999064

Deep Network for the Iterative Estimations of Students' Cognitive Skills

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ABSTRACT The effective educational systems aimed at improving Cognitive Skills (CS) both in and out of institutions. Such system relies on timely prediction of CS during students' activities in intuitions. Meanwhile, literature is saturated with the number of approaches which have used study schedules, biological and environmental factors to predict CS. However, the loopholes in prior studies have become the main source of inspiration for the current attempt. In this study, we propose a Bayesian Neural Network which predicts CS by iterative manipulations of CS under the profound influence of Student's Basic Attributes. Initially, the study classifies the Basic Attributes into three factors (1.age group, 2. gender, and 3. parent's cohabitation status) which have multiple layers. Furthermore, the technique splits the range of CS into 20 periodic outcome variables (with a period of 0.5). Eventually, the network iteratively estimates each outcome of CS by feed-forward process through Basic Attributes layers. We have reviewed the performance of the proposed network by using a students' score dataset. The results have illustrated that the current technique obtained significant prediction accuracy in terms of accuracy measures.

INDEX TERMS Prediction of students' cognitive skills, prediction algorithm, Bayesian neural network, students' cognitive skills.

I. INTRODUCTION

Timely predictions of students' Cognitive Skills (CS) are the dire needs of better educational services [1]. A student must have excellent CS value to achieve outstanding performance in cognitive activities (such as quizzes, midterm, and final year examination) [2], [3]. Students' CS is the capacity to perform cognitive processes, such as reasoning, problem solving, understanding, and remembering [4], [5]. This shows that CS is the ability to accomplish any task that requires reasoning, memory, and problem solving techniques. On the other hand, with weak CS, students cannot achieve good learning, memorizing, and understanding skills to perform cognitive tasks, i.e., good score in quiz, midterm and final year examination. These tasks require a student to mentally process new information (use CS), organize knowledge and allow them to retrieve that information (from memory) for later use [6], [7].

To develop a system which can achieve timely prediction of students' CS is quite challenging because the expected CS are profoundly influenced by distinct attributes, i.e., parent's cohabitation status, socio-economic status, age group, and gender description (male or female) which are referred to as Student's Basic Attributes (SBA) [8]–[10]. SBA offer potential impact for CS which evolve students' performance during the aforementioned cognitive tasks [11]–[14]. Also, featured articles are saturated with the number of findings which have statistically correlated CS with SBA [15]–[19]. Thus, a system with the ability to detect the expected CS can provide many salient features for the career of weak and distinguished candidates, e.g., parents can examine the study schedule, a psychologist can give tips to decrease the frustration, and the individual can put under the proper concentration of a tutor.

The associate editor coordinating the review of this manuscript and approving it for publication was Yudong Zhang.

The recent methods simultaneously addressed the prediction of CS by analyzing study-schedules and Basic Human Factors [20], [21]. These methods used Gauss-Newton-Algorithm, Least Square Method, as well as Matrix Factorization Technique. Gauss-Newton-Algorithm and Least Square Method focused on mathematical modulation of the relationship between CS and students' attributes while fitting mathematical equations for prediction of CS. In [22], Ali Daud *et al.* have presented a new method for the measurement of student's achievement. The loopholes of the prior methods (such as lack of in-depth quantization of CS and SBA as well as iterative estimation of CS under the influence of SBA) pave the way for some new challenges in the area of CS prediction.

We design a Bayesian Neural Network which predicts the CS under the substantial impact of Students' Basic Attributes. First, we initiate a three-factored architecture by quantizing the factors of Students' Basic Attributes. Also, these factors are classified into multiple layers to increase the transparency of the current method, i.e. (1) age group = 15 to 20, (2) sex = girl or boy, and (3) parent's cohabitation status = Together or Apart. The age group consists of six layers while each of the other two factors (gender description and parent's cohabitation status) comprised of two layers. Second, to discover the depth of the CS, we classify it into 20 outcome variables ($0 \leq CS \leq 10$, with a period of 0.5) which is referred to as component-wise quantization of CS [23]. CS is decomposed into many pieces, which are usually known as knowledge component [24], [25]; therefore, splitting CS range into multiple intervals facilitate the proposed system to detect the robustness of the CS.

Third, the technique iteratively computes the posterior probabilities of CS outcome variables under the intense influence of Students' Basic Attributes layers. Eventually, the Network determines the outcome variable of CS with the highest posterior probability. During the validation process, we have used students' score dataset to evaluate the performance of the proposed Network. The acquired observations have shown that it has achieved significant accuracy in terms of state-of-the-art measures.

Thus, we have presented a simple network to address the challenges of CS prediction with in-depth quantization of Students' Basic Attributes that contrasts for two reasons from the approaches mentioned above; 1) it has multiple layers that iteratively estimate CS under the profound influence of Students' Basic Attributes, 2) its prediction performance will be automatically enhanced with the addition of more datasets to the training section (without altering the architecture of the method).

The rest of the study is arranged as follows. Section 2 presents literature studies of students' performance measurement approaches. Section 3 discusses the method of cognitive skills prediction process. Section 4 shows method validation while Section 5 presents the discussion of the study. Finally, Section 6 and 7 concluded the current article.

II. PREDICTION OF COGNITIVE SKILLS VIA STUDENTS PERFORMANCE

Outstanding students' performances are only possible with excellent students' CS value. CS is the capacity to perform reasoning, provide solution of a critical problem, understanding, as well as remembering. This work focuses on prediction of CS in terms of students' performance prediction, i.e., individual score. We are partially inspired by those literature findings of psychology, neuroscience and cognitive science which have statistically linked student's performance with study schedules and student's biological factors [23]. Also, literature is saturated with the number of CS prediction approaches that focused on the computation of an individual's performance during cognitive tasks. For instance, in [26], Ahmad *et al.* have presented an interesting technique to discover the CS of students during the aforementioned critical cognitive circumstances. The technique has used the significant contributions of literature for the collection of prior probability of CS outcome. Nevertheless, it has loopholes due to the static mathematical model for the prediction of student's performance because they only focused few variables while ignoring the iterative calculation of CS based on posterior probability. Additionally, the primary limitations for the development of an effective method for CS prediction are depicted in [27]. This study has efficiently analyzed various state of the art prediction models.

The featured studies provided significant contributions in the form of cognitive skills modulation systems. In [28], the authors have predicted student's performance while using analytical approach to predict the CS of students. These approaches are not adequate to solve the aforementioned challenges because we are in dire need of explicit quantization and classification of SBA for the accurate prediction of CS. The primary challenge is to accurately quantize SBA and students' score for iterative calculation of students' CS. Moreover, state-of-the-art method presents decision tree algorithm for an in-depth investigation of students' performance during cognitive tasks [29]. Such studies depict that the student's cognitive outcome relies on different factors which need to properly investigated and quantized. Also, they have compared four decision tree algorithms J48, NBtree, Peptree which shows that the J48 has outperformed NBtree as well as Peptree. This study has mainly focused using state of the art prediction methods while particularly ignoring the accurate quantization and modulation of the SBA factors. Therefore, the effective educational system is in dire need of two major contributions, i.e., 1. Accurate quantization of SBA and CS, and 2. Iteratively estimation of CS under the profound influence of SBA layers. Furthermore, we have found an existing technique which has used five academics courses and a dataset while applying six distinct classification algorithms. However, they employed resampling and feature selection techniques to address the issues created by the small size of datasets. Various human factors, directly or indirectly linked with CS as discussed earlier; therefore, to cope with

the dynamic nature of the students' performance, there is a demand for the generalized prediction model. AddFitionally, literature are saturated with enormous research findings which have focused quality improvement of education [30]–[32]. Also, a study has shown that the quality improvement technique has efficiently improved the prediction accuracy of the model [33].

However, it is insufficient to address the challenges introduced by the proposed study. Also, it has a lack of technical consideration (accurate quantization) of the SBA layered approach toward the simulation of students' CS. While selecting the umbrella of SBA layers, the proposed study iteratively manipulated students' performance under the influence of SBA layers. It gives iterative procedure to detect students' performance in final examination. It can help us to detect at-risk students. Also, in [34], Štefan Pero et al compared different Collaborative-filtering techniques to predict students' performance. They have mainly focused to investigate the usability of Collaborative-filtering techniques during students' performance prediction. The most challenging task is to simulate the relationship among influencing factors and student's skills because it requires an accurate design of the CS measurement architecture. In the proposed study, we have focused on efficient modulation of the statistical association between CS and SBA. For instance, we can find research findings which have concentrated the correlation among attendance and family background of medical students (i.e., Postcode-based, the attendances of high school, and socio-demographic characteristics) [35]. The achieved analysis results have shown that student's selected characteristics have a strong statistical association (such associations can have negative or positive impacts) with their performances. The aforementioned literature findings indirectly contributed to the proposed study because the selection of prior probabilities dependents on the statistical correlation among CS and SBA.

Furthermore, in [36], the authors have compared the performance of CS prediction technique using four datasets, i.e., student grades data of George Mason University (GMU), University of Minnesota (UMN), LMS data and Stanford University MOOC data. The set of students' skills prediction approach consists of Regression-based methods. In the end, the results have manifested that FM achieved excellent performance outcome as compared to the rest of prediction techniques. These techniques have different loopholes (i.e., missing in-depth quantization, and iterative calculations) to measure the CS of a student during the aforementioned cognitive tasks. Also, the iterative estimations of CS outcomes (concerning each layer of SBA) are essential to predict the expected CS accurately.

Consequently, the prior studies have provided meaningful contributions in students' CS prediction area of research [37], [38]. These literature are the primary source of inspiration for the proposed Bayesian Neural Network.

III. COGNITIVE SKILLS MEASUREMENT PROCESS

The focus of this section is to discover the impacts of Students' Basic Attributes (positive and negative influence) on the values of CS. The goal of the current attempt is to design a Bayesian Neural Network which aimed to achieve the affected values of CS as a function of Students' Basic Attributes. Now, the dire need is to design an approach which can iteratively estimate the statistical correlation among CS and Students' Basic Attributes. Thus, we split the study into the following sub-sections to come up with a precise solution for the discovery of the influence of Students' Basic Attributes.

A. QUANTIZATION OF THE BASIC STUDENT'S ATTRIBUTES

The Basic Attributes perform unfolded distinctive actions on the performance of a student during some specific cognitive tasks, e.g., class activities, examination, interviews. The classification of Students' Basic Attributes is essential to design an efficient educational neural network as well as to ensure transparency and accuracy during the quality enhancement of student's performance prediction. First, we have classified Students' Basic Attributes into three observable variables, i.e., 1) age group, 2) gender description, and 3) parent's cohabitation status of a student. This study has proposed a set of distinct values (outcomes of variables) for the particular observable variable of Students' Basic Attributes which are given below.

- Age group = 15 to 20 years
- gender description = male or female
- parent's cohabitation status = apart or together

Both the gender description and parent's cohabitation status have two sets of outcome variables, i.e., gender = male or female and parent's cohabitation status = together or apart. The domain and range of age group are quantized into six discrete periodic outcome variables (with a period of a 1-year). It shows that the technique maintains a one year gap between each value of the particular age group. The outcome variables of the Bayesian Neural Network are also referred to as layers of the current neural network because these factors immensely change the values of student's CS during cognitive tasks. Second, during quantization, we periodically classified the range of students' CS into 20 periodic values (a periodic division with a period of 0.5) [21]. Therefore, we have achieved 20 outcome variables of CS. This division is also referred to as the component-wise quantization of student's skills. This particular component-wise division ensures an in-depth measurement of CS because the technique iteratively estimates each outcome of CS while considering the profound impact of the Basic Attributes. It also depicts that each factor (Students' Basic Attributes) has multiple iterations while each iteration has 20 sub-iterations for the outcome variables of CS. During this process, the technique iteratively refines the posterior probabilities of CS outcomes. This process exhibits the transparency of the Bayesian Neural

Network during the prediction of the student's performance. More specifically, the particular division has created three-umbrellas activities (Age group, gender description, and parent's cohabitation status layers) for the estimation of student's skills which are given in the following section.

B. MEASUREMENT OF STUDENTS' BASIC ATTRIBUTES INFLUENCE

The study describes that CS and Students' Basic Attributes factors are statistically associated during cognitive tasks, i.e., class activities, and expected student grades. To achieve the particular CS measurement task, the study uses Bayesian Inference Method (BIM) for the accurate calculation of posterior probabilities of CS outcomes, i.e., a set of 20 CS outcomes. The basic need of the current approach is to calculate the posterior probabilities of student's CS while considering each factor of Students' Basic Attributes. Therefore, the BIM is embedded in each layer of the Bayesian Neural Network.

Thus, during the posterior calculation process, each outcome of CS is separately estimated. The BIM performs an essential role during the evaluation of the expected result of CS while remarking the conditional influence of Students' Basic Attributes layers. As the expected result of student's skills is inspired by the age group, gender, and parent's cohabitation status; therefore BIM is the best choice to compute the posterior probabilities of CS [39]. BIM is flexible for the problem of measuring the nonlinear relationship between CS and Students' Basic Attributes because it produces direct inferences to new information. During CS measurement process, the technique has multiple layers, i.e., each factor of Students' Basic Attributes is considered as a separate layer. Each layer produces a processed set of posterior probabilities for 20 outcomes of CS. So, the simulation approach is split into the following sections which precisely explore the activities of each layer of Students' Basic Attributes.

1) INFLUENCE OF AGE GROUP LAYERS

To measure the final posterior probability of a set of CS outcomes (20 values of student skills), first, the study obtains prior probabilities of each CS outcome that rely on the statistical association between CS and Students' Basic Attributes. We achieved a set of peer-reviewed journal papers to estimate the prior probabilities accurately [40]–[42]. We defined some rules to technically explore the significant aspects of the literature, i.e., logical argumentation, experimental methodology and the research findings supported by Students' Basic Attributes theories. Furthermore, the obtained interval of prior probabilities [0, 1] is classified into 20 probabilities. It depicts that each outcome of CS has a distinct prior probability (between 0 and 1). Every prior probability of CS outcome has two events which are both mutually exclusive and collectively exhaustive. Thus, the first event is represented by $prior_{cs}$ which depicts the prior probability of just one outcome of CS. On the other hand, the mutually exclusive event is represented by Mut_{prior} which represents the summation of the prior probabilities of remaining 20 outcomes of CS. So, it is classified into two parts (1) $prior_{cs}$ = prior probability of the first event, 2) $Mut_{prior} = 1 - prior_{cs}$ = prior probability of the mutually exclusive event. Second, the study achieves the conditional probabilities of CS by considering the influence of age (15 to 20). The conditional probability of age group of a student is represented by $Age_{condition}$ (where $condition = 1$ to 6). In each iteration, the counter *condition* is incremented (age-wise). The following equations present the conditional probabilities of both the events (along with mutually exclusive event).

$$CPAgepq = P\left(Age_a|cs_i\right) = \frac{P(cs_i \cap Age_a)}{P(cs_i)} \tag{1}$$

$$MCPAgepk = 1 - Age_{condition} \tag{2}$$

Eq. (1) and (2), *CPAgepq* and *MCPAgek* (while *pq* and *rs* depict different iterations) denote conditional probabilities of the mutually exclusive events while the other element Age_a exhibits student's age group (where $a = 1$ to 6) and cs_i reveals outcomes of CS (from 1 to 20). In each iteration of the p element (where $p = 1$ to 6), the conditional probabilities of 20 outcomes of a student (concerning the particular age group) are assessed. On the other hand, each q consist of 40 sub-iterations which is represented by p and k. Moreover, the particular 40 iterations are classified between *CPAgepq* and *MCPAgek*. Third, the study obtains the joint probabilities of CS outcomes (with respect to the age group of a student) by the following equation.

$$AJ_{xy} = P\left(Age_a, cs_i\right) = \left(prior_{cs}\right) \times \left(CPAgepq\right) \tag{3}$$

$$AJ^c_{xs} = P\left(Age_a, cs^c_i\right) = \left(Mut_{prior}\right) \times \left(MCPAgek\right) \tag{4}$$

In Eq. (3) and (4), the technique reveals AJ_{xy} and AJ^c_s (where xy and s shows two sets of iterations) for the joint probabilities of two mutually exclusive events. In Eq. (3), x (where $x = 1$ to 6) describes six values of age groups while each value of age depicts a separate iteration to obtain joint probabilities of CS outcomes (with respect to the age group of a student). Thus, under the influence of each value of the age group, the technique has achieved 40 sub-iterations. It shows that 20 sub-iterations are obtained using Eq. (3) while the rest of 20 sub-iterations (for the mutually exclusive events) are performed by applying Eq. (4). Also, achieving prior, conditional and joint probabilities are used to measure the posterior probabilities of student's CS. The proposed Bayesian Neural Network has applied the following equation to generate the final set of posterior probabilities (by considering age group),

$$APosterior_{mn} = P\left(cs_i|Age_a\right) = \frac{AJ_{xy}}{AJ_{xy} + J^c_s} \tag{5}$$

In Eq. (5), the element $Aposterior_{mn}$ (where $m = 1$ to 6 and $n = 1$ to 20) exhibits the posterior probabilities of student's skills (with respect to the age group of a student). During this evaluation, the technique has six ($m = 1$ to 6) principal iterations for the age group while each iteration has 20 sub-iterations for the calculation of posterior probabilities of student's skills. This particular process depicts that the

current technique achieved the goal of measurement of CS by considering the age's influence. The technique has produced six sets of posterior probabilities (while each set consists of 40 posterior probabilities). Additionally, the achieved set of posterior probabilities (of 20 outcomes of CS) are further used a set of prior probabilities under the profound influence of gender description. It demonstrates the iterative measurement of CS because each set of posterior probabilities are re-calculated under the profound influence of Students' Basic Attributes factors layers.

2) INFLUENCE OF GENDER LAYERS

The current section of the study represents the influence of gender description. The obtained six sets of posterior probabilities (i.e., during the influence of age group) are re-estimated under the intense effects of male and female layers. Thus, these particular sets of posterior probabilities are considered as distinct sets of prior probabilities. The technique selects each set of priors separately and re-estimate it under the influence of distinct gender layer. Moreover, the approach has two events (aforementioned in age group factor of Students' Basic Attributes), (1) prior probability is represented by $APosterior_{mn}$, and the (2) prior probability of the rest of the 20 student's skills outcomes variable (mutually exclusive) is shown by Mut_{Gprior} $(1 - Mut_{Gprior})$. In every sub-iteration, these prior probabilities are modified according to achieved sets of the previous age group factor of Students' Basic Attributes. Now the current approach achieves the conditional probabilities of CS with respect to gender layers (male or female). The value of a student's gender layer is illustrated by $Gender_a$ (where $a = 1$ to 2). Besides, in each iteration, the value of the a is incremented (from male to female) because we need to obtain the conditional probabilities given male or female. Furthermore, the Bayesian Neural Network carefully estimate the conditional probabilities of the gender description of a student. The following equations show the mathematical models for the calculation of conditional probabilities of both events (along with mutually exclusive event).

$$GC_{pq} = P\Big(Gender_a|cs_i\Big) = \frac{P(cs_i \cap Gender_a)}{P(cs_i)} \tag{6}$$

$$GC_p^c k = 1 - GC_{pq} \tag{7}$$

In Eq. (6) and (7), GC_{pq} and GC_k^c (while pq and k manifest different iterations) represents the conditional probabilities of different events (mutually exclusive events). The variable $Gender_a$ has shown the gender description of a particular student (where $a = 1$ to 2) and cs_i represents CS outcomes (from 1 to 20). In each iteration of p (where $p = 1$ to 2), the conditional probabilities of 20 student's skills outcome variables are estimated concerning gender description. On the other hand, q and k manifest 40 sub-iterations (in each iteration of p). In these particular 40 sub-iterations, $20 \in GC_{pq}$ while the rest of the other $20 \in GC_k^c$. Now, the joint probabilities of CS with respect to gender description are given by the following equations (first event and mutually exclusive event).

$$\begin{aligned} GJ_{xy} &= P\Big(Gender_a, cs_i\Big) \\ &= \Big(APosterior_{mn}\Big) \times \Big(GC_{pq}\Big) \end{aligned} \tag{8}$$

$$\begin{aligned} GJ_{xs}^c &= P\Big(Gender_a, cs_i^c\Big) \\ &= \Big(Mut_{Gprior}\Big) \times \Big(GC_k^c\Big) \end{aligned} \tag{9}$$

In Eq. (8) and (9), GJ_{xy} and GJ_s^c (where xy and s reveals two types of calculations) exhibit joint probabilities of CS with respect to gender description. In Eq. (8), x (where $x = 1$ to 2) illustrates two outcomes (male and female) of student's gender description while each outcome of gender represents a separate iteration to obtain joint probabilities. Thus, under each value of gender, we have 40 sub-iterations (while $20 \in GJ_{xy}$ and the remaining $20 \in GJ_s^c$) to measure the joint probabilities of CS under the profound influence of age layer. Eventually, the study calculates the posterior probabilities of student's CS using obtained prior, conditional, and joint probabilities. The following equation achieves the measurement of posterior.

$$\begin{aligned} GenderPost_{mn} &= P\Big(cs_i|Gender_a\Big) \\ &= \frac{GJ_{xy}}{GJ_{xy} + G_s^c} \end{aligned} \tag{10}$$

In Eq. (10), $GenderPost_{mn}$ (where $m = 1$ to 4 and $n = 1$ to 20) manifests the posterior probabilities of CS; therefore, we have two primary iterations ($m = 1$ to 2) to measure the CS under the umbrella activities of the gender factor. Also, each iterations of gender consist of 20 sub-iterations($n = 1$ to 20). Additionally, the technique has produced 12 sets of posterior probabilities because the six sets obtained from age group layers are re-estimated under the gender factor. Such features have not been achieved by the state of the art techniques [43], [44]. Also, each set consists of 20 posterior probabilities for 20 student's skills variables. Furthermore, the obtained 12 sets (CS posterior probabilities) are used as the prior probabilities sets (of the student CS outcomes) which are re-estimated under the significant impacts of parent's cohabitation factor.

3) INFLUENCE OF PARENT'S COHABITATION STATUS LAYERS

In the parent's cohabitation module of CS measurement, the study considers 12 sets of posterior probabilities which are achieved during the gender layers influence measurement. The technique has considered the sets of posterior as the prior probabilities of student's skills. Thus, the parent's cohabitation status layers are designed to re-estimate these probabilities. Furthermore, the parent's cohabitation module has two primary events (as discussed earlier); (1) prior probability of one CS outcome variable is depicted by $GenderPost_{mn}$ (where $m = 1$ to 20 and $n = 1$ to 20), and (2) prior probability of the rest of 20 mutually exclusive CS outcomes $(1 - GenderPost_{mn}$, i.e., mutually exclusive event of the

selected n counter set). This process also has 24 iterations, and every iteration has 20 sub-iteration for the evaluation of posterior probabilities. To achieve the posterior probabilities of student's CS, the study achieves conditional and joint probabilities of CS outcomes with respect to parent's cohabitation layers. The following equations show the particular conditional probabilities of both events (along with mutually exclusive event).

$$ParCond_{yz} = P\Big(Pstatus_a|cs_i\Big) = \frac{P(cs_i \cap Pstatus_a)}{P(cs_i)} \quad (11)$$

$$ParCond_y^c k = 1 - ParCond_{yz} \quad (12)$$

In Eq. (11) and (12), $ParCond_{yz}$ and $ParCond_k^c$ (while yz and k manifest different iterations) represents the conditional probabilities of parent's cohabitation status with respect to student CS while $a = 1$ to 2 and cs_i represents CS outcomes (from 1 to 20). In each iteration of y (where $y = 1$ to 2), the conditional probabilities of the particular gender description and 20 CS outcome are iteratively measured. On the other hand, z and k shows 40 sub-iterations in each iteration of y. In these particular 40 sub-iterations, 20 are shown by $ParCond_{yz}$ while the rest of 20 belong to $ParCond_k^c$. Moreover, the proposed study measures joint probabilities of CS and a student's parent's cohabitation status which are performed by the following equation.

$$PstatusJ_{xy} = P\Big(Pstatus_a, cs_i\Big) = \Big(GenderPost_{mn}\Big) \times \Big(ParCond_{yz}\Big) \quad (13)$$

$$PstatusJ_s^c = P\Big(Pstatus_a, cs_i^c\Big) = \Big(1 - GenderPost_{mn}\Big) \times \Big(ParCond_k^c\Big) \quad (14)$$

In Eq. (13) and (14), $PstatusJ_{xy}$ and $PstatusJ_s^c$ (where xy and s shows two kind of iterations) show the joint probabilities of CS and parent's cohabitation status. The Eq. (5), x (where $x = 1$ to 2) has depicted two layers of parent's cohabitation status (together and apart). Moreover, the Bayesian Neural Network has performed 40 sub-iterations while 20 are in the form of $PstatusJ_{xy}$ and the remaining 20 are achieved with mutually exclusive events, i.e., $PstatusJ_s^c$. Eventually, the technique performed distinct iterations to measure the final posterior probabilities of CS with respect to the Students' Basic Attributes. Thus, the final round of the Bayesian Neural Network process is achieved by the following equation.m

$$PstatusPost_{mn} = P\Big(cs_i|Pstatus_a\Big) = \frac{PstatusJ_{xy}}{PstatusJ_{xy} + PstatusJ_s^c} \quad (15)$$

In Eq. (15), $PstatusPost_{mn}$ (where $m = 1$ to 4 and $n = 1$ to 20) has measured CS while considering the profound influence of parent's cohabitation status of a student. The technique has achieved posterior probabilities evaluation in 24 main iterations. On the other hand, each iteration consists of 20 sub-iteration to measure CS with respect to the two outcomes of a student's parent's cohabitation status. It also shows that the current module of the proposed study has produced 24 sets of distinct posterior probabilities. Eventually, the technique achieves the most probable outcome of CS with respect to the combined effects of Students' Basic Attributes. Therefore, the study has measured student's skills while considering different combinations of Students' Basic Attributes effects, i.e., (1) age group influence, (2) age group and gender impact, and (3) eventually, the combined effects of age group, gender, and parent's cohabitation status factors. Resultantly, we achieved a detailed knowledge base of posterior probabilities for the particular 20 outcome variables of CS.

Figure 1 depicts the framework of the proposed Bayesian Neural Network which consists of two primary structures. First, it takes Students' Basic Attributes and CS range as inputs for further classification. These factors are classified into multiple layers (i.e., age groups layers, gender, and parent's cohabitation status layers). The study assigns priors and conditional probabilities to CS outcomes and Students' Basic Attributes layers. Second, the posterior probabilities of CS outcomes are estimated under the profound influence of Age group layers, gender layers, and parent's cohabitation status layers respectively.

C. ALGORITHMIC SOLUTION OF THE APPROACH

The Bayesian Neural Network Algorithm represents the posterior probability measurement process for the prediction of a student's CS. It has three primary modules (age group, gender description, parent's cohabitation status) while each module consists of a distinct set of layers. In every layer, the technique measures posterior probabilities of CS outcomes by considering the profound influence of Students' Basic Attributes factors. The current algorithm holds different values (in the form of probabilities) to estimate the expected value of a student's performance. It takes cs, and SBA (Students' Basic Attributes) as input sets while produces multiple sets of posterior probabilities (cs_x where $x = 1$ to n). First, the algorithm produces six distinct sets of posterior probabilities of CS outcomes (where each set consist of 20 posteriors for 20 CS outcomes). The expected performance of a student is estimated with respect to each layer of the age group. Moreover, the obtained posterior probabilities are placed by a single set; therefore, the new set contains 126 items which are considered to be the prior probabilities for the next module of Bayesian Neural Network. The technique re-estimates the 126 probabilities under the profound influence of gender layers. During this process, the Bayesian Neural Network produces two new sets of posteriors which again placed in a new set. This particular new set consists of 252 items for further consideration under the intense effects of parent's cohabitation layers. Eventually, the Bayesian Neural Network processes the posterior probabilities of 252 items with respect to the two layers of the

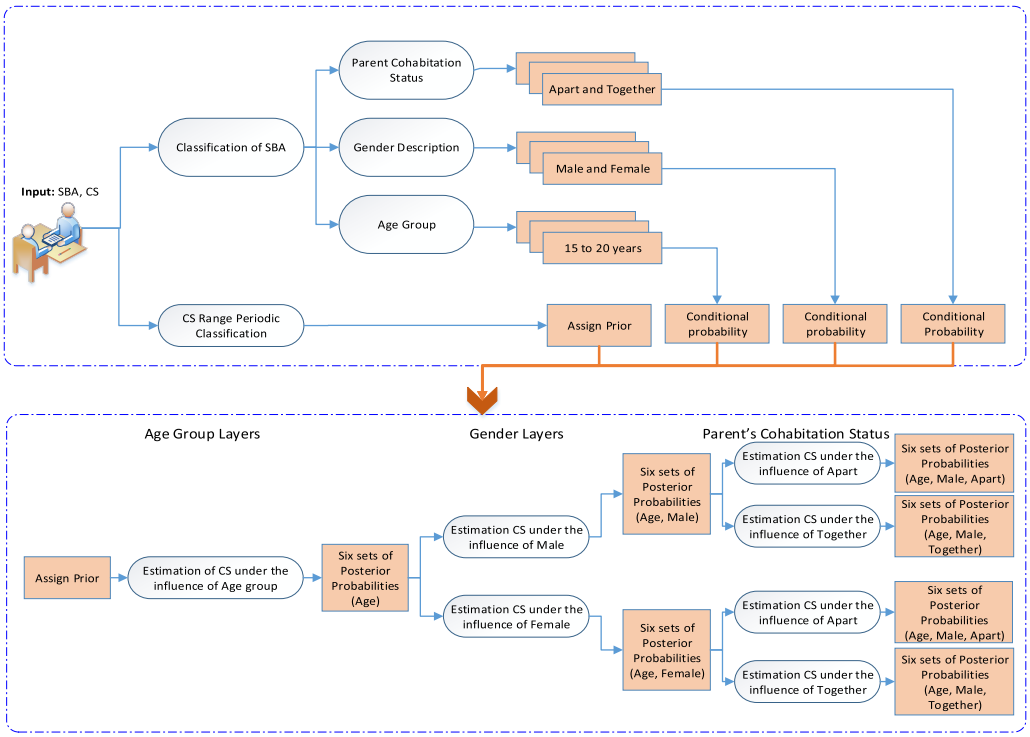

FIGURE 1. The flowchart of the proposed Bayesian Neural Network. The first module gets direct input, i.e., conditional probabilities of Student Basic Attributes(SBA) and prior probabilities of CS outcomes. The second module achieves the final posterior probabilities with respect to age and gender.

parent's cohabitation status. It produces two sets of posteriors while each set consists of 252 items. Thus, in the last module, the Bayesian Neural Network achieves 504 posteriors of CS. Finally, the technique provides three most probable outcomes of CS while considering the following factors of Students' Basic Attributes.

- CS with respect to age layers
- CS with respect to age and gender layers
- CS with respect to age, gender, and parent's cohabitation layers.

The Bayesian Neural Network consists of a separate module for prediction loss which compares predicted value with an actual value of CS. It computes the loss by ($PL = (Actual - predicted)$) calculating the variation among actual and predicted values. This particular process ultimately enhances the accuracy of the Bayesian Neural Network. It matches the actual value with the outcome of CS which have most probable posterior probability. If the deviation exceeding the tolerable error rate, then it re-calculates the posterior probability of CS (cs2). This process proceeds until the Bayesian Neural Network achieve maximum (80+) prediction accuracy.

Algorithm 1 Bayesian Neural Network Algorithm

Input: sets, cs1, *SBA*, cs_x
Output: cs_x, cs2
Initialization :
for each i in *SBAlayer* **do**
  for each j in *csoutcome* **do**
    calculate posterior of j with respect to i
    add and replace j in cs1
  end for
end for
Compute loss of prediction process
if the likely outcome of CS in cs_x is not mapping to the actual value of CS **then**
  for each m in *SBAlayer* **do**
    for each n in *csoutcome* **do**
      Try Updated n of cs2
      calculate posterior of n with respect to m
      add and replace n in cs2
    end for
  end for
  Return refined cs2
end if
Return refined cs_x

IV. METHOD VALIDATION

During the validation analysis, the study used students' performance dataset to assess the performance of the proposed approach. The method validation process is classified into the following sub-sections.

A. STUDENTS' PERFORMANCE DATASET

During the experiment, the proposed deep network was evaluated by using a students' scores dataset. It is an extended

version of the dataset collected during psychological experiments to simulate the relationship between CS and Basic Human Factors [45]. The extended dataset is collected during another set of experiments by evaluating the performances of the students of four institutions which include, participants from Iqra University Karachi, BBA students of Peshawar Agriculture University, Hayatabad Model Schools Peshawar Pakistan, and Iqra Rozatul Quran School. This particular dataset was finalized on 16 October 2019 (2012-2019). The data collection and access to the data was as part of a routine quality improvement of CS prediction methods, with the aim of predicting performance of the students in final examination. Therefore, anonymous data (ignoring personal information) was used at all times.

During the data collection process, we have collected information about the different attributes from every student, i.e., age, gender, class, course, total course load, parents time duration with family, student preferences, sleeping duration, travel duration between school and home, and parents job or business. The course load includes chemistry, computer science, biology, mathematics, English, and physics. The teacher of the specific course has given expected marks in final examination which is based on student performance in class activities (i.e., assignment, quizzes, and other group participation) and mid-term examination.

Finally, the authors demonstrated the aim of the test and convinced them that the data would be used only for scientific purposes. This particular dataset was collected by evaluating the performances of 451 students which produced 1804 records. In addition, we have oversampled and replicated the data to accurately train our model. During this process, we have obtained a dataset of 20000 records. In appendix, Table 2 depicts a sample of dataset. Eventually, the students' performance dataset is used to test the CS prediction performance of the Bayesian Network.

To train our model, we have initiated training process with 11-folds cross validations. The 11-folds have been chosen based on six classes of participants' ages (i.e., 15, 16, 17, 18, 19, and 20 years) two gender description (male and female), two parent's cohabitation status (together or apart), and one random sample. Also, we have obtained significant accuracy in terms of 11-fold cross validation. To achieve accurate parameters, we have selected 150 distinct tests for the 11 group of sample data. The number of observation for training and test set were carried out on different pairs (i.e., 70:40, 60:40, 80:20, 80:20, 80:20, 80:20, 80:20, 80:20, 80:20, 80:20, and 70:30) and then calculated the average performance of empirical results. Furthermore, in this section, we develop the proposed model using the training set.

B. PERFORMANCE ANALYSIS OF BAYESIAN NEURAL NETWORK

First, the Bayesian Neural Network was tested using a random sample which consists of the values of multiple Students' Basic Attributes factors. The primary goal of this test was to validate the overall performance of the method. It has measured the expected outcomes of students by estimating the posterior probabilities of each outcome of CS. The evaluation of posterior probabilities shows that the technique computed expected student's performance by choosing the most probable value of CS (from the rest of 20 posterior probabilities). The probability of the most probable CS outcome lies between 0 and 1. Thus, the technique added authors defined (e.g., $1 - \textit{posterior probability}$) error as a deviation to the measured value. The Fig. (2) manifests the deviation between an actual value and measured value. The blue line graph shows actual CS while the dotted red line graph exhibits the measured values of the proposed CS measurement approach. Furthermore, the accuracy of the Bayesian Neural Network's performance was evaluated using state-of-the-art measures, i.e., precision, recall, and F1 score. The current matrix consists of true positive (TP) and false positive (FP). On the other hand, the measurement process can have true negative (TN) and false negative (FN). The following equation achieves precision of the Bayesian Neural Network.

$$Precision = \frac{(TP_i)}{TP_i + \sum_{i=1}^{3}(FP_i)} \tag{16}$$

In Eq. (16), TP represents true positive, FP shows false positive, TN describes true negative while FN manifests false negative. Through Eq. (16), we have measured the precision of the proposed method. The technique has achieved 0.874 value as a precision for the selected sample set. Furthermore, we have made recall for the measured value using the following equation.

$$Recall = \frac{(TP_i)}{TP_i + \sum_{i=1}^{3}(FN_i)} \tag{17}$$

The predicted values of the particular sample have been evaluated by using Eq. (17). It has produced 0.859 as a recall value. Furthermore, the last measure is referred to as the F1 score which is given by the following equation.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{18}$$

We have measured the F1 score of the current sample using Eq. (18). The technique has achieved 0.8614 as an F1 score of the measured values. It also manifests that the proposed study has obtained the goal of accurate CS measurement. According to the aim of the current research, the achieved precision, recall, and F1 score values have demonstrated that the performance of the Bayesian Neural Network is considerably significant (see Table 1 for more detail).

C. FACTOR-WISE PERFORMANCE ANALYSIS OF

To measure the performance of the proposed approach, we have used distinct random samples of Students' Basic Attributes. The accuracy of the Network was evaluated using each sample separately. First, the performance of the

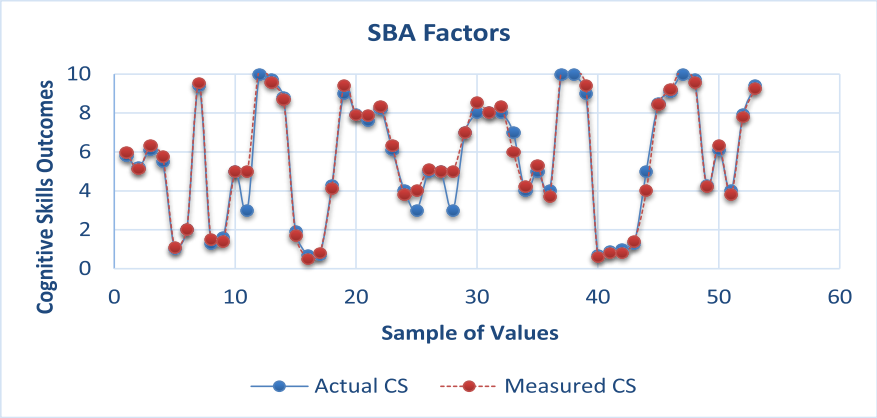

FIGURE 2. Illustrates prediction accuracy of Bayesian Neural Network. A random sample is selected to show the accuracy representation. The red dotted graph represent predicted (measured) values while the blue line graph depicts actual values of the testing set.

TABLE 1. Performance of cognitive skills measurement approach.

Measured CS Sample	Precision	Recall	F1 Score
Students' Basic Attributes Sample	0.874	0.859	0.8614
Age Group Sample (15)	0.833	0.871	0.8155
Age Group Sample (16)	0.849	0.809	0.8711
Age Group Sample (17)	0.887	0.821	0.8577
Age Group Sample (18)	0.831	0.843	0.8259
Age Group Sample (19)	0.884	0.852	0.8209
Age Group Sample (20)	0.823	0.838	0.8722
Gender (Male) Sample	0.844	0.813	0.8489
Gender (Female) Sample	0.873	0.891	0.8198
Parent's Cohabitation Status (Together)	0.829	0.848	0.8266
Parent's Cohabitation Status (Apart)	0.831	0.811	0.8189

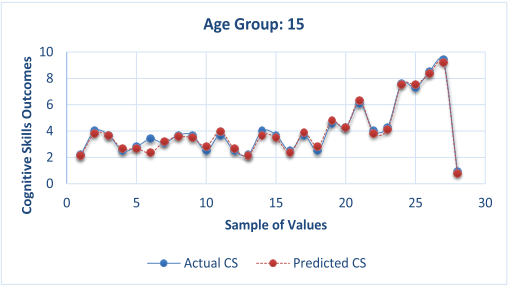

FIGURE 3. illustrates prediction results with a focus on age group 15. The blue line graph represents actual values while the red dotted line graph depicts predict values.

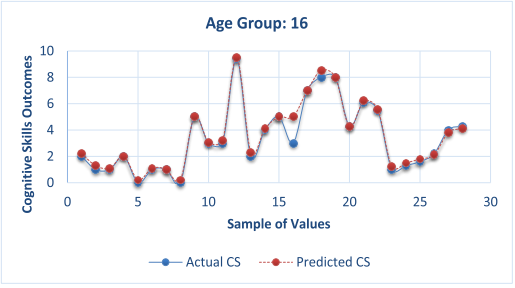

FIGURE 4. Prediction results using random sample with a focus on age 16. It also represent two different graphs, i.e., actual and predicted values.

method was examined using six samples while each sample belongs to a separate layer of the age group. During this process, we have specifically focused on the age group of a student. The results of the experiments are demonstrated in Fig. (3) to (8). The blue graph of the figures has illustrated the actual CS while the red dotted graphs have depicted the measured values by the Network. The results presented that the current approach has simulated the relationship between Students' Basic Attributes and CS of the selected sample. Moreover, the prediction accuracy of the current study was evaluated by the aforementioned state-of-the-art measures. The achieved values of accuracy are shown in Table 1. The results describe that the Network has significantly performed on the selected sample sets of age group. Moreover, the Students' Basic Attributes factor-wise performance of the Network was evaluated by precision, recall and F1 score measures. These accuracy measures assessed the performance of Network layers (age group layers, gender layers, and parent's cohabitation status layers). The results have manifested that each layer of age group has achieved significant outcomes in term of the aforementioned accuracy measures (see Table 1 for more details).

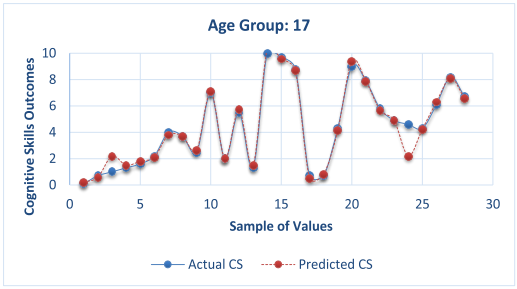

FIGURE 5. Prediction performance of Bayesian Neural Network (Age group 7).

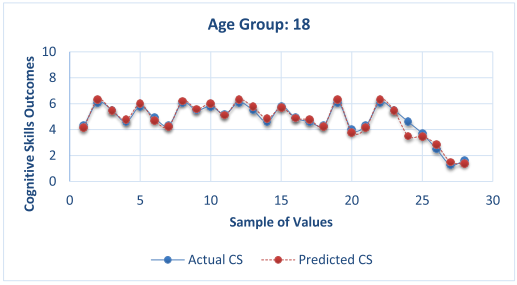

FIGURE 6. Description of prediction accuracy using random sample of age 18.

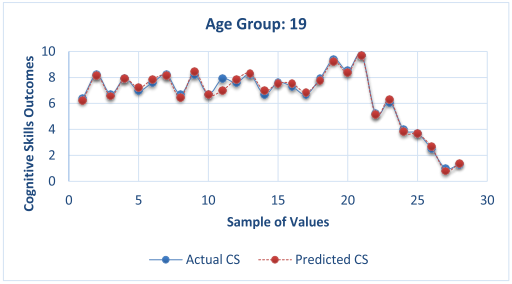

FIGURE 7. Bayesian Neural Network performance with a focus on students' age 19.

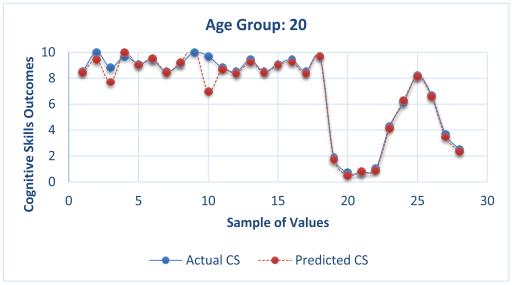

FIGURE 8. It Exhibits the prediction accuracy of age group 20.

Furthermore, the proposed technique was tested using another sample set with a focus on gender description. The Network performed the prediction processes of students' CS which are shown in Fig. (9) and (10). The particular Fig. (9) manifest the results of CS measurement with a focus on male participants. The dotted line graph has shown the measured

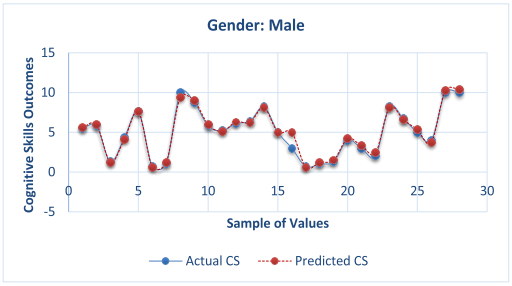

FIGURE 9. Bayesian Neural Network prediction using random sample of male participants.

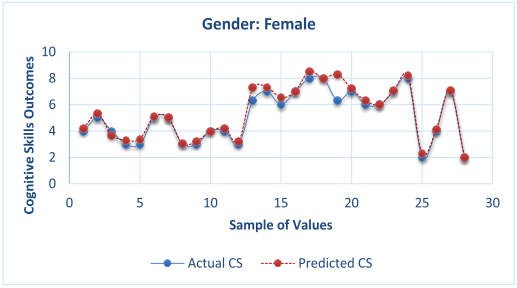

FIGURE 10. Illustrates the prediction accuracy with a focus on female students.

values of students' CS. On the other hand, Fig. (10) represents the CS computation of female participants. The blue and red dotted graphs depicted actual and measured CS respectively. The accuracy of Network using the particular two samples are shown in Table 1.

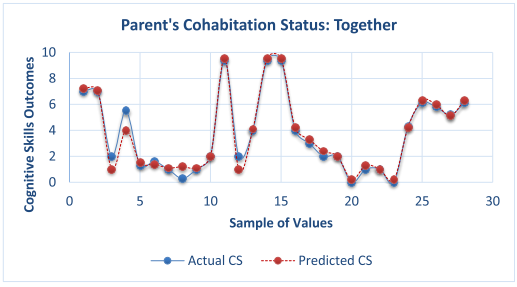

FIGURE 11. Represent prediction performance with a focus on parent's cohabitation status = Together.

Eventually, the proposed approach was validated by two sample sets with a focus on parent's cohabitation status (i.e., together and apart). The technique has operated on the two sample sets separately which has produced two sets of measured values. The results of the experiments are illustrated in Fig. (11) and (12). The y-axis shows CS outcomes while the x-axis describes the number of dataset instances. Fig. (11) represents the measurement performance of Network with a focus on parent's cohabitation status = Together. The red dotted graph has manifested the measured values while the blue line graph has shown the actual outcomes of the sample set. On the other hand, Fig. (12) has revealed

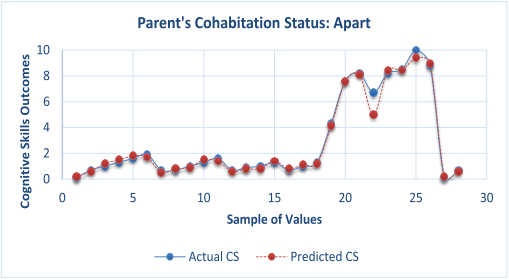

FIGURE 12. Manifest the prediction accuracy using random sample of parent's cohabitation status = Apart.

the results of the current approach with a focus on parent's cohabitation status = Apart. It has exhibited actual and measured values in the form blue and red dotted line graphs respectively. The performance accuracy are illustrated in Table 1.

D. COMPARISON WITH PRIOR APPROACHES

This work provides a new set of a frame of references for future researchers due to the evaluation of Network on the new students' performance dataset. However, the comparison of the proposed Network has been conducted with three CS prediction approaches [21], [22], [45]. The comparison is based on the following frame of reference.

1) FACTOR-WISE COMPARISON

Previous studies are saturated with various research achievements which have statistically correlated CS with students' attributes such as study schedules, and demographic attributes etc. (see section 2 for the cited literature findings). The prior approaches are insignificant to address the intense impact of Students' Basic Attributes. As far as we know, the related studies have lack of algorithms which quantize Students' Basic Attributes into multiple layers and then calculate component-wise probabilities of CS. Component-wise quantization of Students' Basic Attributes and CS have ensured prediction accuracy which is explained in Table 1.

2) ITERATIVE MEASUREMENT

The recent methods have innovations which are mostly related to academic achievements, family assets, and family income, while the profound effect of Students' Basic Attributes (on CS) is usually ignored. The Network iteratively calculates the probabilities (of 20 CS outcome variables) while considering the profound influence of the hidden layers of Students' Basic Attributes. Each of these layers contributes a set of 20 posterior probabilities of CS values which are re-estimated in the next layer of Network. These particular three prior approaches have lack of iterative estimations which are the main source of inspiration behind this study.

3) COMPARISON BASED ON DATA

The current study primarily focuses on the relationship between CS and Students' Basic Attributes while trained and validated on a real-world dataset. To consider the different demographic background and for more data validity, the data has been collected from six different institutions. However, the dataset used by the literature ([21], [22], [45]) is not sufficient for the challenges of introduced by Students' Basic Attributes.

V. DISCUSSION

The proposed study has introduced a Bayesian Neural Network that has calculated students' expected CS using the influence of Students' Basic Attributes. The main contributions of the current attempt are twofold. Initially, the study has split Students' Basic Attributes into three factors, i.e., age group, gender description, and parent's cohabitation status. Also, each factor is classified into multiple layers while each layer has a distinct influence on the expected performance of a student during the aforementioned cognitive tasks. Furthermore, the study has periodically quantized CS into 20 outcomes (with a period of 0.5) (see section 3.1 for more details). Besides quantization of CS and Students' Basic Attributes, the study has used Bayesian Inference Method (BIM) to compute the posterior probabilities of CS outcomes. The proposed approach has measured CS by iterative re-computation of posterior probabilities of CS outcomes while considering the influence of each layer of Students' Basic Attributes (See section 3.2.1 to 3.2.3 for more details). Eventually, the Bayesian Neural Network chooses a CS outcome with a most probable posterior probability. This system has given iterative procedure to detect students' performance in quizzes, midterm, and final examination. It can help us to detect at-risk students. During the empirical analyses, the study was tested on a students' performance dataset. The figures (Fig. 2 to Fig.12) have illustrated the achieved results of the experiments. Moreover, the proposed work has obtained excellent performance accuracy which is shown in Table. 1.

During the extensive comparative analysis, the technique was compared with recent CS prediction methods. The analyses in Section 4.4 have depicted that the current approach has solved the challenge which were unable to be addressed by the existing works.

VI. CONCLUSION

This study presents a Bayesian Neural Network to calculate CS under the profound influence of Students' Basic Attributes (. To predict students' CS, the study has designed a multi-layered network by classifying Students' Basic Attributes into three factors, i.e., age group, gender description, and parent's cohabitation status. Each factor consists of multiple layers which push distinct impact on the CS of students. The Network predict CS while calculating the posterior probability of student's CS for the profound influence of Students' Basic Attributes layers. It depicts that the network iteratively re-estimates the CS of a student with respect to each layer of Students' Basic Attributes. During the validation, the Network was tested on a students' performances dataset. The achieved results have revealed

TABLE 2. Dataset attributes.

1	Age of the student - (from 15 to 22 numeric value)
2	Gender - (binary: 'b' - boy or 'g' - girl)
3	Exposure - (it shows address which is also binary: 'u' - urban or 'r' - rural)
4	Family size - (numeric value: number of people in a home)
5	Parent's status - (binary: 't' - living together or 'A' - apart)
6	Mother edu – (mother education 0-20)
7	Father edu – (father education 0-20)
8	Mother job – (mother job: different jobs)
9	Father job – (father education: different jobs)
10	guardian – (mother, father, or anyone else)
11	Parent's rel – (relationship between parents: numeric from 1 to 6)
12	health – (student health: numeric from 1: very bad to 5: very good)
13	Absences – (number of absentees per month: numeric)

that the proposed network obtained significant prediction accuracy.

VII. LIMITATIONS AND FUTURE WORK

We have observed some limitation while evaluating the proposed Bayesian Neural Network. First, our technique is instead a journey than a destination; therefore, the fundamental limitation is the lack of comparison of prediction accuracy which competitive method. This study used a new dataset while the initial evaluation of prediction accuracy (in terms of precision, recall, and F1 score) is presented for future references. Thus, the extensive comparison is planned in the future. Second, we have yet to perform extensive empirical tests (using some more datasets) to ensure prediction accuracy. Additionally, some other limitations of the proposed Bayesian Neural Network are given below.

- A series of experiments were performed to verify the prediction accuracy of the Bayesian Neural Network, and finally, we have chosen the average prediction results (i.e., mentioned above).
- The current method can produce different results in achieving different sets of prior probabilities for the intervals of CS and Bayesian Neural Network.

VIII. ETHICS STATEMENT

During the data collection, all the procedures performed (involving human participants) were in accordance with the ethical standards of the Helsinki Declaration. The data collection and access to the data, were parts of the teaching quality enhancement activities of the institutions. The primary goal of these activities was to protect students from the adverse effects of frustration severity. Therefore, anonymous data was used at all times.

APPENDIX

See Table 2.

REFERENCES

[1] N. Thai-Nghe, L. Drumond, T. Horváth, A. Krohn-Grimberghe, A. Nanopoulos, and L. Schmidt-Thieme, "Factorization techniques for predicting student performance," in *Educational Recommender Systems and Technologies: Practices and Challenges*. Pennsylvania, PA, USA: IGI Global, 2012, pp. 129–153.

[2] M. Carlsson, G. B. Dahl, B. Öckert, and D.-O. Rooth, "The effect of schooling on cognitive skills," *Rev. Econ. Statist.*, vol. 97, no. 3, pp. 533–547, Jul. 2015.

[3] S. J. Ritchie, T. C. Bates, and I. J. Deary, "Is education associated with improvements in general cognitive ability, or in specific skills?" *Develop. Psychol.*, vol. 51, no. 5, p. 573, 2015.

[4] D. Tod, C. Edwards, M. McGuigan, and G. Lovell, "A systematic review of the effect of cognitive strategies on strength performance," *Sports Med.*, vol. 45, no. 11, pp. 1589–1602, Nov. 2015.

[5] S. Sheldon, S. Vandermorris, M. Al-Haj, S. Cohen, G. Winocur, and M. Moscovitch, "Ill-defined problem solving in amnestic mild cognitive impairment: Linking episodic memory to effective solution generation," *Neuropsychologia*, vol. 68, pp. 168–175, Feb. 2015.

[6] C. Granberg and J. Olsson, "ICT-supported problem solving and collaborative creative reasoning: Exploring linear functions using dynamic mathematics software," *J. Math. Behav.*, vol. 37, pp. 48–62, Mar. 2015.

[7] E. Fischi-Gómez, L. Vasung, D.-E. Meskaldji, F. Lazeyras, C. Borradori-Tolsa, P. Hagmann, K. Barisnikov, J.-P. Thiran, and P. S. Hüppi, "Structural brain connectivity in school-age preterm infants provides evidence for impaired networks relevant for higher order cognitive skills and social cognition," *Cerebral Cortex*, vol. 25, no. 9, pp. 2793–2805, Sep. 2015.

[8] W. D. Manning and K. A. Lamb, "Adolescent well-being in cohabiting, married, and single-parent families," *J. Marriage Family*, vol. 65, no. 4, pp. 876–893, Nov. 2003.

[9] P. R. Amato, "The impact of family formation change on the cognitive, social, and emotional well-being of the next generation," *Future Children*, vol. 15, no. 2, pp. 75–96, 2005.

[10] J. S. Coleman, *Parents, Their Children, And Schools*. Evanston, IL, USA: Routledge, 2018.

[11] J. L. Epstein, M. G. Sanders, S. Sheldon, B. S. Simon, K. C. Salinas, N. R. Jansorn, F. L. VanVoorhis, C. S. Martin, B. G. Thomas, M. D. Greenfield, D. J. Hutchins, and K. J. Williams, *School, Family, and Community Partnerships: Your Handbook for Action*. Thousand Oaks, CA, USA: Corwin Press, 2018.

[12] H. Beare, B. J. Caldwell, and R. H. Millikan, *Creating an Excellent School: Some New Management Techniques*. Evanston, IL, USA: Routledge, 2018.

[13] C. Romero and S. Ventura, "Data mining in education," *Wiley Interdiscipl. Rev., Data Mining Knowl. Discovery*, vol. 3, no. 1, pp. 12–27, 2013.

[14] Z. Li and D. Hoiem, "Learning without forgetting," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 12, pp. 2935–2947, Dec. 2018.

[15] N. E. Hill, D. R. Castellino, J. E. Lansford, P. Nowlin, K. A. Dodge, J. E. Bates, and G. S. Pettit, "Parent academic involvement as related to school behavior, achievement, and aspirations: Demographic variations across adolescence," *Child Develop.*, vol. 75, no. 5, pp. 1491–1509, Sep. 2004.

[16] I. Fister, P. N. Suganthan, I. Fister, S. M. Kamal, F. M. Al-Marzouki, M. Perc, and D. Strnad, "Artificial neural network regression as a local search heuristic for ensemble strategies in differential evolution," *Nonlinear Dyn.*, vol. 84, no. 2, pp. 895–914, Apr. 2016.

[17] M. Perc, M. Ozer, and J. Hojnik, "Social and juristic challenges of artificial intelligence," *Palgrave Commun.*, vol. 5, no. 1, pp. 1–7, Dec. 2019.

[18] D. Helbing, D. Brockmann, T. Chadefaux, K. Donnay, U. Blanke, O. Woolley-Meza, M. Moussaid, A. Johansson, J. Krause, S. Schutte, and M. Perc, "Saving human lives: What complexity science and information systems can contribute," *J. Stat. Phys.*, vol. 158, no. 3, pp. 735–781, Feb. 2015.

[19] V. R. Chomitz, M. M. Slining, R. J. McGowan, S. E. Mitchell, G. F. Dawson, and K. A. Hacker, "Is there a relationship between physical fitness and academic achievement? Positive results from public school children in the northeastern united states," *J. School Health*, vol. 79, no. 1, pp. 30–37, Jan. 2009.
[20] A. S. Lan, C. Studer, and R. G. Baraniuk, "Time-varying learning and content analytics via sparse factor analysis," in *Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, 2014, pp. 452–461.
[21] S. Ahmad, K. Li, A. Amin, and S. Khan, "A novel technique for the evaluation of posterior probabilities of student cognitive skills," *IEEE Access*, vol. 6, pp. 53153–53167, 2018.
[22] A. Daud, N. R. Aljohani, R. A. Abbasi, M. D. Lytras, F. Abbas, and J. S. Alowibdi, "Predicting student performance using advanced learning analytics," in *Proc. 26th Int. Conf. World Wide Web Companion*, 2017, pp. 415–421.
[23] S. Ahmad, K. Li, A. Amin, M. S. Anwar, and W. Khan, "A multilayer prediction approach for the student cognitive skills measurement," *IEEE Access*, vol. 6, pp. 57470–57484, 2018.
[24] A. T. Corbett, K. R. Koedinger, and J. R. Anderson, "Intelligent tutoring systems," in *Handbook of Human-Computer Interaction*, 2nd ed. Amsterdam, The Netherlands: Elsevier, 1997, pp. 849–874.
[25] K. R. Koedinger, A. T. Corbett, and C. Perfetti, "The knowledge-learning-instruction framework: Bridging the science-practice chasm to enhance robust student learning," *Cognit. Sci.*, vol. 36, no. 5, pp. 757–798, Jul. 2012.
[26] S. Ahmad, K. Li, A. Amin, and M. Y. Faheem, "Simulation of student skills: The novel technique based on quantization of cognitive skills outcomes," in *Proc. IEEE 17th Int. Conf. Cognit. Informat. Cognit. Comput. (ICCI CC)*, Jul. 2018, pp. 97–102.
[27] P. Langley, J. E. Laird, and S. Rogers, "Cognitive architectures: Research issues and challenges," *Cognit. Syst. Res.*, vol. 10, no. 2, pp. 141–160, Jun. 2009.
[28] A. M. Shahiri, W. Husain, and N. A. Rashid, "A review on predicting student's performance using data mining techniques," *Procedia Comput. Sci.*, vol. 72, pp. 414–422, Jan. 2015.
[29] M. Pandey and V. Kumar Sharma, "A decision tree algorithm pertaining to the student performance analysis and prediction," *Int. J. Comput. Appl.*, vol. 61, no. 13, pp. 1–5, Jan. 2013.
[30] J. McLurkin, J. Rykowski, M. John, Q. Kaseman, and A. J. Lynch, "Using multi-robot systems for engineering education: Teaching and outreach with large numbers of an advanced, low-cost robot," *IEEE Trans. Educ.*, vol. 56, no. 1, pp. 24–33, Feb. 2013.
[31] J. Shim, D. Kwon, and W. Lee, "The effects of a robot game environment on computer programming education for elementary school students," *IEEE Trans. Educ.*, vol. 60, no. 2, pp. 164–172, May 2017.
[32] J. L. Martin Nunez, E. Tovar Caro, and J. R. Hilera Gonzalez, "From higher education to open education: Challenges in the transformation of an online traditional course," *IEEE Trans. Educ.*, vol. 60, no. 2, pp. 134–142, May 2017.
[33] A. Satyanarayana and M. Nuckowski, "Data mining using ensemble classifiers for improved prediction of student academic performance," Dept. Comput. Syst. Technol., New York City College Technol., Brooklyn, NY, USA, Tech. Rep., 2016.
[34] Š. Pero and T. Horváth, 'Comparison of collaborative-filtering techniques for small-scale student performance prediction task," in *Innovations and Advances in Computing, Informatics, Systems Sciences, Networking and Engineering*. Cham, Switzerland: Springer, 2015, pp. 111–116.
[35] J. Luo, S. E. Sorour, K. Goda, and T. Mine, "Predicting student grade based on free-style comments using Word2Vec and ANN by considering prediction results obtained in consecutive lessons," in *Proc. 8th Int. Conf. Educ. Data Mining (EDM)*, Jun. 2015, pp. 396–399.
[36] A. Elbadrawy, A. Polyzou, Z. Ren, M. Sweeney, G. Karypis, and H. Rangwala, "Predicting student performance using personalized analytics," *Computer*, vol. 49, no. 4, pp. 61–69, Apr. 2016.
[37] Y.-Y. Chan, D. Hui, A. R. Dickinson, D. Chu, D. K.-W. Cheng, E. Cheung, W.-H. Ki, W.-H. Lau, J. Wong, E. W. C. Lo, and K.-M. Luk, "Engineering outreach: A successful initiative with gifted students in science and technology in hong kong," *IEEE Trans. Educ.*, vol. 53, no. 1, pp. 158–171, Feb. 2010.
[38] Ö. Yilmaz and K. Tuncalp, "A mixed learning approach in mechatronics education," *IEEE Trans. Educ.*, vol. 54, no. 2, pp. 294–301, May 2011.
[39] G. E. P. Box and G. C. Tiao, *Bayesian Inference in Statistical Analysis*, vol. 40. Hoboken, NJ, USA: Wiley, 2011.
[40] L. Wossmann, "Schooling resources, educational institutions and student performance: The international evidence," *Oxford Bull. Econ. Statist.*, vol. 65, no. 2, pp. 117–170, May 2003.
[41] J. E. Mitchell, B. Canavan, and J. Smith, "Problem-based learning in communication systems: Student perceptions and achievement," *IEEE Trans. Educ.*, vol. 53, no. 4, pp. 587–594, Nov. 2010.
[42] M. Munoz-Organero, P. J. Munoz-Merino, and C. D. Kloos, "Sending learning pills to mobile devices in class to enhance student performance and motivation in network services configuration courses," *IEEE Trans. Educ.*, vol. 55, no. 1, pp. 83–87, Feb. 2012.
[43] P. C. Scales, E. C. Roehlkepartain, M. Neal, J. C. Kielsmeier, and P. L. Benson, "Reducing academic achievement gaps: The role of community service and service-learning," *J. Experiential Educ.*, vol. 29, no. 1, pp. 38–60, Mar. 2006.
[44] S. R. Sirin, "Socioeconomic status and academic achievement: A meta-analytic review of research," *Rev. Educ. Res.*, vol. 75, no. 3, pp. 417–453, Sep. 2005.
[45] S. Ahmad, K. Li, H. A. Imad Eddine, and M. I. Khan, "A biologically inspired cognitive skills measurement approach," *Biologically Inspired Cognit. Archit.*, vol. 24, pp. 35–46, Apr. 2018.

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