Cognitive Learning Style Detection in e-Learning Environments using Artificial Neural Network

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Abstract—COVID-19 pandemic has impacted all aspects of our lives including learning. With the particular growth of e-learning, teaching approaches are being implemented at a distance on online platforms due to this pandemic. In this context, to make student involved throughout the online course, it is recommended to create an efficient platform similar to the traditional learning mode. In this study, we aims to improve learning style detection process by exploring additional such as cognitive traits. In fact, we have proposed novel approach based on Artificial neural network that classify students according to their level of cognitive learning styles in real-time. The proposed automated approach will certainly provide tutors with exhaustive information that helps them in achieving an improved and innovative online learning method. The results obtained are quite interesting and demonstrate the relevance of our solution.

Keywords—learning style approach, FSLM, artificial neural network, cognitive capacity

1 Introduction

The advantages that e-learning systems provide has attracted a good number of adult learners who seek to enroll in online course that respects their demanding work responsibilities [1]. However, online courses know some limitations in their course delivery system. In face-to-face learning, teachers can easily identify students' difficulties or their needs by observing students' behavior, activities and facial expressions in classroom. However, in online mode, students are being socially isolated in a totally online learning environment without any human interaction [2]. As a result, learner's needs and preferences in online educational activity remain unknown. If the students' learning characteristics could be measured, the tutors could better provide students with the materials according to their needs.

Today's ongoing issue is how to captive the attention of learners to be more involved in their virtual learning activities?

To deal with this challenge, several approaches proposed systems based in learning style to provide students with the appropriate education process [3] [4] [5]. In fact, the learning style has an important impact to ensure personalization within the learning environment and also to help students go further [6].

Individual learner has his personal manner in which he requires the knowledge. For example some students prefer auditory courses while others feel more comfortable with visual or kinesthetic resources. An-other example is that some students prefer to learn by doing experiences while others tend to think and reflect about it. Learning styles don't ex-plain just how student learn, but rather describe all student preferences for how learning material is presented, how they process information and how they retain effectively the information [7].

In this perspective, to motivate and engage students, we are particularly interested in detection Learning Style and integration into teaching process. The concept of learning style tackles mainly (1) the way in which learners prefer to learn as well as (2) how they perceive their learning process. In fact, the main Learning style objective is to classify learners according their learning preferences in order to provide them with materials that cater for their needs and expectations. It's an approach that allows learners to know their strengths and weakness through a virtual learning process. Many psychologists have conceived different models of learning styles. The more popular learning style models are David Kolb's model [8], Peter Honey and Alan Mumford's model [9], Felder-Silverman learning style model (FSLM) [3], and so on. In our context, we adopted FSLM [10]. FSLM is the most popular and used by many studies [11]. It was proposed by Richard Felder and Linda Silverman in 1988. This model classifies students in four dimensions: receiving, processing, perception, and understanding; each dimension includes two poles, namely Visual/Verbal, Sensory/Intuitive, Active/Reflective and Sequential/Global, respectively. In addition, this study also suggested the appropriate teaching styles adapted to each dimension, which may be the basis of an online teaching environment. The principal teaching approaches include visual/verbal, active/passive, sequential/global and concrete/abstract [12]. FSLSM is based on tendencies, indicating that learners with a high preference for certain behavior can also act sometimes differently.

- **Input:** considers how learner prefers the course be presented: visual (VIS) or verbal (VER). VIS learners tend to choose visual presentation such as pictures, diagrams, graphs, or demonstrations, whereas VER learners prefer text form, spoken or writing [13].
- **Perceiving:** tackles the manner in which learner preferentially retains information: sensing or intuitive. Students with a sensing preference are operating using their senses. Students with an intuitive learning style learn by stimulating their intuition and their imagination [14].
- **Processing:** describes how learner prefers to absorb knowledge: active or reflective. Active ones tend to choose learning object that re-quire them to be more experimentalist and collaborative. In contrast, reflective learners learn better alone without interactions with other that may prevent them to be more concentrate. They are more comfortable with situations that require reflection and deep thinking. They are more theoretician than practical [15].
- **Understanding:** addresses the channel in which learner progresses towards understanding: sequentially or globally. Sequential learners learn progressively and are characterized by linear learning progress. They acquire information step-by-step from the detail to global. In the opposite, global learners prefer a holistic view.

They prefer to know the main idea without viewing connections, and therefore, they move from non-understanding to understanding rapidly [16].

In further support of the aforementioned concept of learning style, one cannot disregard the fact that, besides the learning preferences and characteristics, each learner carries his own perceptual and cognitive traits that have a significant impact on how information is cognitively acquired, perceived and processed [17]. Concretely, in this study, we explore the potential of cognitive traits for providing additional information in the detection process of learning styles.

A good deal of information used by humans to predict cognitive learning style is based on the learners' behavior shown throughout his training, and it has been hypothesized that learners' traces are directly linked to the his preferred cognitive learning style [15]. Learning plat-forms provide a continuous and non-intrusive way of capturing learners' behavior. The captured learners' traces are analyzed to detect (1) how learners cognitively behave in their learning process and also (2) in which way they prefer to acquire knowledge efficiently. Different methods have been proposed to automate this detection process by analyzing learners' behavior, will be discussed in the next section of this paper.

In this regard, our proposal consists of the combination of learning style and cognitive capacity that will engage students in online learning process based on their preferred learning manner and also their cognitive ability. To do that, our study aims to automatically classify learners according their cognitive learning style using artificial neural network approach. This classification allows tutors to align the learning materiel with both students' cognitive capacity and their learning characteristics.

The rest of the paper is organized as follows. Section II presents the related works on learning style detection in distance education. Section III introduces our approach to improve the learning styles detection process using information from cognitive traits. Section IV explains ANN and the proposed model that are investigated for students' cognitive learning style detection process in this research study. The experiments, results discussion are presented in Section V and VI. Finally, Section VII draws the conclusion the proposed model and focusing on some possible future research directions considering online learning.

2 Literature review

To detect automatically learning style, there are two different approaches defined by Graf et al. [18][19]; literature-based and data-driven approaches. In one hand, data-driven methods are about to conceive automatic classifiers based on the data. In the other hand, literature-based approaches analyze the learner profile in order to extract hints from it and generate simple if-then rules to detect the learning style. The most known studies based on literature-based methods can be found in Dung & Florea.; S. Graf et al.; Sabine Graf; Latham et al.; and Rami et al., [20] [18] [21] [22] [23]. The researches based on data-driven approaches take advantage of different classification algorithms such as Neural Networks, Bayesian networks and SVM. All these later methods aim to point out some attributes from the learners' traces and then conceive classifiers based on this extracted data.

In our context, we will focus on studies based on neural networks. The neural network is a machine learning algorithm that is inspired from the concept of neurons and the learning capacities of the human brain. Neural networks have been adopted by many researchers to detect learning style: Kolekar et al. [24], Villaverde et al. [11], and others. Some of the recent work which has been done in this area is summarized in Table 1.

The table below synthesizes the recent papers in the area of automatic detection of learning styles based on neural networks. Most of the studies reviewed and presented in Table 1 have used the Felder-Silverman model.

Table 1. An overview of the current studies in automatic learning style detection based on artificial neural network

Paper	Description
A Machine Learning Approach to Identify and Track Learning Styles in MOOCs, 2016, [25]	This paper aims to identify and track learners' learning styles based on their behavior and actions during a MOOC then to provide them with personalized recommendations based on their learning styles. The authors have implemented a neural network to classify the learners in different dimensions of the FSLM model, but results have not been compared.
Identifying and tracking learning styles in MOOCs: A neural networks approach, 2017, [26]	In this paper, the proposed approach uses neural networks to identify learners learning styles, then to provide them the appropriate resources, activities. The method was not implemented, and the results were not compared.
Learning Style Identifier: Improving the Precision of Learning Style Identification Through Computational Intelligence Algorithms, 2017, [19]	This paper presented four automatic approaches for identifying learning styles from the behavior of students in learning management systems, using four computational intelligence (CI) algorithms, namely an artificial neural network, genetic algorithm, ant colony system and particle swarm optimization. An evaluation with data from 75 students was conducted, demonstrating the overall precision of the approaches for each of the four learning style dimensions of the Felder-Silverman Learning Style Model (FSLSM) (1988) as well as the accurate identification of learning styles for each single student. The proposed approach is compared to existing methods, and there was an improvement in the accuracy.
Learning Style Recognition: A Neural Network Approach, 2018, [27]	In this paper, the authors attempted to identify different attributes which can be used to infer the learning style and preferred learning mode of the learner in accordance with Gardner's theory of multiple intelligences. Two different feed forward-back propagation neural networks were proposed, one for the learning style and another for learning mode preferred. The method was not implemented, and the results were not compared.
Model Detecting Learning Styles with Artificial Neural Network, 2018, [28]	The authors used Latent semantic indexing to use prior knowledge of the learner to predict the learner's learning style and then compared it to the data received from the learners. This research has succeeded in developing a model of learning style detection by using a prior knowledge approach. The prior knowledge generation process uses the Latent Semantic Indexing (LSI) approach. e. After the process of generating learning styles with LSI is completed, the next step is to predict learning style by using ANN.

Analyzing these current papers for detecting learning styles reveals some limitation we should address:

– In some publications, the proposed models have not been compared to others for accuracy, precision, and recall.
– Most of the papers that used the FSLM learning style model, they tackled either one or two dimensions of the model.
– Most of the publications we reviewed used only FSLM they did not take into consideration the cognitive trait.

To overcome the problems that occurred from the previous research, this work aims to detect the cognitive learning style and the proposed system has been trained, and validated.

3 Improving the detection of learning styles using information from cognitive traits

The previous section presented the most popular studies conducted in the area of detection learning styles using the students' behavior and traces within a course. However, other factors can also be important in the detection process of learning styles by generating pertinent information related to learners. In this study, we explore the potential of cognitive traits for providing additional information to improve the detection process of learning styles.

Each individual has a set of cognitive capacities. Cognitive capacities are referred to the abilities to "perform any cognitive task" [29]. More specifically, cognition can be defined as "the mental capacities needed to acquire and process information" [29] or more concretely "the mental process of knowing that incorporates aspects such as awareness, perception, perceiving, and reasoning" [30].

Learning and cognitive styles can be defined as preferences and capacities that determine a learner's typical rhythm of perceiving, absorbing and solving problems, as well as the manners in which a learner memorizes and retrieves information [31]. Each learning and cognitive style approach defines a set of patterns of common characteristics to classify learners. Therefore, in any learning process, the significance of the fore mentioned learners' differences, both cognitive and preferential, should be detected and taken into account when designing adaptive learning system.

Based on the abovementioned considerations we introduce the "New" learning style that combines the cognitive traits along with learning characteristics and preferences since they are impacting the way a learner approaches a learning task.

Cognitive capacities are mainly defined by three components:

- **The control of processing:** refers to the mechanisms that identify relevant information and block out irrelevant one [32].
- **The speed of processing:** refers to the maximum speed at which a given mental effort may be efficiently executed [33].
- **The working memory:** refers to the processes that allow learner to keep active an amount of information for a brief period of time [34].

In this study, to improve the detection process of learning styles, the correlation between learning styles and the cognitive capacity was investigated. Therefore, first, we studied each dimension of FSLM and pointed out the nature of cognitive capacity involved in each learning preference [35] [36]. Concretely, indirect relationships between the dimensions of FSLSM and the cognitive capacity were concluded. In the following subsections, the correlation between learning style and the cognitive capacity introduced and discussed.

3.1 Correlation between FSLM and the cognitive capacity

The correlation between Visual/Verbal dimension and cognitive capacity: This dimension refers to whether learners are given text-based material or instructions with graphics. On the one hand, verbal learners are characterized by a passive way of learning and tend to absorb the information and memorize it without making any additional mental effort. On the other hand, learners who prefer to learn from graphics-based learning material tend to have a high cognitive capacity. Visual learners provide a significant mental effort to learn and assimilate concepts through images and videos by producing their own definitions.

To synthesize, low-cognitive-capacity learners benefit from text-based material and therefore prefer a more verbal learning style. However, the preference for a visual learning style implies a high cognitive capacity.

The correlation between Active/Reflective dimension and cognitive capacity: The Active /Reflective dimension is likened to the dimension of doing versus observing, as well as the dimension of doing versus thinking. In this context, active learners are defined as creative and reflective learners are defined as those who are most successful when there is only one answer to a problem. In addition, active learners are related to active experimentation (doing) and reflective learners are related to reflective observation (thinking). Therefore, the active ones show a very high level of cognition while the reflective ones have a good cognitive level but in a passive state of mind. Given that the active and reflective have a good cognitive but with a passive and active trait. Consequently, the active ones have a good cognitive capacity but very active while the reflective ones also have a good cognitive capacity but in a very passive way.

The correlation between Sensing/Intuitive Dimension and cognitive capacity: The main characteristic of the sensory/intuitive dimension is the concrete/abstract nature of the preferred learning material. On the one hand, intuitive learners are characterized by their high cognitive level as they tend to be more interested in abstract and theoretical issues that require considerable mental effort. On the other hand, sensory learners prefer concrete material. They tend to participate in tests and experimentations to prove knowledge and support their skills. Since sensory learners have a preference for concreting abstract concepts, they are therefore characterized as cognitively active.

As a result, intuitive/sensory learners are described as having a very high cognitive capacity.

The correlation between sequential/global dimension and cognitive capacity: We examined the correlation between cognitive capacity and a sequential/global learning style. In fact, we concluded that learners with a sequential learning style have a significantly lower cognitive capacity than learners with a global learning style. A sequential learner needs to study in a linear way to assimilate the course; he is not able to deduce neither to make an additional cognitive effort to elaborate his own definitions. As for the global learner, he/she needs an overview to visualize and assimilate the concept without going into details that are trivial to him/her.

Therefore, high ability learners are likely to prefer the global learning style, while low ability learners tend to have a sequential learning style.

3.2 Synthesis

In the previous subsections, we explored the correlation between the four dimensions of the Felder-Silverman learning style model and learner cognitive capacity. To summarize, learners with high cognitive ability tend to have a reflective, intuitive, sensory, visual and global learning style. On the other hand, learners with low cognitive capacity tend to have a verbal and sequential learning style.

In this perspective, three levels related to cognitive learning style have been identified, as follows:

- **Passive:** for the learner who simply absorbs information without analyzing, interpreting or even reacting and prefers to work alone.
- **Constructive:** the learner prefers to learn abstract material such as theories and their meaning, and tends to be more innovative. They tend to follow linear step-by-step paths in their learning.
- **Interactive:** The learner learns effectively through trial and error, experimentation and group work. They tend to be hands-on.

The three levels related to cognitive learning style and their correlated dimensions of FSLM are illustrated in the Table 2 below.

Table 2. Mapping of three different levels of cognitive learning style levels considered in this paper and their correlated FSLM dimensions

Levels of Cognitive Learning Style	Passive	Interactive	Constructive
Dimension			
Perception		Sensing	Intuitive
Input	Verbal	Visual	
Processing	Reflective	Active	
Understanding	Sequential		Global

4 Cognitive learning style detection using ANN methodology

4.1 Research methodology

The research methodology adopted to detect the cognitive learning style is mentioned in Figure 1, which presents the main steps to detect the cognitive learning style of the learner.

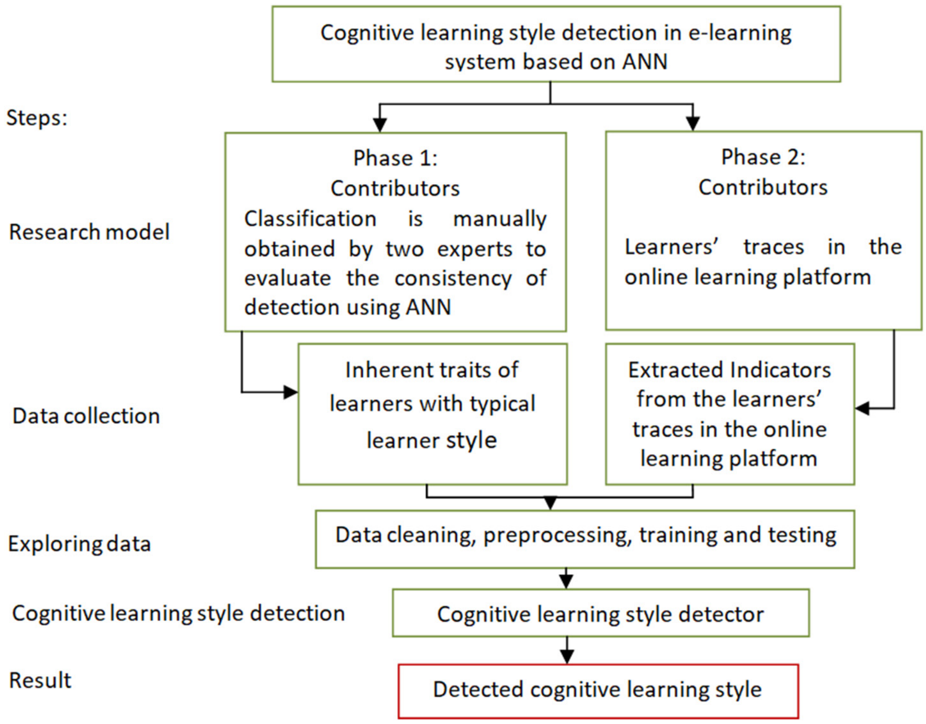

Fig. 1. Research design

We have followed an experimental research design; the contributors of data are the traces of the learner with a specific learning style and student behavior attributes in the E-learning system. Data is collected both through two experts review and through online logs of learners in the system. The whole dataset was coded by two experts according to the three levels of cognitive learning style based on the coding scheme instrument defined by Graf [37].

The results collected from experts intended to check whether our trained model can correctly predict their learning style using the pro-posed attributes or not. For instance, learner 'A' is initially classified by our two experts. A's traces are tracked in the online learning system. The indicators to extract the proposed attributes are taken from log files. The trained model then uses the indicators to predict A's learning style. Finally, to evaluate the consistency of the proposed method, the results obtained by our two experts and the predicted value are equated. If they are equal, the model is consistent, if not, the model is not consistent.

4.2 The proposed ANN methodology

Our main objective is to classify learners by using ANN according three levels of cognitive learning style aforementioned. The detection process is done by exploring the learners' logs and traces driven from the e-learning system as an input of our ANN. The unprocessed dataset was extracted, and processing was done to clean the dataset. The processed data was then used to train and test the ANN. The output of ANN is evaluated with respect to the results obtained manually from two experts. The ANN proposed methodology for detecting cognitive learning style process is depicted in Figure 2.

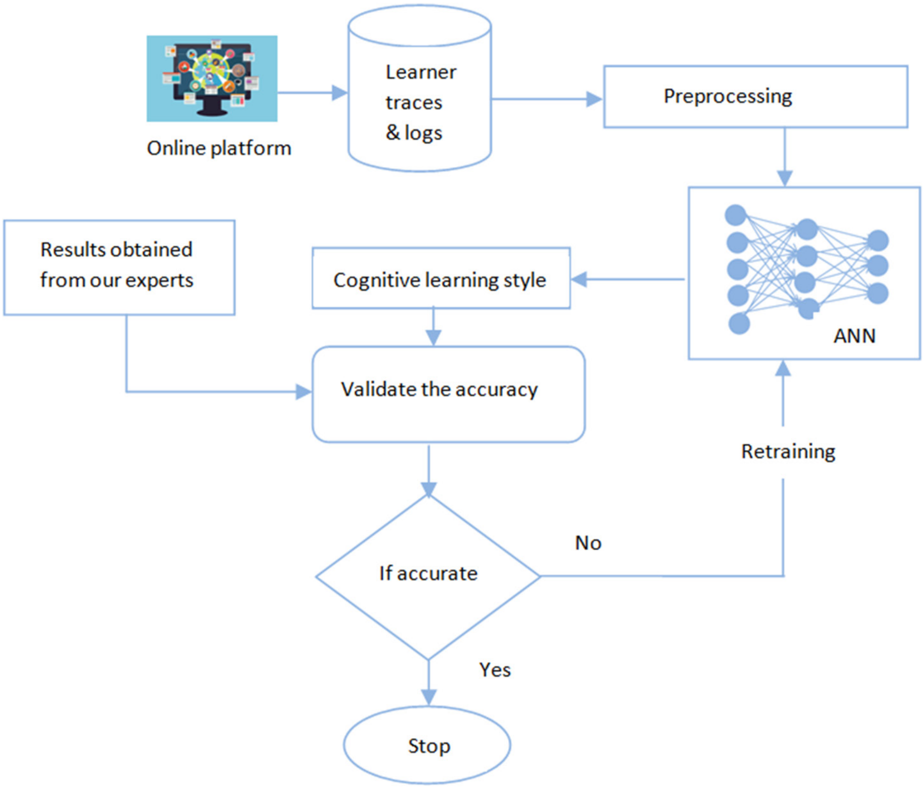

Fig. 2. ANN proposed methodology

Our two expert classified learners that give an insight into what learners with particular cognitive learning style do in online learning. If all/ most of the activities of the learner converge to instructive cognitive learning style, the learning style as predicted by the experts is instructive. This logic is the same in ANN; ANN helps in detecting the level of cognitive learning style according to the inputs supplied.

5 Experiments and results

5.1 Dataset

To classify learners according to the three levels of cognitive learning style, the Dataset have been used in cognitive learning style detection. Our dataset is created with the intent to capture student cognitive learning style in online courses. The dataset explored in this paper comes from samples of different courses in software engineering offered through an online learning platform. The dataset is collected in different spaces of time. For training, we took 70% of the dataset; testing was done on 30% of dataset. The attributes listed in Table 3 are pointed out by exploring the literature review of Graf (Graf et al, 2006) (Graf et al., 2007) [21] [37]. These attributes can be either easily observed or extracted from the learner logs. Choosing complex attributes will create issues in the data collection step, and require a lot of coding to make the platform takes into account more attributes.

Table 3. Attributes and description used to detect the level cognitive learning style

Levels of Cognitive Learning Style	**Attribute Name**	**Description**
Passive	T_read N_exercise_after_read T_vocal T_outlines T_submit_assignment T_solve_exercise T_spent_in_session N_questions_on_details	Time spent on reading material Number of exercises completed after study using reading material Time spent on listening to audio content Time spent in study using outlines Time taken to submit an assignment Time taken to solve exercise Time spent in a session; Number of questions attempted that deal with details of a concept
Interactive	T_Image T_video N_exercise_after_graphic T_concrete N_standard_questions_correct N_msgs_posted N_exercises_visited T_reading_in_forum N_groupdiscussions	Time spent on study using images. Time spent on watching video content. Number of exercises completed after study using graphics/ Time spent on concrete content calculated as: $T_{concrete} = \sum [T_{examples} + T_{casestudies} + T_{complexconcepts}]$ Number of standard questions answered correctly Number of messages posted in the discussion forum Number of exercises visited by the learner Time spent in reading discussions in the forum Number of group discussions joined
Constructive	T_abstract N_creative_questions_correct N_Skipped_Los N_next_button_used N_questions_on_outlines	Time spent on abstract content calculated as: $T_{abstract} = \sum [T_{facts} + T_{casestudies} + T_{Theory}]$ Number of creative questions answered correctly Number of learning objects skipped by the learner. Number of times the next button. Number of questions that deal with the outlines of concepts

5.2 Detecting cognitive learning style using ANN

In our study, we propose cognitive learning style detection process using ANN, which uses three ANNs, one per cognitive learning style level. Such configuration has the potential to improve the accuracy of cognitive learning style detection as it detects all three cognitive learning style levels and each ANN can focus only on detection of one level.

In cognitive learning style detection process using ANN, each of its three ANNs uses the commonly used configuration of a feed forward 3-layer-perceptron [38]. Each ANN has as inputs the relevant behavior pat-terns for the respective cognitive learning style level, as illustrated in Table 3. Accordingly, the ANN for identifying the passive level has 8 inputs, while for the interactive level the ANN has 9 inputs and for the constructive level the ANN has 5 inputs. As the inputs are of different scale, normalization was performed. Since for all patterns 0 was a valid value this was used as the lower bound. Each ANN has a one output which produces a value from 0 to 1 and represents the detected cognitive learning style value of the respective level. An example of the topography used for the constructive level illustrated in Figure 3.

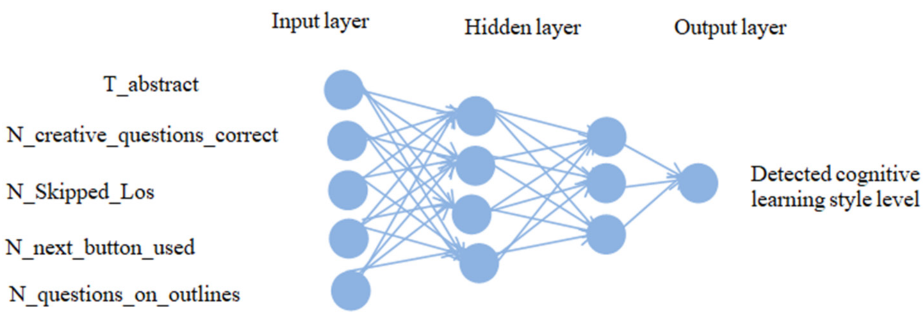

Fig. 3. ANN topography for the constructive level

Each ANN is a supervised learning technique to train and back-propagation as training algorithm [39]. To train the ANN, the ANN runs with the traces of each student in each iteration. Starting with the input data from the first student (attributes listed in Table 3), an output value (i.e., the level of cognitive learning style) is generated. This output value is then compared to the actual learning style of that student (as detected manually by our two experts).

5.3 Result

For the attributes listed in Table 3, we used a dataset with 300 samples from students taking online courses. The pre-processing was done, fit, and transform; the data were normalized between 0 and 1. To be sure of the sufficiency of our proposed system, we trained both ANN and Naïve Bayes. The algorithms were run on Python Kernel 3.1. Table 4 summarizes Accuracy results (classification accuracy, recall precision and f1 score) for two algorithms for different levels of cognitive learning style.

Table 4. Accuracy measures for the machine learning algorithm

Passive				
Algorithms	**Accuracy**	**Precision**	**Recall**	**F1-score**
ANN	85,22%	85%	85%	85%
Naïve Bayes	77,48%	83%	77%	76%
Interactive				
Algorithms	**Accuracy**	**Precision**	**Recall**	**F1-score**
ANN	85,33%	86%	85%	85%
Naïve Bayes	82,66%	83%	83%	83%
Constructive				
Algorithms	**Accuracy**	**Precision**	**Recall**	**F1-score**
ANN	91,33%	92%	91%	91%
Naïve Bayes	87,33%	87%	87%	87%

6 Discussion

To evaluate the performance of the proposed model, we used different metrics for evaluating the ANN and Naïves Bayes compared to the classification manually obtained by our two experts.

We can observe from the Table 4 that, for all levels of cognitive learning style, the ANN has the highest accurate classifier and performs better than the Naïve Bayes.

To improve the results of ANN, we used another metric. The metric is consistency. Consistency is used here as a measure of evaluating how correctly our proposed model detects the learner level of cognitive learning style. % Consistency ((correct predictions by ANN/No of learners from manual marking) *100). For instance, if there are X students of the passive level detected in the manual marking, we check out of the X how many were correctly predicted as passive type using ANN.

To measure this later parameter of consistency, we used dataset of 112 samples of students. Table 5 illustrates the % consistency of ANN as compared to manual marking by our two experts to detect the level of cognitive learning style. Values in the table are compared for each level. For example, the first block consists of the costs for passive. With the manual marking, we had 45 passive learners, and the ANN detected that 40 of them as passive, which is a consistency of 88.88%. The % consistency for all the levels ranges between 82% and 91%, which is a good accuracy.

Table 5. Consistency between manual marking and ANN detection for the three levels of cognitive learning style

Level of Cognitive Learning Style	Number of Students with Learning Style from Manual Marking	Number of Students with Learning Style Deduced by Artificial Neural Network	% Consistency ((Correct Predictions by ANN/No of Students from Manual Marking) *100)
Passive	45	40	88,88%
Interactive	32	29	82,05%
Constructive	35	33	91,42
Total	112	102	91,04%

7 Conclusion

This research has succeeded improving learning style detection process by exploring the additional information related to the student such as cognitive capacities. The cognitive learning style detection paradigm can enhance learners' learning experiences in different online learning activities.

In this paper, we investigated the potential of the Artificial Neural Networks as proposed classifier for the students' cognitive learning style classification. In the experiments, three-level (passive, instructive and constructive) annotation on cognitive learning style detection have been explored, where the ANN shows high accuracy in cognitive learning style classification (passive 85,22%, instructive 85,33%, and constructive 91,33%) in the Dataset compared to Naive Bayes. in our study, the consistency between manual marking and ANN was also measured; the results are promising.

As perspective, we plan to make our practical implementation of cognitive learning style detection based on ANN useful in learning management system.

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