A cognitive level evaluation method based on machine learning approach and Bloom of taxonomy for online assessments

Abdessamad Chanaa, Nour-eddine El Faddouli
MASI Laboratory, Computer Science Departement, Mohammadia School of Engineers, Mohammed V University in Rabat, Rabat, Morocco

Article Info

Article history:

Received May 14, 2023
Revised Oct 30, 2023
Accepted Nov 12, 2023

Keywords:

Bloom's taxonomy
Classification
Cognitive level
E-learning
Machine learning
Online assessments

ABSTRACT

Adaptive online learning can be realized through the evaluation of the learning process. Monitoring and supervising learners' cognitive levels and adjusting learning strategies can increasingly improve the quality of online learning. This analysis is made possible by real-time measurement of learners' cognitive levels during the online learning process. However, most of the currently used techniques for evaluating cognitive levels rely on labour-intensive and time-consuming manual coding. In this study, we explore the machine learning (ML) algorithms and taxonomy of Bloom's cognitive levels to explore features that affect learner's cognitive level in online assessments and the ability to automatically predict learner's cognitive level and thus, come up with a recommendation or pedagogical intervention to improve learner's acquisition. The analysis of 15,182 learners' assessments of a specific learning concept affirms the effectiveness of our approach. We attain an accuracy of 82.21% using ML algorithms. These results are very encouraging and have implications for how automated cognitive-level analysis tools for online learning will be developed in the future.

Corresponding Author:

Abdessamad Chanaa
MASI Laboratory, Computer Science Departement, Mohammadia School of Engineers
Mohammed V University in Rabat
Rabat, Morocco
Email: abdessamad.chanaa@gmail.com

1. INTRODUCTION

In contrast to traditional classroom instruction, online learning challenges the traditional teaching model by giving students access to learning resources, and a variety of learning strategies. It enables students to increase and expand their knowledge regardless of location or time [1]. To accomplish the purpose of online learning, learners must have a better understanding of themselves and precisely identify their learning needs and cognitive level.

Educational psychologists developed a system based on learning objectives that uses the taxonomy's levels to categorize students' level of comprehension and learning [2]. The three domains of Bloom's taxonomy are cognitive, emotional, and psychomotor. Because it is so closely related to students' understanding and knowledge in the classroom, our study has concentrated on the cognitive domain at this point. Quick assessment analysis of a learner's cognitive level during the learning process enables them to grasp their cognitive level and promptly alter their learning methods and materials. Additionally, it can assist teachers in providing timely, individualized instructional recommendations/interventions, more accurate implementation of lesson plans and structures, and supervising the learners' general cognitive level across their learning journey [3].

Learners' cognitive level analysis requires manual coding, which demands a high level of research aptitude and expertise from the analyst. It is also a very time-consuming task. Additionally, Due to the enormous amount of information that needs to be sifted through, many researchers view manual analysis of textual data as a tedious and labour intensive effort. The manual coding approach falls under the category of shallow learning, necessitating the manual selection of many data attributes, being labour- and time intensive, and being limited in its ability to generalize [4]. Remarkable progress has been attained with the widespread use of artificial intelligence (AI), specifically machine learning (ML) techniques for classification tasks. ML constitutes a novel and recent technique for data analysis, it has promising outcomes and substantial abilities [5]. Complex data representation can be automatically learned and added to the analysed model [6]. From this perspective, the purpose of this research aims to automatically assess the learner's cognitive level in online assessments and explore factors that impact the learner's cognitive level during the learning process using the ML approach.

The rest of the paper is organized as follows: section 2 summarizes the Bloom of taxonomy and a literature review about cognitive level extraction in online learning. Section 3 presents our structure, steps and method based on data analysis and ML. We demonstrate the experiment, the analysis and the discussion of the results in section 4. Finally, section 5 highlights the conclusion and discusses future work.

2. LITERATURE REVIEW

Several works use cognitive-level in e-learning to enhance the learning process. For a better understanding of the concepts, the first part of this section highlights an overview of Bloom's taxonomy. On the other hand, the second part is dedicated to presenting some recent works that use Bloom's taxonomy to model the cognitive state of learners and predict their cognitive-level.

2.1. Bloom of taxonomy

Taxonomy of educational objectives is a framework for classifying statements of what we intend/expect learners to learn as a result of instruction. All six of the primary categories in the cognitive domain have well-crafted definitions in the original taxonomy: evaluation, synthesis, analysis, application, comprehension, and knowledge [7]. The general criteria for programming evaluation as well as the hierarchy of Bloom's cognitive levels are displayed in Figure 1. Within this hierarchy, the categories were ordered from concrete to abstract and from simple to complex, where each lower level serves as a foundation for higher levels, meaning that proficiency at one level is necessary to advance to the next, more complex/difficult level [8]. Furthermore, a student who has attained a higher level has passed the previous levels with success. In order to facilitate categorization, we are using a variation of the cognitive process's three stages for this study [9]: high cognitive (CH) level (synthesis and evaluation), medium cognitive (CM) level (application and analysis), and low cognitive (CL) level (knowledge and comprehension).

2.2. Cognitive level

Troussas *et al.* [10] suggested a novel paradigm for the students' cognitive states' automated reasoning. The revised Bloom taxonomy and the k-nearest neighbors algorithm are used to show the cognitive states, which correspond to increasing levels of cognitive complexity. Additionally, a progressive approach based on Bloom's taxonomy was utilized to prepare the assessment questions, and the proficiency level was determined by that method. In this direction, Ullah *et al.* [11] propose a novel approach to programming assessment, which shows that Bloom's taxonomy is a beneficial tool for learning and assessing programming. It achieves a student mapping to the respective cognitive levels of Bloom's taxonomy directly from the written programming code, with no prior mapping questions. With an accuracy of 70%, Jayakodi *et al.* [12] used the cosine and WordNet similarity with natural language toolkit (NLTK) algorithms to create a distinct set of criteria that determine the test question's weight and category based on Bloom's taxonomy. Na *et al.* [13], in order to investigate students' impressions of formative assessment through a survey, it is proposed to create formative assessment as an instructional technique in real-time online classrooms and to investigate the use of Bloom's taxonomy in the production of formative assessment. Based on cognitive theory and fuzzy logic, Chrysafiadi *et al.* [14] suggested a fuzzy rule-based reasoner that determines the required number and degree of difficulty of test items for each level of the revised Bloom taxonomy in order to generate a customized exam. The learners' knowledge level is described using fuzzy logic, and the assessment results demonstrate extremely excellent accuracy in the test item selection for each individual student. Also, using fuzzy restricted boltzmann machine and natural language processing, Sairaj and Balasundaram [15] outline a novel approach for automatically creating questions based on Bloom's cognitive levels. In order to implement assessments to measure students' cognitive levels, Abduljabbar and Omar [16] presented a novel technique that uses a combined strategy based on a voting algorithm and ML classifiers to automatically categorize test questions based on Bloom's taxonomy's cognitive levels. In the same direction, Huilan *et al.* [17], focuse on the cultivation of students' critical thinking through questioning and introducing Bloom's taxonomy and the structure of observed learning outcomes (SOLO) taxonomy. It discusses how to make students-centred and how to train their critical thinking in the training process and cultivate students' critical thinking to accomplish it. Pallegama *et al.* [18] presented a really intriguing concept by talking about an automated system with the ability to ensure that the teaching content and learning activities are within the learning outcomes, as well as to validate the learning outcomes and their levels for each module and lesson based on Bloom's taxonomy. Also, Subiyantoro *et al.* [19] concentrate on applying the Bloom taxonomy to determine the cognitive categorization system. They divide cognitive levels into three divisions using learning vector quantization (LVQ); low cognitive (CL), medium cognitive (CM), and high cognitive (CH). From another perspective Sukajaya *et al.* [20] use Bloom's taxonomy based serious game (BoTySeGa) as a substitute evaluation tool to gauge learners' proficiency in mathematics. Mohammed and Omar [21], provide an automated test question classification technique based on the extraction of two features: word2vec and TFPOS-IDF known as, term frequency (TF)-inverse document frequency (IDF) based on part-of-speech (POS). Also, in order to analyse failed student behaviour and identify their needs, Wu *et al.* [22] created three classification models using data from two sizable online forums, then used the models to categorize postings in a private Facebook group into topics connected to statistics and those that weren't. Heilporn *et al.* [23] provided a thorough and all-encompassing picture of the methods used by instructors to improve student engagement in blended learning, based on cognitive and emotional behavior. A suggested intelligent framework by Barbosa *et al.* [24] makes use of the random forest (RF) classifier and ML methods to deal with the problem of determining which e-learning materials are appropriate for students based on their degree of domain expertise.

Those presented methods elaborate the use of Bloom's taxonomy in many e-learning areas to classify cognitive levels. However, those methods are generally based on complex structures and can not be generalised into any e-learning platform. We consider evaluation and online assessments to be the best tools to measure learner's knowledge and comprehension evolution during the learning process. Moreover, the proposed methods did not take into consideration variables related to the method of resolving online assessments. Also, some affective traits and epistemological emotions like confusion or concentration are very essential variables in the e-learning process since they affect directly the learner's online evaluation results and thus learning outcome.

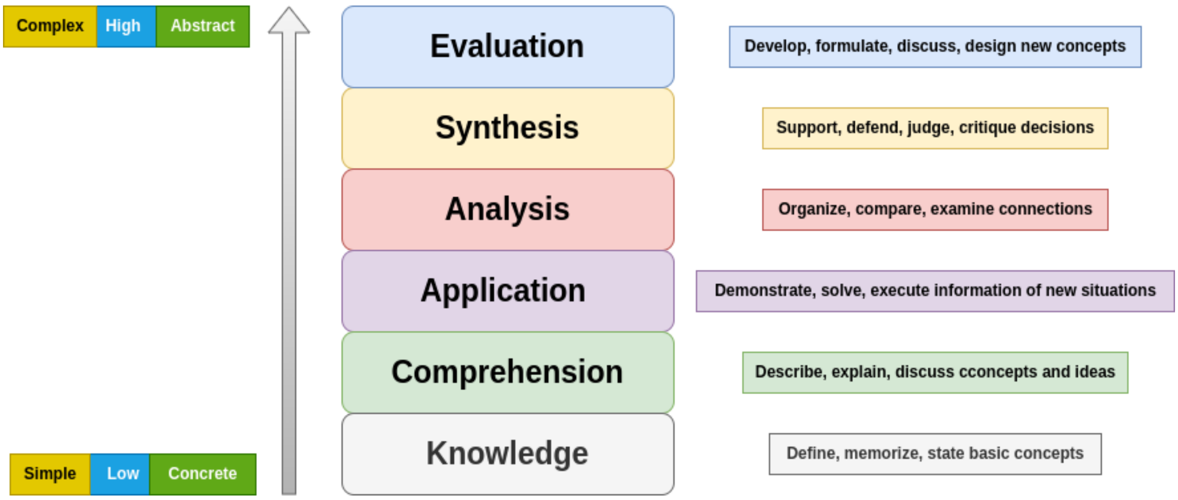

Figure 1. Bloom's cognitive level

3. METHODOLOGY

Our methodology is to create a ML model that takes into consideration many affective and cognitive features in the context of online assessment. Figure 2 shows an overview of our suggested method. Our approach is broken down into three stages: the definition and aggregation of features, the ML model, and the decision-making. In the next subsections, we will elaborate in detail each step individually. Starting with defining our variables/features that could determine the learner's cognitive level in the learning process, the ML approach that will next classify each learner based on those features into different classes to decide at last the accurate cognitive level of each learner and come up with the suitable pedagogical proposition for each learner in the system.

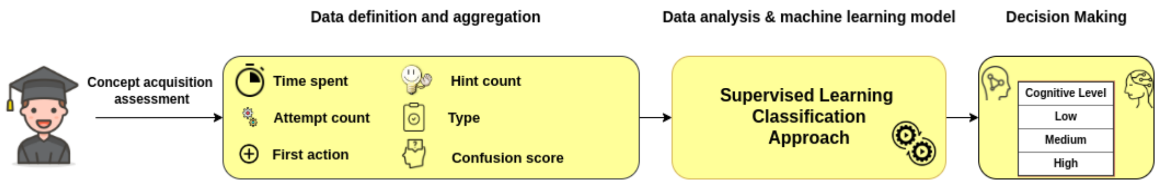

Figure 2. Methodology steps

3.1. The definition and aggregation of features

Since our method is based on online learning assignments, it was hard to carefully choose and aggregate suitable features that may contribute to defining the learner's cognitive level. The main challenge in this research problem is that the online assignment questions are not properly categorized and correct weights are not assigned for each assignment/category/topic in the final decision in scoring learners. Moreover, we can not correctly define learners from score or yield in those assignments. Therefore, we propose a combination of affective and cognitive traits that affect Bloom's cognitive levels of each learner during the learning process on a defined learning concept. We define those variables as (a)-(f):

a. Time spend: it is the time between the start of the assignment and the final sub mission of the answer. It is an important variable to define whether the learner passes a considerable time or a short among of time-solving the problem. Generally, learners with high cognitive levels/engagement are more likely to solve their problem assignments in less time than others.
b. Hint count: the number of used hints on the assignment. Every learner can use a number of hints to facilitate solving the assignment problem. The fewer hints used the higher Bloom's cognitive levels of the learner.
c. Attempt count: the number of wrong attempts to solve the problem. Every learner can use a number of attempts to solve the given problem. Similar to the hints, the more attempts used, the lower Bloom's cognitive levels of the learner.
d. First action: the first action determines the intuition of the learners and his/her cognition level. The available actions are: an attempt or ask for a hint.
e. Type: this characteristic identifies the kind of the issue set's head section. Typically, each problem set is one of the three that follow:
   - Linear: the student completes each task in the prescribed order.
   - Random: the student completes all tasks/problems, however, the order of the problems is varied for every learner (randomly compared to other learners).
   - Mastery: random order, in which before moving on, the learner must "master" the given issue by correctly answering a certain number of questions in a row. Based on this classification, we can determine whether the learner attempts to randomly solve the problem with no cognitive engagement/level or whether he/she is cognitively engaged to solve the problem in a predetermined or correct order.
f. Confusion score: although it is evident that the emotional and cognitive systems operate separately, they nonetheless have an impact on one another. One affective condition that links emotion and cognition to epistemic emotion is confusion. It is seen as an absolute cognitive state and an emotional state [25], but not an emotion [26]. Bloom's cognitive levels are directly related to the confusion score of the learner during solving the problem. The learner with a high confusion score (confused learner), is generally a learner with a low cognitive level. Therefore, the confusion score is an additional feature, yet very important to determine Bloom's cognitive levels of learners.

All those features are gathered, cleaned, and combined to construct the dataset input into the ML model. It is crucial to remember that data is collected and grouped by a specific learning concept. The aim of the study is to learn the cognitive level of each learner around a learning concept in order to be able to analyse the learner's behaviour precisely and anticipate future decisions.

3.2. Data analysis and machine learning model

It is crucial to remember that data pre-processing, a straightforward yet crucial step that ensures data consistency for better analysis, it must be done before data analysis. In this step, data is filtered by removing redundant and irrelevant features, which is known as noise removal. Data analysis is the process of gathering, constructing, and expressing data in order to gather useful information, identify patterns of learning, and forecast future behaviour. This is a crucial step to the ML model. Over the several learning periods of the courseware, building a precise predictive system requires processing and representing the input at each learning phase. For instance, the data are interpreted using statistical metrics. To reduce dimension, feature aggregations and correlations are employed, and ML techniques are utilized for prediction.

ML is an essential part of AI. ML is defined as “the field of study that gives computers the ability to learn without being explicitly programmed” [27]. It is a system of learning through examples. ML intends for a machine to deal with new situations through observations, self-training, and experiences in order to carry out particular tasks. ML is increasingly widely used in many aspects of daily life, including e-learning [5], [28]. The three main types of ML are unsupervised learning, supervised learning, and reinforcement learning. Reinforcement learning makes a series of decisions over time to maximize performance, whereas unsupervised learning evaluates input X without supervision from outcome Y. Input data X is used in supervised learning to predict the label of output data Y.

After the creation of data vectors illustrating the cognitive state of each learner through time. In order to categorize data based on attributes and features, we plan to conduct a supervised ML study to find Bloom’s cognitive levels classes of learners. More specifically, we want to organize items into “classes” with the highest possible affinity within each class. Based on the supervised learning approach, we model the input vector X as the features presented in section 3.1 to predict the output data Y the present three classes of learner Bloom’s cognitive levels: high level, medium level, and low level.

We first conducted a guided study to investigate a collection of well-known classification models in order to choose the top-performing one since it is improbable that the top-performing classification model can be found beforehand. We intend to examine a variety of ML models and choose the best models from them in accordance with the precision and accuracy of the findings.

3.3. Decision-making

Following the extraction of each learner’s cognitive level. The given cognition categorization model can make the supervisory process easier. In reality, adding the ML model to the e-learning platform can significantly improve the quality of decisions and learning alternatives.

The design of the proposed method addresses the problem of the cognitive level of learners and the ability to predict it earlier through online assignments. The idea of analysing and predicting a learner’s cognitive level can shed the light on the cognitive engagement of the learner during the learning process. Tutors or the instructional designers who set up a known cognitive level before the start of the learning process can supervise learners who can not successfully pass the required lower cognitive knowledge level and thus come up with the best solution/intervention to help learners overcome their learning difficulties.

This strategy intends to simplify the entire learning process by effectively automating logical decision-making activities with no need for expensive training intervention. Recent studies in the field of cognitive analysis are attempting to make use of ML techniques’ capacity for automating judgments. This opens up several study areas that have already been studied in the literature, including learning objects recommendation [29], questions classification [30], information retrieval from multimedia data storage [31], and summative assessment classification [32].

4. EXPERIMENT

In order to validate the proposed approach. In this section, we manage the experiment to give details about our approach and verify its practicality. This section is divided into three subsections ; the used data, the experiment settings of the solution and last, the results and discussion. It is important to note that the dataset (after processing) and the source code are publicly available in [33].

4.1. Data

We adopt the dataset drawn from the ASSISTments data for the school year 2012 - 2013 with affect predictions [34], [35]. We reorganized the dataset by selecting, cleaning, and aggregating relevant features to match our methodology. We chose “addition and subtraction of fractions” as a learning concept to study the cognitive acquisition level of learners for this specific concept. The final collected dataset contains 151016 entries of different learners in the systems. The dataset was labelled into three classes (1 for low cognitive acquisition level, 2 for medium cognitive acquisition level, and 3 for high cognitive acquisition level). The dataset is annotated by three professional coders (a senior Ph.D. student and two full professors). The coders explained the annotation approach and rules prior to beginning the coding process. Cohen's Kappa was used to calculate the inter-rater agreement for the corpus that the two coders annotated [36]. We obtained a significant inter-rater agreement (Cohens kappa = 0.83) [37]. The discrepancy between low and medium cognitive levels was usually the cause of the dispute. Ultimately, a compromise was reached by the three programmers. Table 1 exhibits examples of entries from the final dataset.

Table 1. Examples of entries from dataset

Learner	Attempt count	Hint count	Type	First action	Confusion	Time spent	Label score
id0	3	4	Mastery	Hint	0.2704	45	Low (1)
id14	1	0	Linear	Attempt	0	18	Medium (2)
id1	1	0	Linear	Attempt	0	7	High (3)

4.2. Experiment settings

The experiment was conducted using Python3 programming language alongside Pandas and Numpy libraries. There were 15182 unique items left after pre-processing, cleaning, and duplication removal for ML algorithm analysis. The training and test sets are split randomly into 12145 and 3037 entries, respectively, in accordance with the 80:20 rule. To complete the categorization tasks, Scikit-learn was used. An open-source Python ML library [38]. Numerous ML methods are included in it (classification, clustering, and regression).

We compared the following candidate ML models: logistic regression (LR) [39], support vector machines (SVM) [40], gradient boosting trees (GBT) [41], naive bayesian (NB) [42], RF [43], and neural network (NN) [44]. In order to assess the effectiveness of the potential ML models, we adopted the following five distinct metrics: the recall, accuracy, precision, and F1 score. It is important to state that all experiments were conducted in Google Colab, with Tesla P100-PCIE-16 GigaBytes GPU and 25 Giga-Bytes RAM support settings.

4.3. Results and discussions

The purpose of the implementation is to train the proposed model and evaluate its efficiency and accuracy. This section compares the effectiveness of several ML techniques. The top results across the studied datasets are listed in Table 2. We notice that, among all ML techniques, the NN algorithm achieves the best performance. NN achieves an accuracy of 82.2% with a relative improvement of 0.3% compared to GB and 2% compared to SVM and LR. NB shows low accuracy results compared to the other ML techniques. 82.2% as classification result is quite considerable results in classification-based issues. This demonstrates the effectiveness of our model in detecting learners' cognitive levels and the high performance of NNs compared to other ML.

Table 2. The prediction analysis's outcomes

	F1 score	Accuracy	Precision	Recall
SVM	0.7486	0.8086	0.6996	0.8086
NB	0.6560	0.6509	0.7164	0.6509
GB	0.7632	0.8192	0.7168	0.8192
LR	0.7498	0.8093	0.7003	0.8093
RF	0.7626	0.8205	0.7123	0.8205
NN	0.7654	0.8221	0.7188	0.8221

The results are very promising. We can now predict the learner's cognitive level with an accuracy of 82% of each learner in the system through an online learning assessment. This can help the tutor and instructional designer to build better learning content for each category of learner (adaptive learning). Also, learners with low cognitive levels could benefit from a recommendation system with materials that match their low cognitive level. On the other side, learners with a high cognitive level could also profit from a recommendation system that challenges their high cognitive level. We can also enhance learners' learning acquisition by grouping them into homogeneous collaborative groups that match their cognitive level. The power of predicting learners' cognitive level can be the key to minimizing the high drop-out rate on online learning platforms, since the cognitive level and background knowledge are one of the main dropout factors.

5. CONCLUSION

In this research, by coding online learning concept assessments into three classes based on Bloom's cognitive levels of each learner, we want to create an automatic system based on ML for evaluating learners' cognitive levels. We attained a classification accuracy of 82.2% using NN algorithms. Our approach is essentially based on learners' interaction in assessment in online learning to analyse and assess their critical thinking and cognitive behaviour. As a result, this result will assess tutors and instructional designers in building better learning content for each category of learner and supervise learners with low cognitive levels during their learning process. Future works will focus on integrating this model into an online recommendation system where we can evaluate and analyse not only the cognitive level factors of learn ers but also other learners' social and compartmental behaviour during their learning process.

REFERENCES

[1] J. Hammad, M. Hariadi, M. Hery Purnomo, N. Jabari, and F. Kurniawan, "E-learning and adaptive e-learning review," *International Journal of Computer Science and Network Security*, vol. 18, no. 2, pp. 48–55, Feb. 2018.

[2] W. Blyth, B. Bloom, and D. Krathwohl, "Taxonomy of educational objectives. Handbook i: Cognitive domaintaxonomy of educational objectives. Handbook 2: Affective domain," *British journal of educational studies*, vol. 14, no. 3, 1966.

[3] S. N. Kew and Z. Tasir, "Analysing students' cognitive engagement in e-learning discussion forums through content analysis," *Knowledge Management and E-Learning: An International Journal*, vol. 13, no. 1, Apr. 2021.

[4] E. Vasilomanolakis, S. Karuppayah, M. Mühlhäuser, and M. Fischer, "Taxonomy and survey of collaborative intrusion detection," *ACM Computing Surveys*, vol. 47, no. 4, p. 55:1-55:33, May 2015, doi: 10.1145/2716260.

[5] A. Chanaa and N. El Faddouli, "Deep learning for a smart e-learning system," in *Proceedings of the 2nd International Conference on Smart Digital Environment*, in ICSDE'18. New York, NY, USA: Association for Computing Machinery, Oct. 2018, pp. 197–202, doi: 10.1145/3289100.3289132.

[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, Art. no. 7553, May 2015, doi: 10.1038/nature14539.

[7] D. R. Krathwohl, "A revision of bloom's taxonomy: an overview," *Theory into Practice*, vol. 41, no. 4, pp. 212–218, Nov. 2002, doi: 10.1207/s15430421tip4104_2.

[8] L. W. Anderson, "Objectives, evaluation, and the improvement of education," *Studies in Educational Evaluation*, vol. 31, no. 2, pp. 102–113, Jan. 2005, doi: 10.1016/j.stueduc.2005.05.004.

[9] F. A. Adesoji, "Bloom taxonomy of educational objectives and the modification of cognitive levels," *Advances in Social Sciences Research Journal*, vol. 5, no. 5, May 2018, doi: 10.14738/assrj.55.4233.

[10] C. Troussas, A. Krouska, F. Giannakas, C. Sgouropoulou, and I. Voyiatzis, "Automated reasoning of learners' cognitive states using classification analysis," in *Proceedings of the 24th Pan-Hellenic Conference on Informatics*, in PCI '20. New York, NY, USA: Association for Computing Machinery, Mar. 2021, pp. 103–106, doi: 10.1145/3437120.3437285.

[11] Z. Ullah, A. Lajis, M. Jamjoom, A. Altalhi, and F. Saleem, "Bloom's taxonomy: A beneficial tool for learning and assessing students' competency levels in computer programming using empirical analysis," *Computer Applications in Engineering Education*, vol. 28, no. 6, pp. 1628–1640, 2020, doi: 10.1002/cae.22339.

[12] K. Jayakodi, M. Bandara, I. Perera, and D. Meedeniya, "WordNet and cosine similarity based classifier of exam questions using bloom's taxonomy," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 11, no. 04, Apr. 2016, doi: 10.3991/ijet.v11i04.5654.

[13] S.-J. Na, Y. G. Ji, and D. H. Lee, "Application of Bloom's taxonomy to formative assessment in real-time online classes in Korea," *Korean Journal of Medical Education*, vol. 33, no. 3, pp. 191–201, Sep. 2021, doi: 10.3946/kjme.2021.199.

[14] K. Chrysafiadi, C. Troussas, and M. Virvou, "Combination of fuzzy and cognitive theories for adaptive e-assessment," *Expert Systems with Applications*, vol. 161, p. 113614, Dec. 2020, doi: 10.1016/j.eswa.2020.113614.

[15] R. T. Sairaj and S. R. Balasundaram, "Improving the cognitive levels of automatic generated questions using neuro-fuzzy approach in e-assessment," in *2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA)*, Oct. 2020, pp. 454–458, doi: 10.1109/ICCCA49541.2020.9250716.

[16] D. Abduljabbar and N. Omar, "Exam questions classification based on Bloom's taxonomy cognitive level using classifiers combination," *Journal of Theoretical and Applied Information Technology*, vol. 78, pp. 447–455, Aug. 2015.

[17] S. Huilan *et al.*, "Educational management in critical thinking training based on bloom's taxonomy and SOLO taxonomy," in *2020 International Conference on Information Science and Education (ICISE-IE)*, Dec. 2020, pp. 518–521, doi: 10.1109/ICISE51755.2020.00116.

[18] P. M. O. N. Pallegama, K. A. M. R. Kumari, D. M. D. P. M. Dissanayaka, A. V. Y. Ravihansi, A. Karunasenna, and U. Samarakoon, "Evaluating teaching content and assessments based on learning outcomes," in *2020 2nd International Conference on Advancements in Computing (ICAC)*, Dec. 2020, pp. 299–304, doi: 10.1109/ICAC51239.2020.9357319.

[19] E. Subiyantoro, A. Ashari, and Suprapto, "Cognitive classification based on revised bloom's taxonomy using learning vector quantization," in *2020 International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, Surabaya, Indonesia: IEEE, Nov. 2020, pp. 349–353, doi: 10.1109/CENIM51130.2020.9297879.

[20] I. N. Sukajaya, D. Sabrina, and I. Suharta, "Classification of students' mathematics learning achievement on bloom's taxonomy-based serious game using ordinal logistic regression," in *2020 International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, Surabaya, Indonesia: IEEE, Nov. 2020, pp. 132–137, doi: 10.1109/CENIM51130.2020.9297886.

[21] M. Mohammed and N. Omar, "Question classification based on Bloom's taxonomy cognitive domain using modified TF-IDF and word2vec," *PLOS ONE*, vol. 15, no. 3, p. e0230442, Mar. 2020, doi: 10.1371/journal.pone.0230442.

[22] J.-Y. Wu, Y.-C. Hsiao, and M.-W. Nian, "Using supervised machine learning on large-scale online forums to classify course-related facebook messages in predicting learning achievement within the personal learning environment," *Interactive Learning Environments*, vol. 28, no. 1, pp. 65–80, 2020, doi: 10.1080/10494820.2018.1515085.

[23] G. Heilporn, S. Lakhal, and M. Bélisle, "An examination of teachers' strategies to foster student engagement in blended learning in higher education," *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, p. 25, Dec. 2021, doi: 10.1186/s41239-021-00260-3.

[24] G. Barbosa *et al.*, "Towards automatic cross-language classification of cognitive presence in online discussions," in *LAK 2020 Conference Proceedings*, Association for Computing Machinery (ACM), 2020, pp. 605–614, doi: 10.1145/3375462.3375496.

[25] G. L. Clore and J. R. Huntsinger, "How emotions inform judgment and regulate thought," *Trends in cognitive sciences*, vol. 11, no. 9, pp. 393–399, Sep. 2007, doi: 10.1016/j.tics.2007.08.005.

[26] D. Keltner and M. N. Shiota, "New displays and new emotions: A commentary on Rozin and Cohen (2003)," *Emotion*, vol. 3, no. 1, pp. 86–91, 2003, doi: 10.1037/1528-3542.3.1.86.

[27] A. L. Samuel, "Some Studies in Machine Learning Using the Game of Checkers. II—Recent Progress," *IBM Journal of Research and Development*, vol. 11, no. 6, pp. 601–617, Nov. 1967, doi: 10.1147/rd.116.0601.
[28] A. Chanaa and N. El Faddouli, "E-learning text sentiment classification using hierarchical attention network (HAN)," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 13, p. 157, Jul. 2021, doi: 10.3991/ijet.v16i13.22579.
[29] A. Chanaa and N. El Faddouli, "An Analysis of learners' affective and cognitive traits in context-aware recommender systems (CARS) using feature interactions and factorization machines (FMs)," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, Part A, pp. 4796–4809, Sep. 2022, doi: 10.1016/j.jksuci.2021.06.008.
[30] M. Jain, R. Beniwal, A. Ghosh, T. Grover, and U. Tyagi, "Classifying question papers with bloom's taxonomy using machine learning techniques," in *Advances in Computing and Data Sciences*, vol. 1046, M. Singh, P. K. Gupta, V. Tyagi, J. Flusser, T. Ören, and R. Kashyap, Eds., in Communications in Computer and Information Science, vol. 1046. , Singapore: Springer Singapore, 2019, pp. 399–408, doi: 10.1007/978-981-13-9942-8_38.
[31] Dr. V. T. and V. R., "Retrieval of complex images using visual saliency guided cognitive classification," *Journal of Innovative Image Processing*, vol. 2, no. 2, pp. 102–109, Jun. 2020, doi: 10.36548/jiip.2020.2.005.
[32] M. D. Laddha, V. T. Lokare, A. W. Kiwelekar, and L. D. Netak, "Classifications of the summative assessment for revised blooms taxonomy by using deep learning," *International Journal of Engineering Trends and Technology*, vol. 69, no. 3, pp. 211–218, Mar. 2021, doi: 10.14445/22315381/IJETT-V69I3P232.
[33] A. Chanaa, Github. [Online]. Available: https://github.com/Abdessamad139/cognitive-level [Accessed:23-01-2024].
[34] M. Feng, N. Heffernan, and K. Koedinger, "Addressing the assessment challenge with an online system that tutors as it assesses," *User Modeling and User-Adapted Interaction*, vol. 19, no. 3, pp. 243–266, Aug. 2009, doi: 10.1007/s11257-009-9063-7.
[35] Y. Wang, N. T. Heffernan, and C. Heffernan, "Towards better affect detectors: effect of missing skills, class features and common wrong answers," in *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge*, in LAK '15. New York, NY, USA: Association for Computing Machinery, Mar. 2015, pp. 31–35, doi: 10.1145/2723576.2723618.
[36] J. Sim and C. C. Wright, "The kappa statistic in reliability studies: use, interpretation, and sample size requirements," *Physical Therapy*, vol. 85, no. 3, pp. 257–268, Mar. 2005, doi: 10.1093/ptj/85.3.257.
[37] M. L. McHugh, "Interrater reliability: the kappa statistic," *Biochemia Medica*, vol. 22, no. 3, pp. 276–282, 2012.
[38] F. Pedregosa *et al.*, "Scikit-learn: machine learning in python," *Journal of Machine Learning Research*, vol. 12, no. 85, pp. 2825–2830, 2011.
[39] D. R. Cox, "The regression analysis of binary sequences," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 20, no. 2, pp. 215–242, 1958.
[40] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, Sep. 1995, doi: 10.1007/bf00994018.
[41] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *The Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, Oct. 2001, doi: 10.1214/aos/1013203451.
[42] D. D. Lewis, "Naive (Bayes) at forty: The independence assumption in information retrieval," in *Machine Learning: ECML-98*, C. Nédellec and C. Rouveirol, Eds., in Lecture Notes in Computer Science. Berlin, Heidelberg: Springer, 1998, pp. 4–15, doi: 10.1007/BFb0026666.
[43] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, Oct. 2001, doi: 10.1023/A:1010933404324.
[44] J. E. Dayhoff, *Neural network architectures : an introduction*. New York, N.Y.: Van Nostrand Reinhold, 1990. Accessed: Dec. 28, 2023. [Online]. Available: http://archive.org/details/neuralnetworkarc00dayh

BIOGRAPHIES OF AUTHORS

Abdessamad Chanaa is Ph.D. on recommendation systems at Mohammadia School of Engineers (EMI), Mohammed V University in Rabat, Morocco. He is also a Computer Science Engineer from the National School of Applied Science of Marrakesh. His interests lie in the fields of deep learning, neural network and educational engineering. He can be contacted at email: abdessamad.chanaa@gmail.com.

Nour-eddine El Faddouli is full professor at Mohammadia School of Engineers (EMI), Mohammed V University in Rabat, Morocco. He is a Professor of Computer Science in Mohammadia School of Engineers since 1996. In addition, He is director of many thesis projects and supervisor of final year graduate projects in computer science and big data fields. His research interests are: e-learning, big data, pedagogy and education, assessment, higher education, computational linguistics, teaching, and learning. He can be contacted at email: elfaddouli@emi.ac.ma.