IMPLEMENTATION OF MACHINE LEARNING BASED METHODS IN ELEARNING SYSTEMS

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Abstract: *Machine learning methods can be used in various ways in order to improve e-learning systems. These methods can be used to recommend future actions in e-learning system, implement advanced evaluation methods, discover student preferences, identify learning content and resources, create automated tutoring systems, create comprehensive curriculum, implement crowdsource and collaborative learning, etc. This paper investigates how machine learning and its techniques can be used in e-learning platforms and styles of learning. With machine learning, e-learning systems can be designed to be more efficient, for both students and instructors. Students can gain more personalized learning content, which increases students' motivation and learning experience, while instructors can benefit from automatized tasks, which reduce time for learning content organization, visualization and preparation. By analyzing the collected and processed data, instructors can quickly identify "at risk" students, while machine learning algorithms can adjust course content to help each student overcome their weak points. Machine learning models analyzed in this paper are Bayesian Networks (BNs), Decision Tree (DT), Artificial Neural Networks (ANN), Deep Learning (DL), Association Rule Mining (ARM) and Clustering methods (CM).*
Keywords: *E-Learning, machine learning,*

1. INTRODUCTION

In the recent years e-learning has been utilizing vast spectrum of technologies to enhance learning and teaching experience with different applications, learning methods and processes [1]. Researchers have been using different approaches to improve content delivery in e-learning systems. One of the approaches that has been used to shape e-learning system, methods and approaches is machine learning. In cases where "learning by doing" is preferential, machine learning can be helpful in order to improve experiential learning [2]. For example, Pilot Support System collects and analyzes aircraft (i.e. flight path, immediate environment around the aircraft, the weather and terrain information) and pilot data (provided by eye tracking and biological monitor), which are used for pilot and air traffic controllers simulation training. Real set of data helps in conducting experiential learning in simulated environment with the aim for trainees to learn to take appropriate actions on time [3].

E-Learning has also been used: (i) to access extensive educational resources such as MOOCs and internet libraries [4][5], (ii) for online tutoring [6][7], (iii) to allow learning and teaching collaboration [8][9]. These are some of the technological advances that have unfolded in the past decades. One of the candidates to improve these systems and to take them to another level of learning and teaching experience is by incorporating artificial intelligence and machine learning (ML).

Most of the before mentioned systems generate large amount of data (learning contents, assessments, e-learning log files, academic data of students, etc.) that can be useful for ML algorithms integrated in e-learning systems [10]. Incorporating technology and ML techniques in the e-learning represents a complex, but a promising field, with the aim to shift the paradigm of the learning process and discovering meaningful patterns for successful learning [10][11]. For example, ML classification techniques can be used to classify students based on their learning style, discover student preferences, identify learning content and resources, create automated tutoring systems, create comprehensive curriculum, implement crowdsource and collaborative learning, etc. [12][13].

This paper aims to provide a comprehensive view of using ML techniques in the field of eLearning. Specifically, the focus is put on ML models such as Bayesian Networks (BNs), Decision Tree (DT), Artificial Neural Networks (ANN), Deep Learning (DL), Association Rule Mining (ARM) and Clustering methods (CM).

This paper is organized as follows: Section 2 presents an overview of related works. Section 3 describes the method for data collection and analysis of used ML techniques in e-learning. Section 4 discusses found results. Finally, Section 5 concludes this paper.

2. BACKGROUND

Many researchers have identified the need to improve e-learning platforms, tools, processes and methods in order for these systems to take more informed decisions and become more intelligent, with the aim to improve learning and teaching processes [14]. Some of the areas where e-learning has been enriched with ML algorithms include:

- Delivery of learning content
- Personalization
- Collaborative learning
- E-Learning support tools.

ML techniques can play a significant role in identifying discouraged or disgruntled students based on their posts in the discussion forums, real time facial expressions or similar techniques that can help instructors to identify students that need more attention and motivation. Furthermore, ML techniques can be used to automate e-learning and to make decisions about changing learning materials and activities [15]-[18]. Some of the e-learning systems monitor real-time facial expression in learning environments in order to detect demotivation or decreased concentration during the learning process [19]. For example, Facial Emotion Recognition System (FERS), recognizes the emotional states and motivation levels based on student facial expressions captured in video-conference systems such as Skype. Different ML methods (Support Vector Machine (SVM), k-nearest neighbor (kNN) classification method, Random Forest (RF) and Classification and Regression Trees (CART) algorithms) use facial detection, features and attributes, along with changes of emotional state of learners in order to determine motivation level of learner during the learning process [20].

Personalization represents a topic that is gathering significant attention within the e-learning field and it attempts to not only customize the learning environment, but also to personalize all aspects of the entire learning experience [21] – [24]. Personalized e-learning, therefore, encompasses the ability to customize aspects such as classification and recommendation. E-Learning systems can recommend different content based on student clustering, content classification, learning styles, skills, prior knowledge, and learning preferences, such as: (i) new courses/books to take [25][26], (ii) course format [27], (iii) additional learning material and resources that caters to learner preferences [28][29], (iv) learning content presented to learner [28][30][31], (v) assessments based on student learning pace, etc. [32] - [34]. Recommender systems are only part of personalized systems, which can also be used to: (i) predict students' final grades and classify them into different groups based on their performance [35] - [38], (ii) identify weak students that may need help in the course [39][40], (iii) identify concepts or learning outcomes the students seem to be struggling with [41], etc.

Working in groups and collaborating with peers has shown its benefits in learning and retaining the knowledge [42] [43]. Collaboration on the common project can encourage students not only to be more motivated in learning and accomplishing the common goal, but can also encourage students to effectively communicate with each other and to collectively analyze and discuss possible solutions for the assigned problem. ML can enhance such learning experience in the following manner: (i) analyze the level of collaboration between students in the group projects [44] – [46], (ii) make better decisions in assigning students to groups based on their learning styles and preferences with assumption that students with similar learning styles can cooperate better and share the information among them in a better way [47] – [49].

Benefits of including ML techniques in the e-learning support tools can be used for load forecasting such as traffic throughput and the speed of content delivery, which can both help to determine necessary infrastructure resources. For example, decisions that the course format is modified from video streaming to material in the form of text in order to reduce the traffic load can be made based on the patterns and models developed using ML [50] – [52].

In this work the aim is to:

1. Investigate the status of implemented ML techniques in e-learning.
2. Conduct the cross-analysis among the used ML techniques and identify possible relationships between them.

The following research questions are addressed in this work:

Q1: What machine learning methods have been used in e-learning systems?
Q2: What are the main indicators used by ML techniques in e-learning systems?
Q3: What kinds of tools were used?
Q4: What are the common assumptions and conclusions?

3. DATA SOURCES AND PAPER SELECTION

In order to address the research problem, papers related to using ML techniques in e-learning systems, published from 2010 to 2019 were considered. Papers were searched from the Web of Science (WOS), Google Scholar (GS), Research Gate (RG), and Academia (A) databases. Papers were searched based on the keywords that included: (intelligent OR adaptive OR customized OR machine learning methods) AND (eLearning OR education OR tutoring) AND (system OR software OR application OR tool) AND (evaluation OR assessments). Collected papers were evaluated and screened based on the following criteria:

1. Only journal research papers were included in the present study. Book reviews, conference papers, book chapters, abstracts, news, editorials, and reviews were excluded.
2. The papers that were considered were closely related to ML algorithms and their implementation and usage in the e-learning systems, tools and methods.
3. The papers that were considered reported details about the used ML methods, tools, and indicators. Conceptual papers that did not

describe the details of ML techniques were excluded.
4. Considered papers were published from 2010 to 2019.
5. Only papers reported in English were considered.

This systematic review is given in Figure 1 and it was conducted based on the preferred reporting items for systematic reviews and meta-analysis (PRISMA) [53].

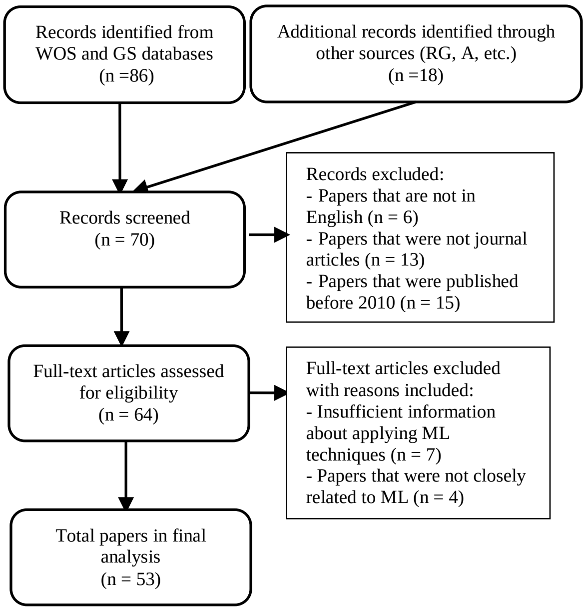

Figure 1: The process of PRISMA for data collection/analysis

4. RESULTS AND DISSCUSSION

In order to answer posed research questions, based on data sources and paper selection, five variables were extracted: (i) the name of the system, (ii) ML techniques that were used, (iii) purposes of applying prosed system/ML methods, (iv) used indicators and (v) software tool that has been used for ML analysis.

4.1. What machine learning methods have been used in e-learning systems?

The most commonly used ML methods to enhance e-learning platforms, tools and methods are listed in Table 1. It can be seen that Bayesian Networks and Artificial Neural Networks are most common. On the other hand Deep Learning is researched in the least amount of papers.

Table 1: Frequency of used ML techniques in the analyzed papers.

ML methods	Percentage
BN	55%
ANN	38%
DT	21%
ARM	17%
CM	11%
DL	9%

4.2. What are the main indicators used in ML techniques in e-learning systems?

ML methods typically use different indicators in its algorithms. In selected research papers indicators used for eLearning, such as learner preferences, behavior, knowledge, skills, and interactions, were analyzed. All learning indicators (behavioral which are derived from the raw data or course achievement) are summarized and explained in Table 2. It can be seen that the indicator *Assessment/Tests* and *Grades* are most common because they were mostly used as a metric to predict learning success. Indicator *GUI and user interactions* help e-learning systems to be improved from the point of human-computer interaction. These indicators were mainly used to determine how and where to display learning resources (i.e. determining what to display first based on the student preferences, video or text). *Learning session* indicator and *Participation in the forum* can represent metrics to determine student motivation, while *Web links viewed* indicator can suggest to tutors what additional resources are needed and what requires additional explanation.

Table 2: Summary of used learning indicators

Indicators	Description	Percentage
Assessments / Tests	- The number of assessments student has started - The number of assessments student has completed - An average score of all assessments which student has completed - A degree of how early student completes assessments	85%
Grades	- The final grade of the prerequisite exams - The exam grade in the end of the semester	35%
GUI and user interactions	- Number of clicks, position of click, etc.	15%
Learning sessions	- Total number of accesses to the e-learning system - Total time spent in learning/reviewing learning content - The frequency of logins (number of logins per day, continuity in logins - every day, several logins per week, etc.)	10%
Web links viewed	- History of accessed web resources as an external links	5%
Participation in the forum	- Total forum discussion messages read/posted (new and replays)	2%

4.3. What kind of tools were used?

It is of interest to analyze various applications and tools used to support collection and analysis of data for ML algorithms. These tools are used for data mining tasks such as data preparation, classification, regression, clustering, association rules mining, and visualization. List of identified tools that were used are summarized in Table 3. Unfortunately, most papers do not report on used tools and these are listed as “N/A.” It can be seen that from the identified tools WEKA is the most used (23%), followed by MATLAB (11%), and other software Python

/ R / TensorFlow (7%). WEKA and MATLAB contain collection of ML algorithms for data mining tasks that provide: (i) tools for training and comparing different ML methods, (ii) and commonly used classification, regression, and clustering algorithms. Python, R, and TensorFlow also contain large library repository and allow for easy integration with other programming languages such as C, C++ or Java.

Table 3 - Summary of learning indicators

ML tools	Percentage
WEKA	23%
MATLAB	11%
Python / R / TensorFlow	7%
SPSS	1%
N/A	58%

4.4. What are the common assumptions and conclusions?

Common assumptions and conclusions can be analyzed from a positive and negative point of view.

From a positive perspective, the ML methods applied in e-learning could be a foundation of further support for individuals during the entire learning process. Reviewed research works have achieved and displayed numerous successful results in this domain. Used indicators analyzed by ML methods at the early stage of learning could be used to categorize learners and identify “at risk” students based on their online activity. For example, the students who are categorized as procrastinators could be periodically reminded to access the online materials at the remaining stages. At the end of learning, these measures are helpful to use for evaluation of learner learning behavior.

Although the present analysis demonstrates the benefits of identifying significant indicators and applied ML methods, several negative assumptions should be noted. The prediction could be too prescriptive. For example, just because a learner prefers a certain type of learning it does not mean this is a constant preference as it may change with time or situation. Also, the e-learning examples used in this research were quite diverse including both mandatory and elective courses, which also may effect learners’ motivation and decision-making. Some of the background information such as online learning experience has not been sufficiently explored and considered, although this information may be useful to increase the predictability of students’ performances. Finally, applying an adequate learning style does not necessarily mean success in completing the course, and as such, course achievements should be interpreted with caution.

5. CONCLUSION

Growing amount of data collected in e-learning systems have led to the need to analyze and extract useful information from them. Machine learning techniques have been proposed as a means to satisfy this need, as it was shown productive in other fields such as healthcare, business, and energy. This work analyzed various machine learning methods used e-learning in order to deal with different challenges, such as personalization, content delivery, collaborative learning and used support tools. This work included 53 reviewed journal papers. It was concluded that the most used ML technique in e-learning are Bayesian Networks, while the most used indicators were the ones relating to assessments and tests. Even though many researches (58%) do not report tools used for ML analysis, from the ones that did report it, it was concluded that WEKA is the most used tool. Finally, the paper concludes with positive and negative findings of the used ML techniques in e-learning systems.
Future work will analyze a larger number of papers with greater emphasis on comparative analysis of the results achieved. The aspect of cross evaluation of the obtained results has been neglected in this paper, and it should be a part of future analysis.

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