Machine Learning Approach for an Adaptive E-Learning System Based on Kolb Learning Styles

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Abstract—In order to effectively implement adaptive learning within E-learning systems, it is crucial to accurately define the learner's profile that reflects the characteristics necessary for optimal learning. Traditional methods of identifying profiles often rely on questionnaires to collect data from learners, which can be time-consuming and result in irrelevant data due to arbitrary responses. As a solution, we propose an intelligent and dynamic model for adaptive learning that takes into account the entire learning process, from diagnostic assessment to knowledge assimilation. Our approach utilizes the k-means classification algorithm to group learners based on similar characteristics, as defined by the KOLB model. To enhance the accuracy of our model, we also incorporate neural networks to automatically predict learning styles and using decision tree to propose a adaptative pedagogical content to learner. By doing so, we aim to improve the overall performance of our proposed model.

Keywords—e-learning system, artificial intelligence, k-means, artificial neutral network, decision tree

1 Introduction

All learners learn differently. It is illogical for all learners to have the same strategy for mastering courses, doing projects, and doing assignments. This issue is addressed in both presential and distance learning. A learning style refers to an individual's preferred way of processing information and learning new things. Learning styles are often used to understand how individuals best receive and retain information. There are a several learning style models, including: VARK model (Visual, Aural, Read/Write, Kinesthetic) by [1] Honey and Mumford model (Activist, Reflector, Theorist, Pragmatist) by [2], Kolb's Experiential Learning model (Diverging, Assimilating, Converging, Accommodating) by [3]. Gregorc Style Delineator model (Concrete Sequential, Abstract Sequential, Abstract Random, Concrete Random) by [4], Dunn and Dunn model (Environmental, Emotional, Sociological, Physical, Psychological, Verbal, and Logical) by [5]. Understanding learning styles helps e-learning systems provide students with personalized content to meet their needs and improve the learning process [6].

Many methods have been proposed to identify students' learning styles. such as surveys or questionnaires, which may not be accurate or reliable measures of how a student learns.in this topic [7] suggest that people have different learning styles, and that it is important for educators to be aware of these styles and to design learning experiences that cater to them. However, they argue that traditional methods of assessing learning styles, such as questionnaires, may not be reliable indicators of a person's actual learning style. [8]: Dunn's model of learning styles suggests that people have different preferences for how they take in and process information, and that these preferences can be used to create more effective learning experiences. However, he has also criticized the use of questionnaires to assess learning styles, arguing that they are not always accurate or reliable. [3]: Kolb's model of learning styles suggests that people have different preferences for how they learn, and that these preferences can be used to design more effective learning experiences. However, he has also suggested that traditional methods of assessing learning styles, such as questionnaires, may not be the best way to determine a person's actual learning style. Other reason why traditional methods of collecting and analysing data about a learner's learning style have several drawbacks that make them less than ideal.

We can find that they are being time-consuming, limiting in the types of data that can be collected, subject to bias, and limited in their ability to adapt to the changing needs of the learner. One of the primary issues with traditional methods is that they often require a significant amount of time to collect and analyzes data about a learner's learning style. This can be particularly challenging for educators who need to collect information from a large number of learners in a short amount of time. Furthermore, traditional methods are often limited in the types of data they can collect, which can make it difficult to get a comprehensive understanding of a learner's learning style. For example, questionnaires and surveys may only provide limited information about a learner's learning style and preferences, and may be subject to bias as they often rely on self-reported data that may not accurately reflect a learner's learning style. Learners may not be aware of their own learning style or may not be honest about their preferences when answering questionnaires or surveys. Finally, traditional methods are often limited in their ability to adapt to the changing needs of the learner. For example, a questionnaire may be used to collect information about a learner's learning style at the beginning of a course, but it may not be able to track changes in the learner's learning style as they progress through the course. These limitations make traditional methods less than ideal for understanding and adapting to the complex and dynamic nature of a learner's learning style.

To overcome these limitations, many automatic methods have been proposed, aiming to automatically detect students' learning styles based on their behavior's while interacting with e-learning systems. Section 4 presents our automatic approach that combines unsupervised and supervised learning. In our approach, we first use k-means (unsupervised learning) to cluster students based on their learning style. Once we have these clusters, we can use an ANN (supervised learning) to make predictions about each student's learning style based on their input data. Finally, we can use decision trees (supervised learning) to tailor instructional resources to each student based on their learning style. The rest of this paper is organized as follows. Section 2 defines artificial intelligence and compares automatic data collection with the traditional method. Section 3 presents a literature review of related work. Section 4 describes the methodology of our approach.

2 Artificial intelligence method for automatic identification of learning styles

There are many definitions of artificial intelligence (AI) provided by different authors; According to [9], AI is a research on agents that receive perceptions from the environment and execute actions and [10] defines AI as the process of equipping machines with the ability to operate intelligently and "intelligence" is the trait that allows an entity to function effectively and proactively within its surroundings [11] describe AI as the use of algorithms to develop machines that are capable of performing tasks that typically require human intelligence, also [12], defined AI as The field of science and engineering focused on creating intelligent machines is known as artificial intelligence (AI). It involves the study and development of computer systems and machines that are capable of performing tasks that normally necessitate human intelligence, including learning, perception, reasoning, and problem-solving. Different authors may categorize AI types in different ways, but here are some examples of how some authors have categorized AI types, according to [9], AI can be classified into four categories: systems that think like humans, systems that act like humans, systems that think rationally, and systems that act rationally, as stated by [13], AI can be divided into three main categories: rule-based systems, connectionist systems (i.e., neural networks), and evolutionary systems (i.e., genetic algorithms), in the view of [10] AI can be classified into three main categories: analytical AI (i.e., rule-based systems and symbolic reasoning), human-inspired AI (i.e., neural networks and genetic algorithms), and humanized AI (i.e., natural language processing and robotics), as reported by [14] AI can be divided into two main categories: symbolic AI (i.e., rule-based systems and logic) and sub-symbolic AI (i.e., neural networks and other machine learning approaches). Overall, there is no single, agreed-upon way to categorize AI types, and different authors may use different categories or approaches. However, some of the most commonly cited categories include rule-based systems, connectionist systems, natural language processing, robotics, and various forms of machine learning.

2.1 For our topics

Using artificial intelligence to collect data. [15] In their study, they used machine learning techniques to analyze data from social media platforms and extract information about users' emotions and opinions. [16] In their research, they used a combination of natural language processing and machine learning techniques to analyze online reviews and extract information about customers' preferences and experiences. [17] In their study, they used machine learning algorithms to analyze data from wearable sensors and extract information about users' physical activity and health. [18] In their research, they used artificial neural networks to analyze data from smart home sensors and extract information about residents' activities and preferences. [19] The authors used a deep learning approach to classify students' learning styles based on their online activity data, and found that this method was more effective than traditional methods of self-reporting or surveys.

Comparison between traditional methods and AI methods in collecting data. Some potential differences between using traditional methods and using AI for collecting data on learner learning style based on some relevant authors' viewpoints. As noted by [20] traditional methods of collecting data on learner learning style may be limited by subjective judgments, response biases, and memory limitations, which can lead to inaccurate assessments. In contrast, AI-based approaches can collect and analyze large amounts of data in real-time, which can improve the accuracy of the assessment, and according [21] traditional methods of collecting data on learner learning style may not be able to capture the complexity of individual learning needs and preferences. In contrast, AI-based approaches can use machine learning algorithms to analyze the data collected and provide personalized recommendations for each individual learner. [22] see that the traditional methods of collecting data on learner learning style may be limited by the time and resources required to administer assessments and surveys to large groups of students. In contrast, AI-based approaches can collect data automatically and continuously, allowing for real-time monitoring and analysis of a large number of students simultaneously. As derived from [23], using AI to collect data on learner learning style raises ethical and privacy concerns related to data security, data ownership, and informed consent. Traditional methods of collecting data may be more transparent and accountable, as they typically require active participation and consent from the student. Overall different authors may have different perspectives on the benefits and limitations of using traditional methods versus using AI for collecting data on learner learning style. However, some of the most commonly cited advantages of using AI-based approaches include improved accuracy, personalization, and scalability, while some of the potential challenges include ethical and privacy concerns.

3 Related works

Many reasons pushed authors to suggest using artificial intelligence (AI) in e-learning systems: Personalization: AI can be used to create personalized learning experiences for individual students by analyzing data on their performance, engagement, and preferences. This can help to improve learning outcomes and increase student motivation and engagement [24]. Adaptability: AI can be used to adapt the content and delivery of learning materials to the individual needs and preferences of each student. This can help to ensure that students are receiving the appropriate level of challenge and support, and can reduce the likelihood of students becoming disengaged or dropping out of the course [25] Feedback and assessment: AI can be used to provide real-time feedback and assessment to students on their performance, allowing them to track their progress and identify areas where they need to improve. This can help to improve student engagement and motivation, and can also help instructors to identify areas where they need to provide additional support [26]. Analytics: AI can be used to collect and analyze large amounts of data on student behavior, performance, and engagement, providing instructors and administrators with insights into student learning patterns and course effectiveness. This can help to inform decision-making and improve the overall quality of the e-learning experience [27].

Recent studies have investigated the application of machine learning (ML) techniques to produce customizable e-learning systems based on Kolb's learning style, building on the potential of AI in e-learning systems.

The potential of machine learning (ML) methods for adaptable e-learning systems based on Kolb's learning style has recently been studied in study. For instance, [28] suggested a model that determines the student's preferred learning style and offers individualized learning activities and content to meet their demands. In comparison to other methods, the authors claim that their technique is more accurate in predicting students' preferred learning styles. An adaptive e-learning system was created by [29] that offers tailored learning paths and materials based on the Kolb learning type inventory. According to the authors, their machine learning algorithms were able to adjust to the students' changing demands and offer real-time feedback, which improves their learning experience. Similar to this [30] used machine learning strategies in conjunction with Kolb's learning style questionnaire to give students a tailored and adaptable e-learning experience. The performance and involvement of students in the learning process were both improved, according to the authors' system. According to these studies, machine learning techniques can increase the efficiency of e-learning systems by adjusting the content and delivery to meet the needs and preferences of specific learners.

Recent studies by [31] and [32] show that the integration of machine learning in e-learning systems can further increase the potential benefits of AI by offering even more precise customisation and adaptation based on a student's preferred learning style. Moreover, machine learning algorithms can give students immediate feedback and evaluations, enhancing their motivation and engagement while also giving teachers and administrators access to information about the effectiveness of their courses and the learning patterns of their students.

Overall, authors suggest that AI can provide several potential benefits to e-learning systems, including personalization, adaptability, feedback and assessment, and analytics. However, it's important to note that implementing AI in e-learning systems also raises some challenges related to ethical and privacy concerns, algorithmic bias, and the need for effective training and support for instructors and students.

3.1 Some e-learning system that use AI and their limitations

We provide insight into the use of a combination of AI algorithms in e-learning systems and the limitations that must be considered when implementing such systems. [33] The authors present a hybrid AI system that combines multiple AI techniques, such as fuzzy logic, decision trees, and artificial neural networks, for personalized e-learning. The authors discuss the limitations of the system, including the difficulty of selecting the appropriate AI techniques and the challenge of integrating the different techniques into a single system, [34] presents an adaptive e-learning system based on AI approaches, including artificial neural networks, decision trees, and genetic algorithms. The authors discuss the limitations of the system, including the challenge of accurately predicting student learning styles and the difficulty of integrating the different AI approaches into a single system, [35] presents an intelligent e-learning system that combines artificial neural networks and fuzzy logic for personalized e-learning. The authors discuss the limitations of the system, including the difficulty of designing and implementing the system, the challenge of accurately predicting student learning styles, and the limitations of the AI algorithms used in the system. Also [36] provides a literature review of the use of AI techniques, such as machine learning, decision trees, and fuzzy logic, for enhancing e-learning personalization. The authors discuss the limitations of the AI techniques, including the difficulty of accurately predicting student learning styles, the challenge of integrating the AI techniques into a single system, and the limitations of the AI algorithms used in the system, [37] proposes a system that integrates multiple AI techniques, including decision trees, artificial neural networks, and k-nearest neighbors, to personalize e-learning content and assessments for individual students. One limitation of this work is that it focuses primarily on the use of AI for personalization, and does not address other key applications of AI in e-learning, such as performance prediction and adaptive learning, and [38] presents a framework that integrates multiple AI techniques, including decision trees, genetic algorithms, and artificial neural networks to personalize e-learning content and assessments based on student learning styles and preferences. One of the limitations of this work is that it does not provide a detailed evaluation of the effectiveness of the proposed framework, and does not compare it to other existing approaches. [39] describes a system that uses a combination of AI techniques, including decision trees, Bayesian networks, and artificial neural networks, to model the learning progress of students in an e-learning environment and provide personalized feedback and recommendations. One of Constraints of this study.

This work is that it is based on a small dataset, which may not be representative of the diverse range of student behaviors and learning styles that are typically encountered in e-learning systems. We found that [40] proposes a system that combines multiple AI techniques, including decision trees, k-nearest neighbors, and artificial neural networks, to provide adaptive and personalized learning experiences for students in an e-learning environment. Deficiencies of this research is that it does not provide a detailed evaluation of the proposed system, and does not compare it to other existing approaches. These authors [33] present a hybrid AI system that combines multiple AI techniques for personalized e-learning. However, the authors acknowledge some limitations in their work, such as the difficulty of selecting the appropriate AI techniques and the challenge of integrating the different techniques into a single system. [41] in their articles they present an adaptive e-learning system based on AI approaches. However, they acknowledge the limitations of their work, including the challenge of accurately predicting student learning styles and the difficulty of integrating the different AI approaches into a single system, And [34] present an intelligent e-learning system that combines artificial neural networks and fuzzy logic for personalized e-learning.

However, they acknowledge some limitations in their work, such as the difficulty of designing and implementing the system, the challenge of accurately predicting student learning styles, and the limitations of the AI algorithms used in the system. [42] review the use of various artificial intelligence techniques, including artificial neural networks, decision trees, and genetic algorithms, in e-learning systems to provide personalized and adaptive learning experiences. Limitations of the AI techniques used in e-learning systems, such as artificial neural networks and decision trees, include the need for large amounts of training data and the potential for overfitting. [43] proposes a system that uses artificial intelligence techniques, including decision trees and k-nearest neighbors, to personalize e-learning content and assessments for individual students limitations of the AI techniques used in this approach, such as decision trees and k-nearest neighbors, include the need for large amounts of training data and the difficulty in incorporating additional variables into the personalization process. [44] provides an overview of the use of artificial intelligence techniques, including fuzzy logic and artificial neural networks, in e-learning systems to support personalized and adaptive learning. Limitations of the AI techniques used in this approach, such as fuzzy logic and artificial neural networks, include the need for large amounts of training data and the potential for overfitting. These authors [45] describes a system that uses artificial intelligence techniques, including decision trees and Bayesian networks, to model the learning progress of students in an e-learning environment and provide personalized feedback and recommendations. The AI techniques used in this approach, such as decision trees and Bayesian networks, include the need for large amounts of training data and the difficulty in modelling complex student behaviors.

The existing research on integrating multiple AI algorithms in e-learning systems has some limitations. However, combining different AI techniques in e-learning can offer more effective solutions by utilizing their respective strengths and compensating for their weaknesses. It's worth noting that further research is needed to fully harness the potential of AI in e-learning and overcome the current challenges and limitations. In the next section, we will discuss a proposed model with three phases, followed by a conclusion and the outlook for our work.

4 Our approach EClad Kolb System: e-learning classification, learning prediction and adaptation using decision trees base on Kolb learning style

Individual learners have their own unique learning preferences, knowledge levels, and styles. To account for this, we have proposed a comprehensive and intelligent model for adaptive learning in an e-learning environment. This model (Figure 1) is based on the integration of artificial intelligence technologies while respecting the pedagogical context, it includes this step:

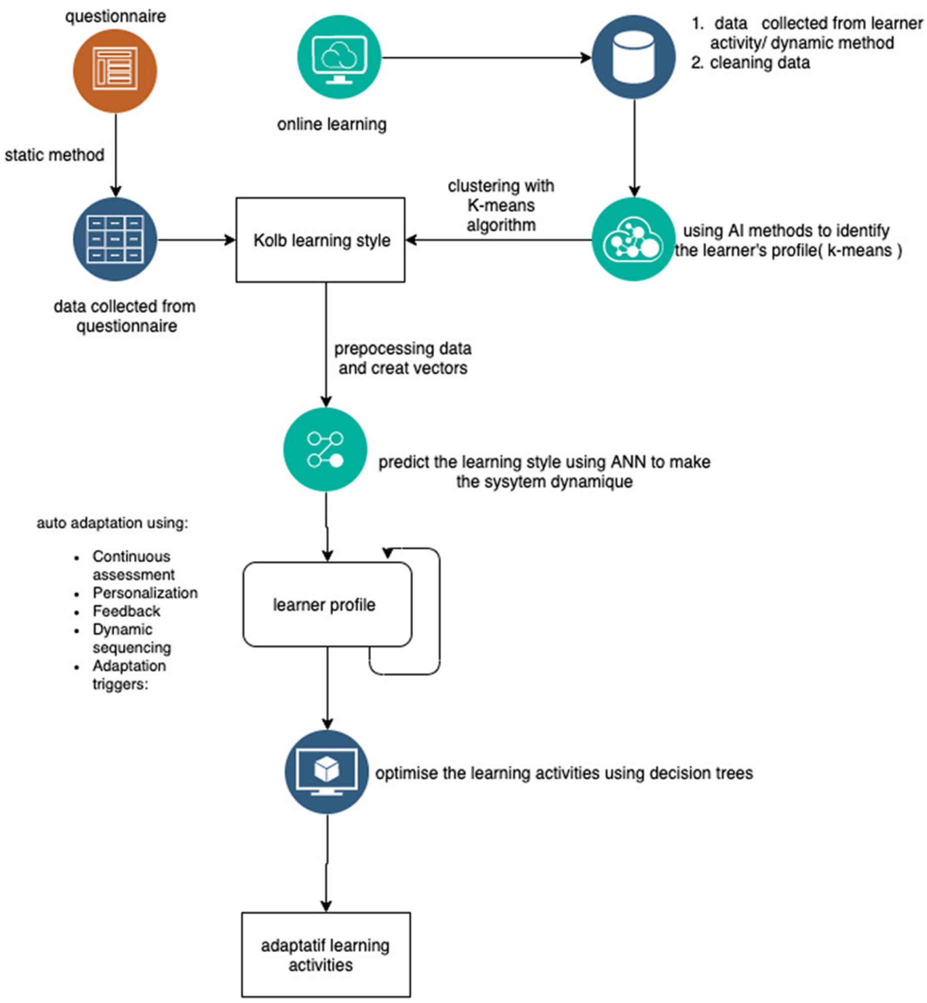

Fig. 1. Our approach EClad Kolb System

Classification and identification of learning styles. This step aims to determine the profile of learners according to the Kolb learning styles. The identification of the profile is based on the analysis of the traceability of the learners' journey through the interaction with the system. This analysis allows us to collect data from the log files, on which we can classify learners according to their styles using the k-means classification algorithm.

Prediction of learners' learning styles. after classifying learners according to Kolb's learning style combinations, we made the profile identification process dynamic and automatic by integrating neural networks for style prediction.

Proposal of adaptive learning activities. This step proposes adaptive activities to learners according to the identified profiles. We proposed a Decision Tree.

Auto adaptation for learner profile during the learning process. in this step we will use a combination of continuous assessment, personalization, feedback, dynamic sequencing, and adaptation triggers to create an e-learning system that automatically adapts to the learner's profile during the learning process.

4.1 A detailed artificial intelligence approach for adapting an e-learning system based on KOLB learning styles

Approach of using a combination of:

- k-means algorithm for classification of learners based on their learning style:
- Then use an Artificial Neural Network (ANN) to predict the learning style of a learner while they are learning in the system.
- We will use a decision tree algorithm to adapt the learning activities based on the predicted learning style of the learner.
- Implement continuous assessment, personalization, feedback, dynamic sequencing, and adaptation triggers into the e-learning system's design and functionality to make an auto adaptation for learner profile during the learning process

By using a combination of these algorithms, we can create a data-driven, adaptable e-learning system that can effectively support the learners and help them achieve their learning goals. It's important to validate the accuracy of the predictions made by the ANN, as well as regularly monitor and update the decision tree to ensure that it continues to make effective recommendations for the learning activities.

4.2 Data-driven approach for our e-learning system based on learner learning style

To support learners in their preferred learning styles, an e-learning system can be developed using machine learning techniques. The process involves collecting data on learners' preferred learning styles through self-assessment surveys or other assessment tools. The collected data should be cleaned, pre-processed, and transformed into a format that can be used by machine learning algorithms.

The next step is to use the k-means clustering algorithm to group learners based on their learning styles, which will reveal common patterns and trends in the data. An Artificial Neural Network (ANN) can then be trained on the data to predict the learning style of a learner in real-time, allowing the system to adjust the learning activities accordingly.

Furthermore, a decision tree algorithm can be applied to model the relationships between a learner's learning style and the most effective learning activities for that style. The decision tree can provide recommendations for the learning activities that are most likely to be effective for each learner based on their predicted learning style.

Finally, the algorithms can be integrated into the e-learning system and tested to ensure its effectiveness. Ongoing evaluation of the system's performance is necessary, and adjustments should be made as needed to ensure that it continues to support the learners in their preferred learning styles.

5 Conclusion

The integration of artificial intelligence technology has greatly improved the e-learning system by enabling adaptive learning, which is a field of extensive research. The main objective is to provide personalized learning experiences by offering learners content that is relevant to their needs, with adaptive activities tailored to their learning style, presentation preferences, and media type preferences. To achieve this goal, we propose an adaptive and intelligent model comprising three components. Firstly, we use a k-means algorithm to classify learner profiles based on their Kolb style. Next, a neural network is utilized to predict the learning style for new scenarios. Finally, we recommend suitable content to the learner using a decision tree based on their learning style. Moving forward, we plan to further develop and implement this model within the e-learning platform.

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