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Overview of Machine Learning Technologies and its Use in E-Learning

Shital Bhor , Renuka Mehetre , Dr. Prof.Rokade.M.D

Student, Department of Computer Engineering, Sharad Chandra Pawar College of Engineering, Otur, Savitribai Phule University, Pune, India

Assistant Professor , Department of Computer Engineering, Sharad Chandra Pawar College of Engineering, Otur, Savitribai Phule University, Pune, India

ABSTRACT: Thanks tonew technology, the internet, andconnected objects, we are generating huge amounts of data. Putting this data into context and organizing it so that itcan be perceived,understood, and reflected is critical. Taditionally,people analysed the data. However, as the amount ofdata is exceeded, individuals are increasingly turning to automated systems that thecan emulate for them. A system that can learn from both data anddata changes to solve a problem is called machine learning.Artificial intelligence has a significant impact on e-learning research, and machine learning-based methods can be implemented to improveSkills Reinforcement Learning Environments (TELE). This article reviewsrecent discoveries in this field of research. First, we introduce thekey concepts related to machine learning. He then publishes aboutrecent papers using machine learning in the context of e-learning.

KEYWORDS: e-learning, augmented technology learningenvironment, data, student tracking, machine learning, deep learning

I. INTRODUCTION

Almost everything we do today leaves a digital footprint thatdescribes our activities, indicates where we are, and provides many other pieces of informationabout what we say, what we live, and more.thanks to data storage capacity and the digitization of society. , most devices, machines and everything we useproduce data. For example, we can extract information fromtoll booths, parking lots, smartphones, social networks, videos,photos, etc. We need to extract value and find meaning from allcollected data.data analysis allows you to understand and predictphenomena, model behavior.Previously, people analyzed data and wrote algorithms, and themachine used them to solve problems. Today,people input data and let the machine learnon its own from that data without being explicitly programmed. We're talking about the power of data. This is the learning principle of themachine.Actually, analyseof complex data through machine learning methods hasemerged as an important era in several scientific researchdomains such as medicine [1] [2], e-commerce [3], industry[4][5], education [6][7], social networks [8][9], economicsand finance [10], etc.

Figure 1 shows machine learning relationships to someother concepts of data science and artificial intelligence. Infact, data mining use statistics to extract hidden information(patterns) from raw data [11]. However, ma-chine learning asa subfield of computer science and artificial intelligence,learns from patterns to predict. The Deep Learning is one ofthe main technologies of ma-chine learning and artificialintelligence.This is the next generation ofmachine learning, characterized by learning atlevels and requiring the machine to learn a bit more at each level.

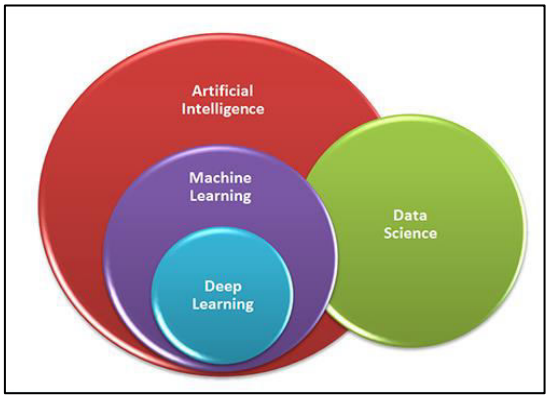

Fig.1MachineLearningrelationshipstootherrelatedfields

II.MACHINELEARNING

Inmachine learning, a computer learns how to perform an action on sample data. We know that giving the machine more thanattempts (E) for a particular task (T) improves its performance by(P) [12]. For example, let's saycauses your mail client to classify your email as spam. ExperienceE In this case, it must be a character set that has already been classified as spam.Task T is to automatically classifynew characters. Performance to be improved Pis the level of classification accuracy performed by machineon a new set of emails.

A. Machine learning process:

The entire machine learning process consists of sevensteps as described below [13]. The first step is data collection.Thisis a very important task because it determines how good the predictive model is. However, most of the data we collect is either unstructured, noisy, or needs to be in some other format to be useful for machine learning. Therefore, the data must besanitized and pre-processed. After that, you can start building your machine learning model. Problemhas been resolved.This is necessary for best results.The next task is training. In this step, we use the part of the data to incrementally improve machine learning's ability to predict. Once training is complete, it's time to test themodel and see how it can perform with other unseen parts of thedata. Performance scores are measured on a number ofparameters, including accuracy, reproducibility, and completeness.Sometimes you can go back and improve your training and then test again.The final step is the result of machine learning. It can be either a prediction or a conclusion.

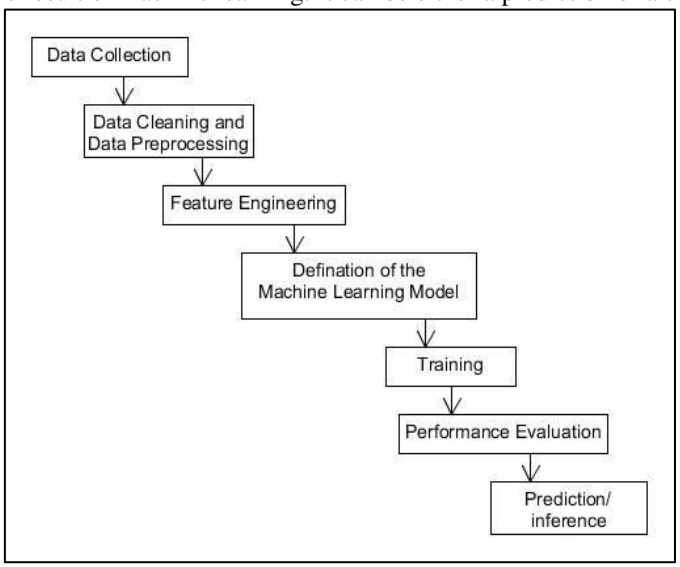

Fig. 2 Components of a general machine learning model

B.Machine Learning Paradigms:

Machine learning can be classified according to the approach used for the learning process. Four major categories havebeen identified: supervised, unsupervised, semi-supervised, and reinforcement learning [12]. Insupervised learning, we have a set of training data orlabeled data whose structure and outcome are known.We train a machine learning model with this data tounderstand the patterns in the data. After the model has passedtrainings, it can be used to predict the outcome of the unknown data [14]. Conversely, unsupervised learning methods learn structures from the data itself without the need for pre-labeling [15]. This means that you can find patterns in labeled data using unsupervised machine learning. However, full label information for number is not available. Semi-supervised learning provides a robust frameworkfor using unlabeled data when obtaining labels is limited or expensive [16]. The last approach to machine learning is used when we know what we're looking for but don't know how to get it.The principle of theis to test several solutions and then see which of thes give you the desired result. A reinforcement learning problem can be formulated as an agent that must make decisions in its environment. Agentis learning good behavior. This means he gradually changes or acquires new behaviors and skills. Thus, the hardening agent ( ) does not require full knowledge or control ( ) of the environment, but only needs to be able to interact with and gather information from the environment [17].

III.MACHINE LEARNING E-LEARNINGAPPS

Today, students, employers and many other fields want everyone to learn and develop their knowledge. more famous. All of this has resulted in a significant increase in the number of Advanced Technical Learning Environments (TELEs) offering public or private online courses and other types of services. As a result of analyzing the large amount ofdata produced by TELE through machine learning,results were obtained.It is useful to learn how to improve e-learning using this powerful new technology.

A.Sentiment Analysis:
Recently, the success of MOOC (Massive Open Online Course)is being evaluated by student satisfaction with thecourse [18]. Sentiment analysis can be used to identify complex emotions [19] to predict student satisfaction. In [19], the researchers seek to identifyMOOC forum posts, the polarity of student emotions, and positive and negative emotions.They compare the five most commonly used supervised machine learning algorithms for prediction-related contributions to MOOCs: logistic regression, support vector machines,decision trees, random forests, and naive Bayes. Results showthat random forest is the most reliable method. MOOC Understanding the role of emotions in students' learning experiences is critical. On the one hand, according to– [20], control over achievement can contribute to increasing learning engagement. We built asupervised machine learning model to automatically classifyachievement emotions based on SVM [20]. SVM is adopted becausegives better performance results than Naive Bayes, Logistic Regressionand Decision Tree. On the other hand, [21] uses big data from completed homework,comments and forums to track student sentiment trends to analyse course acceptance. Based on semantic analysis and machine learning [21], we explore the relationship between emotional disposition and learning effect.

B. Prediction of Student Behavior:
An interesting review of the literature [22] addressed the use of machine learning to predict student behavior. Two objectives of the study were identified: to classifystudents and predict dropout.

- Student Category:

Clearly personality, background knowledge, skills and preferences play a decisive role in the learning process. Therecommender system is responsible for providing each student with the most relevant content. Profiling and classifying students is a key task not only to personalize learning, but also to identify dropout factors and many other purposes. Our recent work on classifying

students using machine learning is summarized in Table 1.

TABLE I. STUDENTCLASSIFICATION

Paper	Machine Learning Algorithm	Classificationgoal	Results
[23]	k-means Support Vector Machine (SVM)Naïve Bayes	Classification of engaged and disengaged faces of students with dyslexia	accuracywith97–97.8%
[24]	Back propagation(BP), Support Vector Machine (SVM), Gradient Boosting Classifier(GBC)	Classification of student performance	Accuracy:BP =87.78%, 83.20%= 83.20%,GBC=82.44%
[25]	Decision Tree,Logistic regression,k-nn, SVM, randomforestalgorithms	Classification of successful and unsuccessful students	K-nn givesthe higheraccuracy =85%
[26]	K-modes clustering algorithm Naive Bayes classifier	Classificationof learner'slearningstyle	Accuracy =89%

Departure forecast:

Various machine learning techniques were used to analyze the traces of interactive behavior left in TELE. According to [27], which focuses on student click data, logistic regression (LR) was the most frequently used technique to predict dropout in MOOCs with an accuracy of 89%. SVM and Decision Tree take the second place, however Natural Language Processing Technique is in the third place.

B. Self-regulated learning

With the monitoring of a small external teacher in most TELEs, students are required to make decisions regarding their own activities [28]. In such a case, individuals with strong self-regulated learning (SRL) skills, characterized by the ability to plan, direct, and control their learning process, may learn faster and better than those with weaker SRL skills [29]. Being one of the e-learning platforms supporting SRL strategies [30], MOOCs focus on students self-assessing the quality or progress of their work, setting goals and planning, and giving them the opportunity to re-read notes, protocols, tests, or teaching materials for test preparation, etc. Despite all these features, it remains important for many researchers to improve learners' SRL based on a machine learning approach.Based on student records and survey responses,[31] contribute to a better understanding of how students learn and how instruction should be designed to support SRL in an asynchronous online course at a women's university in South Korea. In this study, the researchers approach discovering student profiles and examining the process of student SRL overtime. First, they proposed three key attributes of SRLThe time investment in content learning, study regularity, and help-seeking that apply to asynchronous online courses serve as the basis for SRL analysis and led to the selection of log variables. Second, they identified student subpopulations using the K-medoids clustering algorithm using the silhouette method. After discovering the existing clusters and their learning patterns,[31] use random forest classification as a decision tree-based machine learning algorithm to predict cluster membership by referring to each week's log variable.

IV.CONCLUSION

E-learning researchers have devoted considerable effort to analyzing student data using machine learning methods to enhance the learning experience. This seems wise because the learner is considered the main component in e-learning. However, we do not conduct any research work, which we do to the best of our knowledge, to use learning data to measure content quality in order to improve it

Therefore, in our future work, we will focus on evaluating e-learning content using machine learning. The main goal is to help course designers in the educational reengineering process based on machine learning and based on many factors, especially the interactions of past students.

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