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Feature Evaluation of Emerging E-Learning Systems Using Machine Learning: An Extensive Survey

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ABSTRACT As of late, with the progression of AI and man-made brainpower, there has been a developing spotlight on versatile e-learning. As all ways to deal with e-learning lose their allure and the level of online courses builds, they move towards more customized versatile learning so as to collaborate with students and achieve better learning results. The schools focus on the examination, mindfulness, and arranging techniques that infuse innovation into the vision and educational program. E-learning issues are a standard examination issue for us all. The motivation behind this research analysis is to separate the potential outcomes of assessing e-learning models utilizing AI strategies such as Supervised, Semi Supervised, Reinforced Learning advances by investigating upsides and downsides of various methods organization. The literature review methodology is to review the cross sectional impacts of e-learning and Machine learning algorithms from existing literatures from the year 1993 to 2020 and to assess the essentialness of e-learning features to optimize the e-learning models with available Machine learning techniques from peer-inspected journals, capable destinations, and books. Second, it legitimizes the chances of e-learning structures introduction, and changes demonstrated through AI and Machine Learning algorithms. This examination assists in providing helpful new highlights to analysts, researchers and academicians. It gives an exhaustive structure of existing e-learning frameworks for the most recent innovations identified with learning framework capacities and learning tasks to envision ML research openings in appropriate spaces. The survey paper identifies and demonstrates the important role of different types of e-learning features such as Individual pertinent feature, Course pertinent feature, Context pertinent feature and Technology pertinent feature in framework performance tuning. The performance of Machine Learning algorithms to optimize the features of E-Learning models were reviewed in previous literatures and Support Vector Machine technique was found to be the one of the best to predict the input and output parameters of e-learning models and it is found that Fuzzy C Means, Deep Learning algorithms are producing better results for Big Data sets.

INDEX TERMS Machine learning survey, ML techniques, e-learning, evaluation.

I. INTRODUCTION

The Learning styles can play an important role in adapting e-learning methods that indicate the path that students prefer. With knowledge of different styles, computers and students can provide valuable advice and guidance to improve the learning process. In addition, an e-gradient system that allows a computerized, statistical algorithm opens up the possibility of overcoming the shortcomings of the traditional detection methods mainly used in the questionnaire [1]–[5]. These persuasive factors lead to a lot of research on the combination of learning designs and adaptive learning methods. As the web quickly becomes quotidian tool for business and amusement, the employment of the web for education and learning

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is changing into a typical extension. As an academic tool, the web provides a global open platform for storing data and presenting it in text, graphic, audio and video formats, and in communication tools for synchronous and asynchronous communication [6]. The alarm is defined in its broadest sense as the guidance given to any electronic medium, including the Internet, intranet, extranet, satellite broadcast, audio/videotape, interactive TV, and CD-ROM. The meaning of e-learning refers to web-based education and learning [7]–[9] derived by the existing literatures. Knowledge development within the modern era is a technical support activity [10]. The value of e-learning lies in its ability to teach, operate and maintain e-learning programs anywhere, anytime, beyond just moving education and learning online [14]. Second, enormous interests in ICT foundation are expected to create, convey and oversee e-learning programs, and to change educators into proficient e-learning offices [11]–[15]. Therefore, successful e-learning implementation depends on developing a strategy that meets the learner's needs and the company's business goals [12]. The E-learning solutions started to boom to solve the challenges of physical class room learning. The design of E-learning models requires the crucial process of feature selection from genomic data [16]. The types of data such as student details and course details and the relationships between them requires management of big data which can be solved by latest Machine learning and Data Analytics technologies. One of the other overhead is to utilize the effective computational efficiency [17] for different types of e-learning models, tuning the performance of e-learning models can be again addressed by Machine Learning techniques [18].

A. SURVEY METHODOLOGY

This study is the comprehensive review of E-learning feature selection opportunities to guide the researchers in the aspect of model feature selection from Big data structure and it is the review of the performance of existing Machine Learning algorithms for various data set of e-learning models that guide the researchers to obtain suitable ML strategy for appropriate E-learning model. The paper presents data and evidence from existing journal paper findings of optimization, prediction accuracy rates by different Machine Learning techniques. In addition, the insights on various Machine Learning methods in the design of E-Learning systems were discussed through previous papers from journals and conferences. The existing literatures have been retrieved through Google, Google Scholar, Web of Science, Scopus and Saudi Digital Library search engines. The search keywords used are 1) E-Learning frameworks evaluation, 2) Current challenges of E-Learning framework design, 3) Machine Learning techniques for E-learning, 4) Survey on ML techniques, 5) Papers published from Jan 2009 to Dec 2020.

B. SELECTION OF STUDIES

Totally 300 papers are fetched through search engines, out of which 121 papers has been identified to review the e-learning features and evaluation. The retrieved papers from the database are selected for analysis based on literature survey plan. After the screening process, about 160 papers are ignored which are irrelevant to the topic of study. The topic of the study is survey the existing literatures related to evaluating E-Learning parameters using Machine Learning systems. There is no specific research hypothesis set to study and review of the e-learning models but the focus of the present research on the survey following research questions aimed particularly at solving the research challenges towards designing models and predicting and optimizing parameters.

The survey is conducted to find results for the following questions

1. How do we predict the feature variables of the e-learning datasets?
2. What are the ways in which Machine learning algorithms are utilized to Predict, Classify the E-Learning parameters?
3. What is the contribution of Machine Learning methods in solving research challenges related to labeled and unlabeled datasets over a period of years?

C. ORGANIZATION

The present study is structured as: Section II describes recent work related to e-learning features predictions. Section III presents a brief study of e-learning structures using a variety of machine learning techniques. Section IV depicts the different difficulties of e-learning implementation and exploration chances of arrangements that can be investigated utilizing these advancements. At long lastly, Section V closes this investigation.

II. MATERIALS & METHODS

A. FEATURES OF EMERGING E-LEARNING FRAMEWORK

It is well known that E-Learning framework refers to the process of sharing the knowledge among people despite of geographical boundaries and limitations with enabling technologies. In this section the major feature design challenges [14] in e-learning framework is discussed based on the dimensions [19] such as features influencing individuals, features influencing courses, context and technology which will be the guidance for the e-learning researchers to design, improve the e-learning frameworks and to evaluate the models. Figure 1 depicts the types of parameters involving in the design strategy of e-learning models.

1) FEATURE PERTINENT TO INDIVIDUALS

The features pertinent to the individuals are one of the most used features and have been considered to evaluate the performance of the e-learning systems in existing work as the user's satisfaction is important for any system implementation in real time. The users of the e-learning system vary from students, teachers to organization people. The individuals here refer to the users of e-learning models such as students and teachers and management. The major individuals

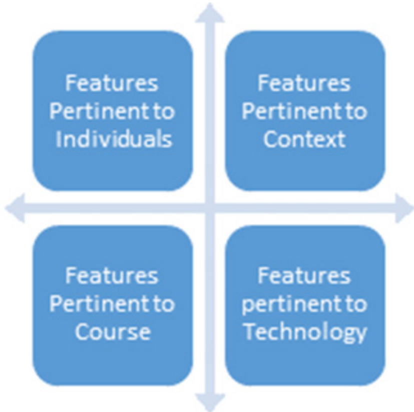

FIGURE 1. E-learning features.

representing features are user opinion, students' performance and knowledge, Student's ranking credits, learner's behavior, students' assessment, and students ranking credits as mentioned in Table 1. From the e-learning researcher perspective, it is important to understand the individual's type of feature's role of framework and research methodologies to have successful design and optimization, which was summarized with the existing work as follows. Features pertinent to Individual in different study are User-perception, user-opinion [20], Student's choice of course [21], [22], End user(Student) performance and end-user knowledge [23], [24], Learner's facial expression [25].

2) FEATURE PERTINENT TO COURSES

The feature pertinent to the Course of e-learning help in designing the course factors such as curriculum, pedagogical model, subject content, teaching and learning activities, localization, flexibility and support from faculty to students and support for the faculty. We surveyed the existing e-learning researches addressing the Course features and the research approaches suitable to handle these features in e-learning models. Features pertinent to course in different study are session-likeliness of the course [25] Student-Learning style, Student thinking pattern [26].

3) FEATURE PERTINENT TO CONTEXT

Organization of users, courses and technology done by the context, which has been provided by the organization or the management, is great and play a minimal role. The organizational factors are knowledge management, economy and funding, Training for faculty and staff, Role of the teacher and student, E-Learning attitude and finally the rules and regulations derived by standard organizations and governmental laws. The previous work of context feature evaluations are as follows. Features pertinent to Context in different study are course-session, course-material [27].

4) FEATURE PERTINENT TO TECHNOLOGY

Technology required to build the e-learning system are access method such as online, offline, the cost of software resources, software interface design implications, and the data and time aspects incurred for e-learning models. Following previous work discusses the role of technology features and how they handled to improve the performance of e-learning systems.

Reinforcement learning methods such as HMM (Harward Manage Mentor) and SVM (Support Vector Machine) [20] were utilized to evaluate the user perception. Using data mining techniques such as MI (Mutual Information), IG (Information Gain), and CHI Statistics (CHI) the Reinforcement methods were opted. Classification algorithms ADTree, Apriori Association Rule algorithm & Simple K-means Algorithm are used to cluster the dataset of student preference level [21], there had been utilized clustering techniques called Simple K-means and association rule algorithm and Apriori to group the courses according to the preference level of students [22]. The study states that Apriori [23] finds the optimal course for the students to choose. Support Vector Machine [23], [25] based E-learning models were found to be accurate with 0.986 F-measure compared to ML (Multilayer Neural Network) and SL (Simple Logistic) models [23]. Naïve Bayes, Random Forest and Hidden Markov model that were deployed to evaluate the accuracy of e-learning system out of which Random Forest Tree gave the optimum results with low error rate of 26.716% and high accuracy of the student evaluation system [24]. The researcher has used several classification methods here to understand the emotional state quickly and achieve the best accuracy ratio using k-NN (96.38%) and SVM (97.15%) algorithm and that was the research methodology adopted. The research methodology adopted here is AI (ML) strategies and relapse examination to distinguish enlightening meetings (sessions) dependent on understudies' remaining burden, commitment, trouble, and steadfastness features. The popular ensemble classifier namely Bagging [113] one of the best ensemble methods embedded with ML gives good kappa value 0.604 and 78.04% accuracy value for RF model which benefits the e-learning system developers to understand and troubleshoot session problems while designing [25ADTR] [27]. The evolving biometric innovation model [28] called Facial Acknowledgment and Key Stroke Dynamics (FRAKD) has been proposed to reduce the complications of testing irregularities of students. Monitoring the student test attempt activity is one of the types of Context feature which has been evaluated in this e-learning system. The automated response system [29] is the Technology feature evaluated by the authors. The biggest drawback of the e-learning model is that it does not answer learner's questions in a timely manner, which reduces the learning curvature of the student. The research methodology followed is designing an automated query response system, the researcher devised the e-learning framework with automated intelligent Web Bot system and evaluated the performance with the machine learning classification in an e-learning environment overcome the barriers of online learning. The researchers used information mining from the educational databases to define faster query response system enabling database mining applications. This approach

TABLE 1. E-learning features vs ml models.

E-Learning Feature	ML models and Technique	Prediction Accuracy rate	Criteria evaluated using ML
User opinion [20]	HMM,SVM, MI,IG, CHI	F-Measure 0.803	Accuracy rate of user opinion predicted
Course recommendation to students[21]	ADTree classification algorithm, Apriori Association Rule algorithm, Simple K-means Algorithm	Apriori Association gives best cluster of courses	Courses mapping is obtained
Timely system response to the students [29]	Genetic Algorithm, Machine Learning techniques	-	Automated Web Bot gives timely reply
Students performance, knowledge [23]	SVM	F-Measure-0.986	Predicts the rate of student's knowledge
Students emotions[25]	k-NN, SVM	SVM accuracy ratio-97.15%	Accurately predicts students emotions
Online session assessment [27]	Ensemble classifier Bagging embedded with ML	78.04% accuracy	Predicts the beneficial sessions
Student Ranking Credits [51]	ECOC combined Classifier	F Statistic is 3.05	Predicts College Opportunity
Learning styles and learning objects[26]	Bayesian Estimation	Bayesian infer the increase in visual category	Estimates Learning style
Learner Behavior sequence [84]	Fuzzy Cluster technique	78% matches with real word data	Predicts learner behavior
Learner sequence Learning pattern [82]	FCM, K-Means clustering	FCM shows 96.89% accuracy, K-Means shows 80.12% accuracy	Classified Learners sequence
Student graduation results [53]	Perceptron ANN	Predicts successful 77% Unsuccessful 68%	Predicts graduation successful ness
AUI features [60]course	Felder Silverman model	Classifies learning models	Learning models predicted
Course information [59]	ANN, LMA algorithm	R value 9.08	Evaluates future GPA
Learning processing data [39]	Conv-GRU-AvgP in P-xNN	Accuracy 80.4%	Predicted Learning performance
Students assessment [61]	Deep Learning Tensorflow Engine	80%-91% of accuracy	Predicts students future pathway
Student Test Results[114]	Random Forest	26.7% error rate	Predicts students performance
Student engagement in courses[115]	K Means clustering	Silhouette coefficient for Two level cluster is 0.7003	Classify student groups

utilizes combined K-Means clustering, Apriori association rule, among these, Apriori association rule algorithm provides good experiences with good time and space complexity.

5) RECOMMENDATIONS

Table-1 specifies the feature predictions by different ML techniques where it implies the variety of features to be considered for effective design and evaluation of e-learning systems such as user opinion, course recommendation to students, timely system response to the students, student performance, knowledge, students emotions, online session assessment, student ranking credits, learning styles and learning objects, learner behavior, learner sequence, learning pattern, student graduation results, course information, learning processing data, learning assessment pertinent to the classes of e-learning features such as individuals, context, course and technology which is the ideal involved in the optimization of E-learning models. It is understood that none of the types

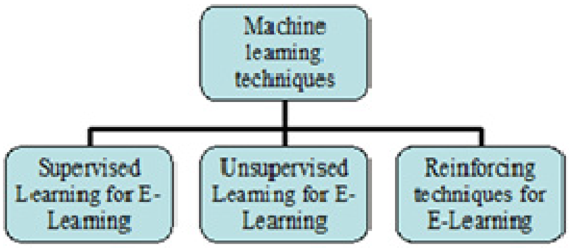

FIGURE 2. ML classification for e-learning.

of e-learning features leading in feature selection process, which includes all the types {Individual, Context, Course and Technology}, are equally weighted feature types in order to be considered for learn e-learning system parameters with respect to deployment environment.

III. ANALYSIS OF E-LEARNING SYSTEMS USING MACHINE-LEARNING METHODS

This section demonstrates the feasibility of Artificial Neural Network and ML models as well as techniques to evaluate the e-learning features and predict the parameters which may be used to redefine the design of e-learning systems. Machine learning algorithms are broadly classified as supervised, unsupervised, and reinforced. Reinforced learning is an advanced ML technique, which is widely used in most research domains, and the ML classification for the analysis of an e-learning framework is demonstrated in Fig. 2.

A. SUPERVISED LEARNING TECHNIQUES

E-learning has arisen as an elective approach that liberates students from a restricted conventional learning environment. However, e-learning is not yet a serious methodology and has numerous weaknesses, including the absence of correspondence with associates [30]. In any case, because learning materials, assets, and intelligent learning are essential for a dynamic, open, and complex arranged network, wasteful or malignant administrations cannot be avoided, making valid issues for e-learning [30]–[32]. Supervised learning models involve machine learning from typical appropriate models [33]. Set of inputs are given to the machine as training data and tested with other sets of data. This technique reacts according to a given set of feasible solutions.

1) CLASSIFICATION AND REGRESSION TECHNIQUES

E-learning models were personalized using the classification and regression techniques. The datasets used were classified as labeled.

For a labeled dataset

$$D: X = \{x^n \in R^d\}_{n-1}^{N} \quad Y = \{y^n \in R^d\}_{n-1}^{N} \tag{1}$$

$$x^{(n)} = [x_1^{(n)}, x_2^{(n)}, \ldots, x_d^{(n)}]^T \tag{2}$$

where X denotes the feature set containing N samples, and each sample is a vector and called a feature vector and a feature sample. Each dimension of the vector is called

TABLE 2. Student's action representation as feed-forward neural networks inputs [39].

--	Action
x_0	Reading material
x_1	Answer changes
x_2	Exercises
x_3	Mail usage
x_4	Exam revision
x_5	Information access

an element, attribute, or feature. Y represents the label set that denotes the label to which the feature vector belongs. Supervised learning determines the correlation between the feature set and the labeled set. as given by the equations 1 and 2. The supervised learning method [34] evaluates individual student's learning style based on their activities, profiles, kinships, courses of users, and other collaborative features. Another study [35] avoids the co-linearity of the parameters in a financial prediction by utilizing a logistic regression, which is a type of supervised learning technique. The e-learning system [36] is reliable and is based on a feed-forward neural network, and the student activity is considered as a feed-forward neural network input layer, as listed in Table 2. mention the level student knowledge predicted by NN.

To predict the level of student knowledge after undergoing the online learning mode, the supervised backpropagation learning technique reaches a high state. Another interesting ANN type, namely, a feed-forward neural network with a batch gradient descent, is preferred for classifying student learning styles [36]. This study [37] suggests versatile learning in demonstrating English as a Second Language (TESL) to an e-learning system (AL-TESL-e-learning system) that takes into account the student characteristics. This examination inspects the learning-results of different understudies, such as intuitive, active, and sequential learning-results. The ANN model achieved a 69.3% accuracy by applying a learning algorithm to obtain the output layer of the students' learning behaviors. A supervised learning models, i.e., a feed-forward neural network, was developed, and a back propagation algorithm was implemented, which adopted a classification technique to predict the level of student knowledge from different types of learning approaches. In the ANN BP model, the generalized difference of the hidden layer is defined as in equation 3.

$$D_j^* = \in_{i=1}^{n} (w_{ij}(t) * D_i(t)) * A_j(t) * (1 - A_j(t)) \tag{3}$$

where the generalized difference of the cumulative hidden layer is multiplied by the derivative function. The ML model evaluates the relationship between the student characteristics and the learning performance. In [38], theoretical method-based spiking neurons address the lack of existing learning-laws. In particular, the filter law is based on a high-filter output spike rail, which is a profoundly proficient spike-based neural classifier. Classifiers [40] based on an ad hoc code are of interest because they are hypothetically more efficient than utilizing a rate-based code when preparing data in faster time scales.

2) BAYESIAN METHODS

The purpose of the Bayesian technique used in machine learning is to derive an ML model from Bayesian inferences. Bayes inferences estimate the parameters without much complexity. The new application of a Bayesian rough set (BRS) model from [39] was designed to provide learner data. BRS model is modified based on Bayesian confirmation measures (BCM) to improve the accuracy of the original folk set decision to evaluate and handle the final result class of decisions about the student expertise. The student profile database was used as the Universal Dataset U, and the conditional attribute C = {Q1, Q2, Q3}, decision attribute D = {final}, and frequency attributes are used in the BSR model to classify the result set with the values of (Excellent, Very Good, Good, Fair, and Poor) by pursuing the BCR.

The Bayesian confirmation theory is derived as in equation no.4

$$\begin{aligned} P(X/E) &> P(X) \\ P(X/E) &> P(X/(\neg E)) \\ P(E/(X) &> P(E/(\neg X))) \end{aligned} \tag{4}$$

Here, E is the evidence, X is the hypothesis, and E and X are positively correlated. The BRS model evaluates the criteria for students to update their learning style using some evidence of the selected learning materials in e-learning systems [39], [41]–[43]. The dynamic Bayesian network (DBN) developed for the e-learning system estimates the students' learning styles using qualitative and quantitative components such as understudy's learning material [44]. The difference between the normal Bayesian network model and the dynamic Bayesian network model is that the DBN changes dynamically with the feature considerations in the network models according to the environment. The objective of the DBN model is to determine the variables first, and then find the correlation between the variables for a classification. According to e-learning model, the author designs user types such as sensing/intuitive (perception), visual/verbal (input), sequential/global (understanding) based on FSLSM, which can assume a significant job in adapting e-learning methods that indicate the path preferred by students. These remarkable elements explore different areas of the integration process by reviewing 51 studies exploring the integration of the learning styles and adaptive learning methods [45], [46]. The process of optimizing the e-learning model [47] emulates various features for selecting the learning style theory

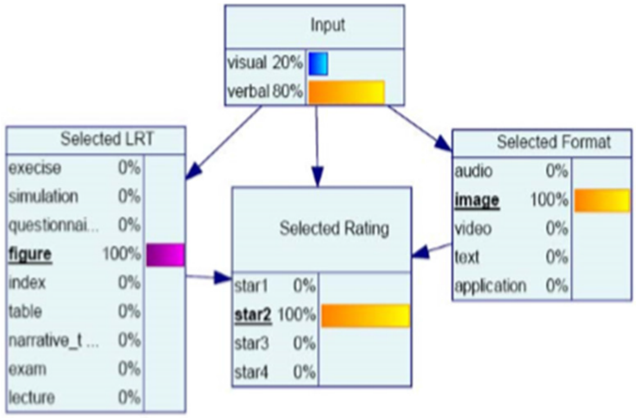

FIGURE 3. Student modeling in e-learning systems [49].

from the e-learning environments, online learning style predictors, automated learning styles, and other learning style applications in classification using dynamic Bayesian networks (DBNs). Bayesian knowledge tracing (BKT) is also a popular approach for prototyping the understudy learning style. However, as mentioned in Fig. 3, the range and relationships between different activities in the field of study can be represented elaborately based on the structure of the BKT model. The Dynamic Bayesian Network model uses the controlled optimization algorithm [48] to predict the features across five large datasets in various fields of study, including mathematics and physics. The dynamic course recommendation system (RS) and Felder-Silverman learning style model (FSLSM) suggest a new way of identifying student behavioral characteristics to identify a student's learning style. Equation (5) predicts the correlation between the learning object and learning style.

$$P(x, y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{5}$$

where x is the set of learning behaviors, and y is the set of learning objects. The learning behavior of the understudies was tested in the e-learning framework designed based on a dynamic recommendation system, which is a Bayesian model, and as a result, students can effectively improve their learning skills and learning experiences.

3) DECISION TREE LEARNING METHODS

Decision trees are widely used decision-making techniques for learning grouping algorithms. These algorithms are regularly alluded to as factual classifiers because they utilize factual measurements to determine the stretching of the hubs [50]. To group a case, decision trees sort the example down the tree from the root hub to a particular leaf hub. Every hub inside the tree speaks to a trial of a specific component of the example, whereas each branch speaks to the potential worth of the tried component. ID3, ASSISTANT, and random forests [102], C4.5 algorithms are among the most notable decision tree algorithms. Viably, C4.5 picks the best partitions of the tests into more modest subsets in one class or another. To determine the division rule, a standardized data gain metric (distinction in entropy) was utilized. The element selected is the one with the most elevated data gain.

4) ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is a well-known directed characterization method. It is frequently utilized whenever we have large amounts of labeled dataset with numerous dimensions, in which a non-straight theory is desired [94]. An ANN attempts to imitate the way our cerebrum functions, and for all of its various capacities, it has been demonstrated that the mind utilizes one ''learning algorithm'' [95]. Like neurons that go about as computational units taking electrical contributions (through dendrites) and channeling them toward a yield (axon), an ANN algorithm receives a model wherein the highlights go about as dendrites (nerve cells) and yields an estimation of the speculation task. Frequently, one ''covered up'' layer is utilized, which is demonstrated as a transitional layer. This layer helps obtain more data from the arrangement of highlights accessible as a feature of the preparation information and is known as the actuation layer. The sigmoid capacity utilized in a strategic relapse is utilized for each layer of the organization. Because a sigmoid task is utilized in an ANN, the cost utilized to decide the estimations of the coefficient vector Ø_opt^f chosen at layer f is similar to that utilized for a strategic relapse. Reducing the graduation rate of the students is important [53], [54] and is an increasing issue in advanced education. An artificial neural network prediction system helps to predict the student success rate in graduation studies. Dataset classification applied to ANNs has led to the development, training and testing of e-learning models to predict student graduation results. The back-propagation three-layer perceptron network helps to predict successful and unsuccessful graduation students for the sample student profile dataset of 1407 [55]. ANN models help in predicting the learning outcomes of students [56], [57] by optimizing their course priority dataset. One of the measures of e-learning systems is analyzing students' meta-cognitive characteristics using educational data mining (EDM), and is successful in predicting the aid of a student performance such as participation, self-control, peer engagement, teaching experience, and time of teacher-student meetings. The advent of the ANN model explains how to use Artificial Neural Networks with e-learning interactions and social analytics, which can effectively predict the student performance to reduce the risk of a failure in an enrolled e-course [58]. As such, one of the e-learning models was designed as an ANN [59], personalized using the standard Levenberg–Marquardt algorithm (LMA) to evaluate the students' GPA from normal learning information as the input set. In [60], a customization of the multi-specialist learning framework depends on a learning style model that requires a psychological science poll to decide the understudy's learning style. An ANN model, called a GRU network was utilized to predict student's performance [111]. A parallel expandable neural network (xNN) describes the prediction results of the students' learning outcomes [62]. The parallel mini-batch structure of xNN was tested with datasets such as the WorldUC dataset and Liru online course dataset, which helped in the prediction of the most relevant learning materials by accelerating the learners' knowledge background datasets [63].

5) DEEP LEARNING NETWORKS

One unique class of managed Machine-Learning techniques is Deep Learning [10], [52]. Fundamentally, deep learning can be an idea of a large-scope neural network. In any case, because of the way that profound learning is additionally capable of performing programmed solo element extraction, and is usually alluded to as highlight learning [64], [10], it cannot be called a conventional neural organization. Henceforth, Deep Learning is viewed as an extraordinary instance of managed AI. Overall, Deep Learning attempts to show deliberations found in information by utilizing a chart with numerous handling layers [64]–[66]. These handling layers contain units that apply straight and non-direct changes to the information to be extricated; however, a large amount of helpful data can be expected. Deep Learning techniques are fundamentally the same as Artificial Neural Networks. Indeed, an ANN can be considered as a Deep Neural Network learning technique [75]. However, Deep Learning techniques are wider and can be applied to both labeled and unlabeled datasets. In addition, they can be applied to a large number of neural networks. Ng, fellow benefactor of Coursera and the Chief Scientist at Baidu Research, stated that profound learning is simply applying an ANN for a huge scope that can be prepared with more information, and thus has a better execution [64]. There are wide range of profound learning calculations other than ANNs. Predicting a student's academic performance is an important research topic in an e-learning environment [67] that uses machine learning and data mining techniques to analyze data from educational systems. However, it is difficult to measure student achievement because it is expressed by different factors. The relationships between the variables and components that predict performance participate in a complex linear fashion. Traditional data processing and machine learning techniques cannot be used directly for these types of data and problems [68]. The classification model used to forecast the student score levels is shown in Fig. 4. The effective use of in-depth learning in an e-learning environment learns multilevel expressions [69]. Deep learning network models are efficient in big data analysis, such as the processing of 530 college students. An in-depth model analysis is conducted for the dataset of not only traditional academic achievements, including mathematics, Chinese, English, physics, chemistry, biology, and history, but also for a dataset of services, behavior, sports, and art [70]–[74]. A deep learning model called the Tensor flow [76]–[81] engine is an example of including the number of intermediate nodes and the number of in-depth study layers for a cumbersome dataset. That is, from the database

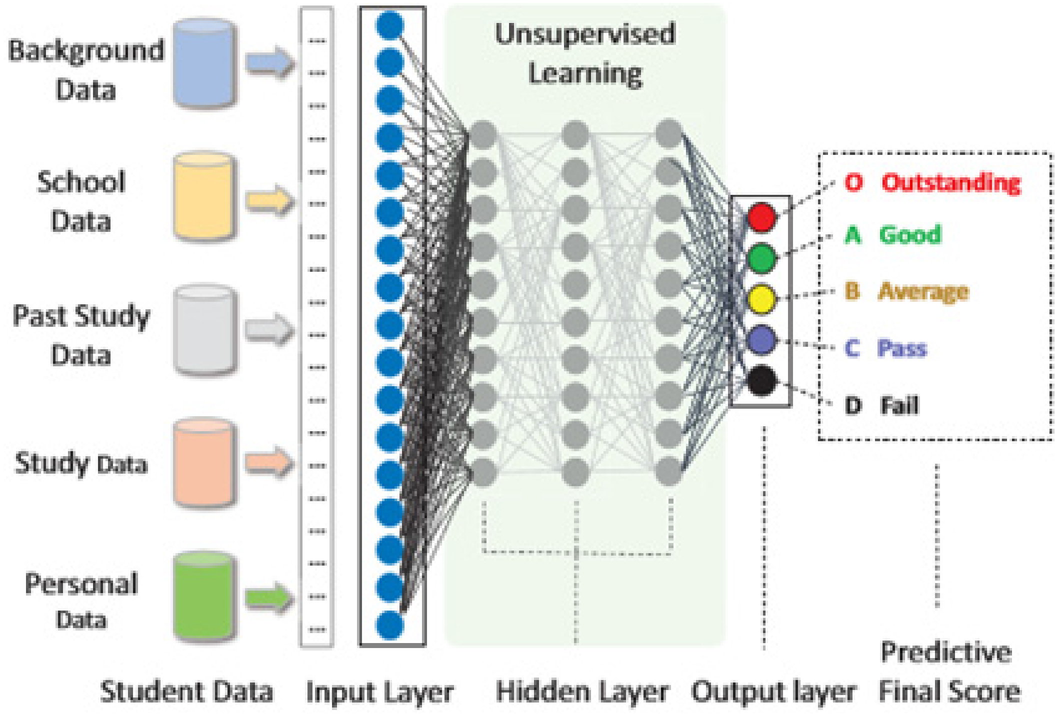

FIGURE 4. DNN predicting the student performance in e-learning environment [69].

of 2,000 students, 75% of this data were used as training data and 25% were used as test data to predict students' future pathways with accuracy rates ranging from 80% to 91%.

The optimal configuration of a tensor-flow deep learning model achieves a high predictive accuracy for large databases. Similar to the Tensor flow model, another model [80] utilizes the feature selection correlation methods, C-square and Euclidean distance, to predict weak students. The researchers also compared the prediction results with Naive bayes, K-neighbor, and End tree's artificial neural network classifiers and determined accurate prediction results.

B. UNSUPERVISED LEARNING

1) CLUSTERING METHODS

Clustering is a hybrid approach of the composition of AI technology and statistical tools for evaluating and modifying e-learning methods. The student's profile plays a significant role in the assessment cycle and in the suggestions for improving the e-learning measure. Fuzzy clustering techniques [82] (fuzzy C means (FCM) and kernelled FCM (KFCM)), analyses, and results are useful for classifying learner profiles, presenting several stages of the job, and exploring ways to modify the substance and structure of e-learning frameworks. The kernel fuzzy C (KFC) algorithm uses the kernel function K (x, c) and the Gaussian radial basic function (GRPF) as follows:

$$K(x, c) = \exp\left(\frac{-\|x-c\|^2}{\lambda^2}\right) \tag{6}$$

Here, the adjustable parameter is [82].

Figure 5 demonstrates student predictions using a clustering model, which suggests a general approach to a programmed identification of a learning style dependent on a given learning style model. There are two main stages in this task. First, researchers use a web application mining technology to retrieve log files from learners. Second, they use a clustering algorithm to classify the extracted learner lines according to a specific learning style. In other approaches [83], the authors use the Felter–Silverman model as the LSM and FCM as the clustering mechanism, where fuzzy C means classifies the learner sequence with 96.89% accuracy and K-means classifies it with 80.12% accuracy, and thus the FCM clustering algorithm outperforms K-means [82] Clustering using K Means perform better in classifying student's groups based on student engagement level in classes [114].

FCM and KFCM are clustering algorithms that predict learner behaviors in e-learning models [85], [82]. Another e-learning model practiced by Cognitive Tutor for College Genetics [86] measures the students' future performance (PFL) using a cross-validated prediction method that shows better results of prediction of such performance than a Bayesian prediction technique. Preprocessing technology used in the educational data mining [87] of EDM was applied in the selected database. Initially, incomplete and serious random data were removed from the sample. After pre-processing, they implemented two steps: clustering and forecast analytics. First, the author implemented a clustering process because it was necessary to identify groups of students based on their responses. After understanding

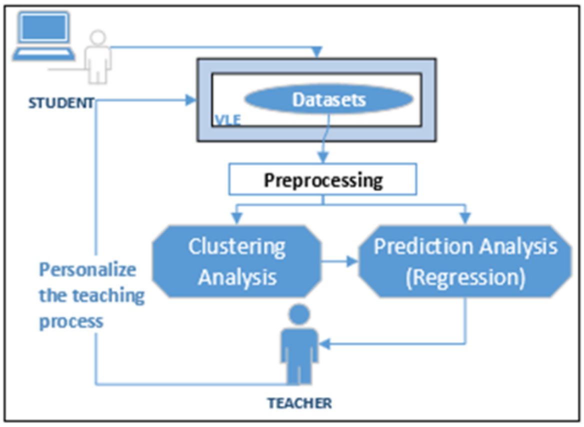

FIGURE 5. Student performance prediction using clustering [82].

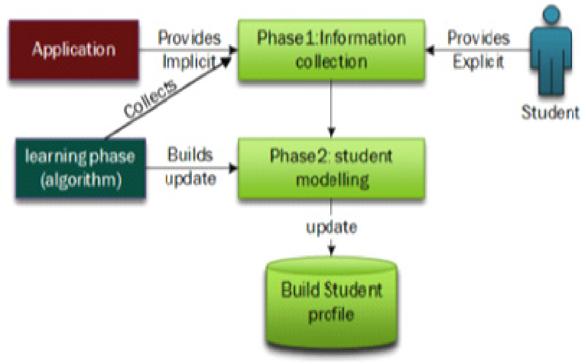

FIGURE 6. Data distillation using training the student model [50].

the groups, they predicted student behavior for each cluster defined in the final step [88]. The research [84] defines a regression method used for forecasting, as described in the clustering K-i algorithm. The study identified a group of five students as experts, good, regular, bad, and critical answers. As a result, predictive analytics defines the teacher's application score (''average application score'') as the most interesting component. This approach implements a stepwise delayed regression, a semi-robotized measure that creates a model by continuously including or evacuating factors dependent on the D value of a given coefficient. Thus, another conclusion is that the existences of the variables ''false'' and ''correct first attempt'' has place to the three regression models derived from the method.

C. SEMI SUPERVISED MACHINE LEARNING ALGORITHMS

Semi-supervised learning methods are suitable for e-learning problems of known input parameters and unknown output parameters. E-learning problems pertain to unlabeled data to be processed, and semi-supervised learning algorithms leverage a better classification of unlabeled data. The novel [89] method introduced by the author applies the e-learning framework, smooth neighbors on teacher graphs. Data distillation [50] is the implementation of an Omni-supervised ML procedure applicable for labeled and unlabeled datasets. Data filtering is used to integrate predictions from multiple transitions of unnamed data that use the same model and automatically create new tutorial notes. As shown in Fig. 6, the student learning attributes are transformed into different models, and the parameters are ensemble from different models to predict the particular learning outcome. This study [90] explored the field of e-learning and provided an overview of the current e-learning structure of other studies. Students were evaluated on this term for their importance. In [91], [92], the authors describe a machine learning framework that identifies students, describes useful features for this task, utilizes a few order calculations, and evaluates them using important criteria for school administrators. The research findings reveal that the ML method CIFAR-10 with 4000 labels obtains an error rate of 3.8% and an SVHN with 500 labels each, and found no progress even when the number of labels was low. For a magnified MNIST [90] with 20 labels, the error rate was reduced from the previous 4.81% to 1.36%, showing strong characteristics for quieter labels. One of the advantages of the semi-supervised learning model is the Omni supervised learning model, which elevates the performance of the prediction system in training a machine. Data distillation performs well for large datasets to predict the expected annotations using the ensemble method and a reduced training rate, which is an insightful fact for evaluating the e-learning method using the semi-supervised training model. The semi-supervised ECOC combined classifier achieves better classification results with a reduced number of training trials of approximately 10%, and with a very large dataset containing more than 100,000 data.

1) REINFORCED LEARNING TECHNIQUES USED IN E-LEARNING FRAMEWORK

The ANN model provides input information as an incentive for the context in which the model needs to respond. The input parameters are used as regulatory adaptation, for training the system, and for stimulating rewards toward a solution in a natural environment. This technique employs a case structure and an automatic control. Some of the test models, including Q-learning and learning arranged by momentary differentiation learning, were used to apply the above examination of the e-learning structure [96], [97]. Reinforced learning (RL) has become a central role model for taking care of learning the control issues in mechanical autonomy and man-made consciousness. Researchers in the area of reinforcement learning are focusing on issues that need to be managed, which are increasingly being discounted. However, as Schwartz (1993) stated, the classification of tasks is more natural and computational in reinforcement learning, and thus the range of the controller is minimized over a given period of time, which is the optimal characteristic limiting the trial cycle.

A new average payment reinforcement learning algorithm for a random approximation in solving the policy evaluation equations is derived in [98] to optimize control in Markovian decision tasks. These methods are similar to the popular TD

TABLE 3. Comparison of different machine learning techniques using e-learning framework.

Year	Methods	Algorithms/Techniques	Advantages	Applications
2009, 2014, 2015, 2017, 2018, 2015, 2019, 2020,	Decision Tree	Fuzzy TOPSIS[60,108] HEIs, Fuzzy DEMATEL [90] MADM, Fuzzy COPRAS [106] C Programming language [107] CSFs, AIVFAHP [96-99]	Genuine Estimations Intuitive	Medical research Data transformation
1993, 1996, 2002,2003, 2005,2009, 2019	Bayesian	BRS [62] DBN [63], BCM [100] BKT [67] FSLM [108]	Solid decision Good prediction accuracy	Encoding Data prediction
2010,2012, 2015, 2017, 2007	Clustering	Matrix Based, K-means [69] FCM,KFCM [81,85] LSM [109,110]	Guarantees convergence Choosing manually	Data analysis Image processing
2014, 2015, 2017, 2018, 2019	ANN	ANN + Semantic Clustering [45] xNN [47] Convolution GRU [48,49]	Less statistical training Detect complex nonlinear	Medical Diagnosis Voice recognition
2016, 2018, 2016	DNN	LMS [111] Tensor flow [84] Feature selection methods[77]	Faster learning Detect all possible predicted variables	Signal processing Health care industries

and Q-learning methods that have already been developed in a discount payment case. The algorithm obtained here is an important variant of Schwartz's R-learning algorithm, which gives the initial experience results a curve to validate a new algorithm, which may be pursued for e-learning knowledge predictions. Another example of a decision tree learning method is to predict the usability of a custom virtual learning environment (VLE) e-learning platform using data mining techniques. The VLE contains several dynamically active server pages (ASPs), frame sets, style sheets, and GUI graphics. Course content is distributed through three contexts: materials with additional pages for guidance and support, assignments, and library resources. This design is based on a growing academic community in which learners can choose alternatives through the curriculum. For example, a perspective content prompts the teacher to complete an assignment at a relevant point in the content [99].

The data mining technique [99] is customized in VLE and evaluated as 77% of user likeliness toward online learning from a large dataset of user feedback. Another multi-standard decision-making technique, TOPSIS, was used to confirm the results. The algorithm proposed in this study makes it easy to reduce the problem of choosing a learning system by combining ambiguous TOPSIS and the requirements [100], [101]. A statistical analysis of the interest of medical students in SURGENT revealed that an anonymous postgraduate medical student survey (73% response rate) was used by researchers as benchmarks to assess of the course and results. Among the students, 98% used SURGENT and 69% spent 30 min or more on the program. The researchers found a 9% improvement in the statistical curve in the surgeons' learning capability compared with the previous year during a surgical trial. The web-enhanced interactive surgical module of the undergraduate curriculum can successfully convey information and understanding beyond textbooks. SURGENT offers additional textbooks and ward experience to help students develop clinical decision-making skills [100], [101]. DEMATEL techniques are categorized as reinforced-learning decision tree techniques that perform well for e-learning feature assessments.

D. RESEARCH GAP AND CHALLENGES

The previous section provides an overview of the capabilities of growing e-learning frameworks using Machine Learning technology. Despite the many attempts of previous researchers, there are still some challenges to optimizing e-learning framework parameters, which are associated with different aspects of e-learning. Some of these works can be

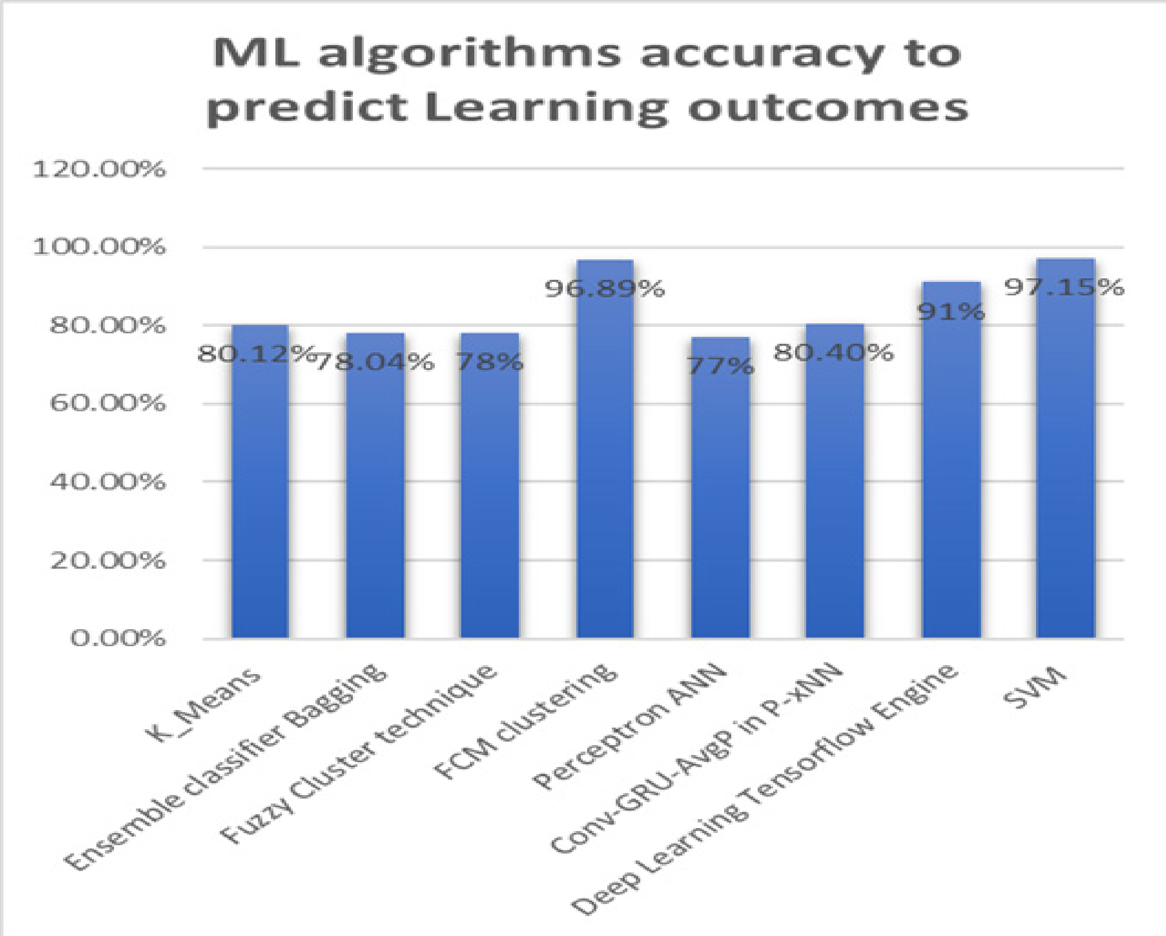

FIGURE 7. Comprehensive ML accuracy in e-learning models.

viewed from an educational perspective and from a technical perspective [103], and the personalization of e-learning is a major area of interest in this field. From the research survey conducted on the existing frameworks, it was observed that the customization of e-learning systems requires two main tasks: classification and recommendation of datasets. First, the dataset was classified into different classes based on a specific size. Recommendations suggest trends that can increase or improve the performance levels using the above classification. Machine learning assistants improve the e-learning framework optimization by replacing existing intelligent learning programs with ANN models [104]. Learning activity is used appropriately to provide relevant data to different learners. For example, it allows learners to create tunable models of machine learning properties that allow them to adjust the level and coordination of information so that learners can read both on the Internet and offline [105].

E. MAJOR REVIEW FINDINGS

The role of machine learning assistants has been analyzed and obtained in different studies. Supervised and semi-supervised learning has strengthened research studies, and few studies have been conducted on supervised and semi-supervised approaches based on the knowledge of researchers, revealing that the empowerment of learning methods similar to regression, regularization methods, instance-based methods, association rule learning, decision tree learning, deep learning, Bayesian approaches, clustering methods, kernel methods, association [114] rule learning, and artificial neural networks evaluate e-learning systems with different criterion domains. Each of these methods is compared based on their techniques, benefits, and applications, as listed in Table 3. The table details suggest decision tree techniques such as fuzzy TOPSIS, HEIs, fuzzy DEMATEL, MADM, fuzzy COPRAS, C programming language, CSFs, and AIVFAHP provide good and reliable decision estimations on e-learning features as learning styles in a design context. ML techniques, namely, Bayesian methods BRS, DBN, BCM, BKT, and FSLM render accurate and good predictions of e-learning features and good decisions of feature extractions. The clustering technique categorizes the student group by applying methods such as matrix based, K-means, FCM, KFCM, and LSM approaches. The purpose of using an ANN, semantic clustering, xNN, and convolution GRU models is to solve big data problems.

E-Learning feature evaluations achieve good accuracy rates of up to 91% for large datasets through the advent of artificial neural networks and deep learning neural networks. Important e-learning feature measurement accuracy rates are summarized to compare and contrast the applicability of ML evaluations to fine tune the e-learning frameworks: In the analysis of machine learning algorithms available for improving the e-learning accuracy, a support vector machine outperforms other frequently used ML techniques such as k-means, FCM clustering, and perceptron ANN model with a 97.15% accuracy rate in comparing the prediction of student knowledge levels and optimizing other parameters in e-learning models. From the demonstration shown in the figure 7, it is understood that fuzzy C means, ANN, and deep learning algorithms provide greater accuracy in predicting student learning styles with large input datasets within in a short time, and that the time complexity of these algorithms is sound and ideal for the classification and prediction of e-learning parameters. The second objective of our research survey "What are the ways in which Machine learning algorithms are utilized to Predict, Classify the E-Learning parameters?" is obtained in section III.

IV. CONCLUSION

AI is a broad exertion to execute inventive e-learning systems. This study offers different surveys utilizing the e-learning system remembered for the development exercises. E-learning faces various challenges, for instance, how to acquaint substance and how to alter the e-learning experience. We additionally talked about a portion of the assignments actualized by AI and information examination in web based figuring out how to comprehend the development of effective and fruitful web based learning model plans with the target of improving the learning nature of understudies and offers answers for the issues identified with e-learning customization. The literature survey report is introduced in Table 3 shows that Bayesian method had been received from mid-2000 to present date infers it as a best forecast strategy for e-learning framework boundaries. Furthermore, the approach called Decision Tree sounds better with instinctive dynamic and began to rise up out of mid-2010 to present date. The effect of Big data requires the need of grouping system to order the huge datasets and foresee the exact e-learning boundaries which was referenced in the report Table 3 with the course of events of rise of the strategy as 2007-2017. From 2014 onwards ANN demonstrating strategies began to exist and develop to learn nonlinear framework models to the machines. The progression of Machine Learning calculations was actualized in Deep Learning NN models and rises from 2016 onwards. The third research objective of our research "What is the contribution of Machine Learning methods in solving research challenges related to labeled and unlabeled datasets over a period of years?" is obtained here. As we end up our survey analysis, the far reaching study of this exploration work directing spurs for the development of better E-learning models in the difficult heterogeneous conditions and various research opportunities have been explored to give knowledge to researchers who require more surveillance in field of E-Learning with ML.

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