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An Hybrid Ontology Matching Mechanism for Adaptive Educational eLearning Environments

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Providing the same pedagogical and educational methods to all students is pedagogically ineffective. In contrast, the pedagogical strategies that adapt to the fundamental individual skills of the students have proved to be more effective. An important innovation in this direction is the adaptive educational systems (AESs) that adjust the teaching content on educational needs and students' skills. Effective utilization of these approaches can be enhanced with artificial intelligence (AI) and semantic web technologies that can increase data generation, access, flow, integration, and comprehension using the same open standards driving the World Wide Web. This study proposes a novel adaptive educational eLearning system (AEeLS) that can gather and analyze data from learning repositories and adapt these to the educational curriculum according to the student's skills and experience. It is an innovative hybrid machine learning system that combines a semi-supervised classification method for ontology matching and a recommendation mechanism that uses a sophisticated way from neighborhood-based collaborative and content-based filtering techniques to provide a personalized educational environment for each student.

Keywords: Adaptive educational system; eLearning; machine learning; semantics; recommendation system; ontologies matching.

Mathematics Subject Classification 2020: 22E46, 53C35, 57S20.

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1. Introduction

The need to use eLearning platforms for distance education grew with the pandemic of COVID-19 (Ref. 1) that disrupted the education and training of an entire generation. The pandemic also showed the continual requirement for eLearning systems, which must be adaptable, time-saving, and cost-effective. Also, these systems must include procedures for self-directed toward achieving the academic goals of learners and should be self-motivated.[2] The rapid development of cloud computing, semantic web (SWeb) methodologies, and especially the AI technologies offers new opportunities in the future development of innovative systems that will allow the more intelligent management of learning content for providing personalized educational environments that will enhance the eLearning education.[2]

The most significant developments concerning the combination of AI and SWeb in education and, more specifically in the current eLearning systems focus on[2–5]

(1) information management with appropriate ontologies for optimized performance.[6,7] Using ontologies in collaborative environments where collective content is produced will allow correlations between heterogeneous sources (documents, emails, etc.) to retrieve all relevant information easily.[8]
(2) digital libraries that need to comply with the semantic ontologies and semantically organize their librarian catalogs so that search engines can locate the appropriate content.[9,10]
(3) the development of innovative applications and eLearning platforms, which use semantic ontologies, that will allow the transformation of distance education, creating friendly search engines semantic "maps" of learning material and content.[11,12]

Based on the above assumptions, this paper proposes a novel adaptive educational eLearning system (AEeLS), which with extensive use of AI methods,[13] allows the modeling of the process of retrieval and management of information based on semantic criteria for the needs of individualized education of each student.[14,15] The proposed system is a novel eLearning system that adapts the provided educational content to the specific educational needs of each trainee or group of trainees to achieve sophisticated learning. Also, it provides specialized support to the trainees taking into account the learning needs and the particular characteristics of learners in addition to their evolution during their study.[16]

The principle of differentiated learning is a modern educational method that aims to offer high-quality education through differentiated approaches that take into account the special educational needs and capabilities of each student, their special interests, their unique experiences, their learning rhythms, their learning style, their cultural background, and their self-perception.[13] Even in this case, however, the level of students is never the same, resulting in the adaptation of teaching to the different levels of learning ability within a classroom. The internal differentiation required in these cases should include various practices and individualized forms of organizing the learning process. This research aims to combine SWeb and AI in a unique framework in an eLearning system, delivering representations and definitions of learning categories, attributes, and relationships between educational concepts to make distributed educational data easily accessible.[17,18] Also, we must note that the research aim is not to produce the best results but to provide a novel model that can gather and analyze data from learning repositories and adapt these to the educational curriculum according to the student's skills and experience.

The sections appear in the rest of the paper in the prescribed order: Sec. 2 presents the related work about the applicable adaptive educational system (AES) that has used AI models. Section 3 illustrates the suggested logical framework and describes the methodology, Sec. 4 presents the dataset used and the outcomes of the proposed algorithmic approach, and definitively, Sec. 5 contains the conclusions.

2. Related Work

Online collaboration has highlighted that the eLearning approach is essential to the modern educational system based on semantic technologies. SWeb[19] is structured data representation via the combined use of hyperlinks as entity identifier names, language for machine and human-comprehensible sentences/statements using the standard structure, and a variety of notations for creating RDF language sentences in documents,[20] e.g., RDF-Turtle, JSON-LD, RDF-XML, and others.[10,21] Universities, organizations, and companies have adopted eLearning as a more flexible and effective way to train their students, executives, or employees. However, the current and future trends in eLearning prove that it is a field for continuous innovation and research based on advanced methods like ontology matching.

Ontology matching is a hopeful method of the semantic heterogeneity dilemma. It uncovers correlations among crucially linked knowledge entities of the ontologies. These correlations can be applied to numerous tasks, such as ontology integration, query responding, and data conversion.[22] Thus, matching ontologies allows interoperating and information transfer and data integration in the paired ontologies.[17,23]

Ontology matching aims to establish correlations among conceptions in ontologies to create an arrangement between ontologies, where an account contains a set of correlations among their rudiments so that significant similarity can be equivalent. Given two ontologies, OS (source ontology) and OT (target ontology), and entity es in OS, the procedure ontology matching M is denoted as a process that find the entity et in OT, that es and et are deemed to be equivalent.[22,24,25]

It should be emphasized that the ontology matching process can be subsumption, equivalence, disjointness, part-of, or any user-specified relationship.[13,25,26] The most significant matchings or alignments can be categorized in three particular sections[17,27]:

(1) Similarity versus logic: This category concerns the similarity and logical equivalence among the ontology terms.

(2) Atomic versus complex: Concerning that category, the alignment considers if it is "one-to-one" or "one-to-many."
(3) Homogeneous versus heterogeneous: In the third category, the alignments examine if it is on terms of the same type or not (e.g., classes to classes, individuals to individuals, etc.).

Usually, an ontology matching tactic applies numerous and different categories of matches such as labels, instances, and taxonomy forms to recognize and estimate the resemblance between ontologies.[9,18] The most straightforward strategy is to aggregate the similarity standards of each object pair in a linear prejudiced mode and decide on a suitable threshold to recognize matching and nonmatching pairs.[22,26]

In contrast, the machine learning-based ontology matching methods have been proven to get more precise and reliable matching consequences.[17,26,28] Comparing the machine learning approaches, supervised methods usually get better results.[23,25] Specifically, the supervised machine learning methods use a set of validated matching pairs as training instances to apply a learning patterns strategy that can find accurate matches from all the applicant matching pairs. On the other hand, unsupervised machine learning methods use arbitrary and heuristic techniques to match pairs without an orderly and modeled methodology.[29]

However, the main weakness of the techniques with full supervision is that they need a substantial amount of labeled training examples to create a predictive system with acceptable performance. The training dataset is mainly accomplished by hand instructor, which is a complicated and inefficient procedure. In addition, the current method only gives the comparison values purely as numeric features without considering their critical appearances.[30]

Some scientific papers are associated with numerous issues applicable to the advancement AEeLS of this work. For example, the research[31] discovered several tactics for learning metadata mining. One of the most valuable open challenges is the recognition of learning objects and the metadata that can be gained from them. Also, both Mao *et al.*[32] and Liu *et al.*[33] demonstrate how ontology matching can be specified as a binary classification problem, forcing the use of the most well-known machine learning algorithms. The earlier work introduces an approach for locating relations among two ontologies using support vector machines (SVMs). The investigational findings show promising are remarkable when contrasted compared to additional mapping techniques.

In addition, Ref. 34 proposes a novel ontology matching method, demonstrating a precision of 95% in their investigational outcomes. Also, in the research,[35] the authors have suggested an ontologies method for the educational domain modeling. Other research works[36] explore the ontology mapping problem based on concept classification by decision tree algorithms that introduce a similarity measure among two portions fitting to distinct ontologies. A different approach was presented by Vidal *et al.*[37] that introduced a graph-based semantic explanation method for improving informative content with linked records to gain information exploration with superior recall and precision. Metaheuristics have also been essential in eLearning.[15,38] In this sense, Luna *et al.*[39] proposed a novel concept for finding and studying rules by applying evolutionary metaheuristic procedures.

Also, there are several research works in the area of ontologies that use data mining techniques[40] and machine learning algorithms such as neural networks,[41] K-nearest neighbor,[42] and SVM classifiers.[43] In addition, aiming at the recommendation accuracy of user-item rating matrix sparse generation, many research works proposed using the collaborative filtering (CF) recommender algorithm.[44]

Finally, other research methods on distance learning are concentrated on recommending a narrative approach of micro-lectures via mobile technologies and web platforms. In contrast, others are centered on developing educational perspectives.[45]

3. Methodology

The main idea of our approach is that the domain ontology is not only a vital instrument of learning but an object of examining student skills to gain the required eLearning resources. Recognizing the importance of drawing a compromise between eLearning methodologies requirements and students' skills in the assignment of the learning process has triggered the need for a multicriteria decision system that selects the right student for the right learning content. Because the students' skills evolve, their regular update is necessary. This leads to developing a reference model for its management, update, and maintenance.

This paper proposes the AEeLS that is part of a larger and long-term research project that has not yet been published. In general, this project proposes a multicriteria decision support system that integrates an ontology system to select and recommend adapted learning material to the eLearning students. This referred project has four phases: in the first phase, learning requirements are represented as ontology. In the second phase, the system collects students' resumes and constructs an ontology model for the features of the students.[46] In the third phase, the system collects the appropriate training courses from www based on SWeb technologies. Finally, it proposes a multistep mechanism of the ontology-based multicriteria decision-making method that enables the retrieval of suitable eLearning sources for the right student. The AEeLS is a subsystem of the ontology-based multicriteria decision-making method from the fourth phase of the above project.

An education ontology typically provides a vocabulary that describes a domain of interest and specifies the meaning of terms used in the language. Depending on the precision of this specification, the notion of ontology encompasses several data/conceptual models, for example, classifications, database schemas, and fully axiomatized theories. The proposed framework aims at information integration based on the SWeb, so the different parties can match other ontologies to use educational material based on their learning needs. Thus, using ontologies does reduce high-level heterogeneity based on aspects of the proposed ontology matching method.

This ontology matching method is a promising solution to the semantic heterogeneity problem as it quickly finds correspondences between semantically related entities of the connected educational resources. These correspondences can be used for various tasks, such as educational material merging, query answering, data translation, or navigation of the academic repositories. Thus, matching ontologies enable interoperating the knowledge and data expressed in the matched ontologies.

The proposed ontologies matching mechanism (OMMs) is based on advanced computational intelligence and machine learning techniques.[22,25,26] The purpose is to develop a fully automatic method for extracting information and controlling the effectiveness of student needs.[47] In particular, this subsystem automates the extraction, analysis, and interconnection of educational web content material based on relevant ontologies for further processing. It also allows for effectively detecting contradictory instructions or content interrelated to the transmission of the particular information to certify that they cannot be used for the disorientation of learning purposes.[22] To achieve this, ontology matching techniques using AI methods are used.[25,26]

A critical characteristic of the proposed model is the training process with the semi-supervised learning technique in the creation of a robust logical framework using pre-classified sideways with unlabeled instances. This tactic works when the input patterns with and without labels belong to a similar marginal distribution or follow a mutual formation. Essentially, unlabeled data offer valuable evidence for discovering the whole dataset data structure, though separately, the arranged data are presented in the learning procedure. Thus, even the most thoughtful ontologies complications can be developed successfully based on the crucial oddities that describe them.[27]

The algorithmic approach of the suggested AEeLS comprises the first stage, an ontologies matching[22,25] process from World Wide Web in order to find the relevant educational content as it seems in the illustration of the proposed model, in Fig. 1. In the second stage, the content checked for the precision and accuracy and a recommendation mechanism (RMm) proposes new relevant material in order to produce an extremely fitted curriculum for each student (Stage 2 in Fig. 1). Figure 1 is a depiction of the suggested AEeLS logical framework.

3.1. *Ontologies matching*

The ontologies are a formal structured information framework and a clear definition of a standard and agreed-on conceptual formatting of possessions and interrelationships of objects in a specific area of interest. Ontologies are semantic data models that define the types of things in a domain and the properties that can be used to describe them. Ontologies are generalized data models, meaning they only model available kinds of things that share certain properties but do not include information about specific individuals in the domain. For example, instead of describing a book and its characteristics, an ontology should focus on the general

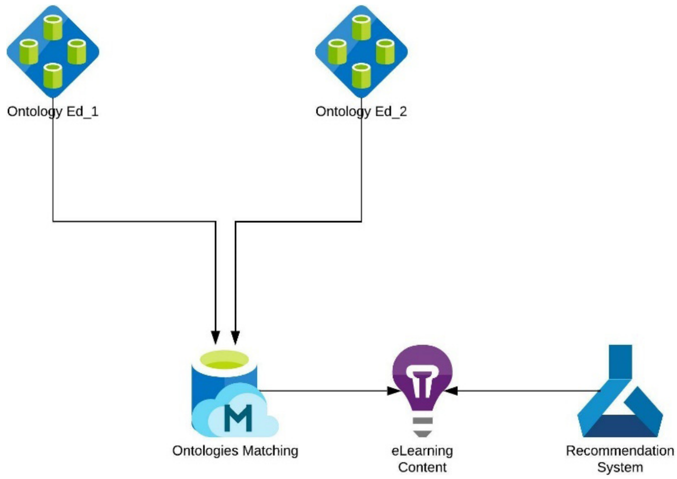

Fig. 1. AEeLS model.

concept of books, trying to capture elements that most/many books might have. Doing this allows reusing the ontology to describe additional books in the future.

There are three main components to an ontology, which are usually described as follows:

(1) Classes are the distinct types of things in our data.
(2) Relationships: Properties that connect two classes.
(3) Attributes: Properties that describe an individual class.

The main components of the ontologies are classes, properties, instances, and axioms. Types exemplify adjustments of objects within a specific area. Properties define the various characteristics of theories and constrictions on these characteristics. Instances represent the concepts, and axioms are proclamations in the form of logic to constrain values for classes or properties.[22,26] Both of them can be formed into separate hierarchies. Officially an ontology can be defined as follows[48]:

$$O = \{C, P, H^C, H^P, I, A^O\}, \tag{1}$$

where C and P represent classes and properties, H^C and H^P are their hierarchy, I is a set of instances, and A^O is a set of axioms. When we combine the classes and relationships, we can view the ontology in a graph format:

The OMM uses a semi-supervised learning ontology matching innovative method to take advantage of a small set of labeled entity pairs to enhance the training procedure. The technique first utilizes the central relationships in the resemblance area, and after receiving more training instances, it classifies the rest of the entities pairs into matched and nonmatched classes.[4] Finally, the suggested method defines a new set of constrictions to adapt the probability matrix in the labeling process, which helps to increase the performance of matching outcomes.[49] The Fig. 2 depicts an

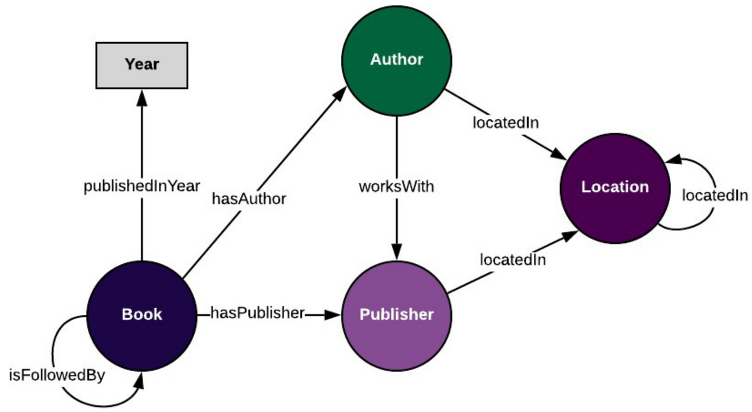

Fig. 2. Example of an ontology that describes the information on books, authors, and publishers.

example of an ontology that describes the information on books, authors, and publishers.

The semi-supervised learning method is suitable for the OMM as it ensures high-speed, vigorous, and efficient classification performance. Moreover, it is an easily adjustable and applicable method. Also, it is a practical machine learning technique that can model the ontologies matching challenge based on a section of a few pre-classified data vectors, exposing the relationships among the taxonomy constructions of ontologies.[27]

Specifically, the OMM applies a hybrid algorithmic approach that combines the Naive Bayes classifier, collective classification, a combinatorial optimization method, and fuzzy c-means clustering algorithm to produce a quicker and more elastic combined fuzzy semi-supervised learning scheme.[14] The most significant novelty and improvement of the suggested method is the easy validation of the classification procedure for the first time seen data, based on robust calculable features.[50] The following subsections offer the theoretical context of the system's core.

The Naive Bayes classifier[51] is an applied learning technique based on a probabilistic demonstration of a data structure representing a set of random variables and their suppositious individuality, in which complete and shared probability distributions are validated. The impartiality of the procedure is to classify an example X in one of the given classes $C_1, C_2, \ldots, C_n$ by a probability model well-defined rendering to the model of Bayes theorem. These classifiers do probability valuation rather than predicting, which is frequently more beneficial and operative. Here the forecasts have a score, and the determination is the depreciation of the probable rate. A prior probability characterizes each class.[14,52]

We make the assumption that the respective example X belongs to a class C_i and based on the Bayes theory we estimate *a posteriori* probability.[53] The measure P relating to a Naive Bayes classifier for a set of examples expresses the probability that c is the value of the dependent variable C based on the values $x = (x_1, x_2, \ldots, x_n)$ of the properties $X = (X_1, X_2, \ldots, X_n)$ and it is given by the subsequent equation (2) where the feature x_i is measured as independent[51]:

$$P(c|x) = P(c) \cdot \prod_{i}^{n} P(x_i|c). \tag{2}$$

The estimation of the above amount for a set N instances is done by using Eqs. (3)–(5):

$$P(c) = \frac{N(c)}{N}, \tag{3}$$

$$P(x_i|c) = \frac{N(x_i, c)}{N(c)}. \tag{4}$$

For a typical x_i with distinct values, the probability is projected by Eq. (5).

$$P(x_i|c) = g(x_i, \mu c, \sigma c_2), \tag{5}$$

where $N(c)$ is the number of instances that have the value c for the dependent variable, $N(x_i,c)$ is the number of cases that have the values x_i and c for the characteristic X_i and the dependent parameter individually and $g(x_i,\ \mu c,\ \sigma c_2)$ is the Gaussian probability density function with an average value μc and variance σc for the characteristic x_i.

Collective classification[54] is a combinatorial optimization method, in which we are providing a set of connections, $V = \{V_1, \ldots, V_n\}$ and a neighborhood function N, where $Ni \subseteq V\backslash\{Vi\}$. Each node in V is an undiscriminating variable that can take a value from an appropriate area. V is supplementary separated into two sets of nodes: X, the experiential variables and Y, the nodes whose values need to be defined. Our task is to label the nodes $Y_i \in Y$ with one of a small amount of labels, $L = \{L_1, \ldots, L_q\}$; we will use the shorthand y_i to infer the label of node Y_i.

Similarly, according to Zadeh[55] each element "x" of the universe of dissertation "X" fits into a fuzzy set (FS) with a degree of membership in the closed interval [0, 1]. Thus, the following function (6) is the mathematical base of a FS[55]:

$$S = \{(x, \mu s(x)/\mu s : X\{[0, 1] : x\})\mu s(x)\}. \tag{6}$$

Equation (7) is an occasion of a standard triangular fuzzy membership function (FMF).[14,52] It must be clarified that the "a" and "b" parameters have the values of the lower and upper bounds of the raw data independently[14]:

$$\mu_s(X) = \begin{cases} 0 & \text{if } X < \alpha, \\ (X - a)/(c - a) & \text{if } X \in [a, c), \\ (b - X)/(b - c) & \text{if } X \in [c, b), \\ 0 & \text{if } X > b. \end{cases} \tag{7}$$

In general, classification approaches decrease the dimensionality of multifaceted datasets by grouping the data into a set of classes. Rendering to the typical (crisp) classification methods, each example can be allocated only to one category. Thus, the class membership value is either 1 or 0. On the other hand, in fuzzy classification, an example point can be allocated to numerous courses with different degrees of membership (DoMs). The fuzzy c-means clustering procedure primarily gives random values to the cluster centers. Then it assigns all data vectors to all clusters with varying DoMs by calculating the Euclidean distance. The Euclidean distance of each data point x_i from the center of each cluster $c_1, \ldots, c_j$ is intended based on Eq. (8).[56]

$$d_{ji} = \|x_i - c_j\|^2, \tag{8}$$

where d_{ji} is the distance of x_i from the center of the cluster c_j. Then the DOM of each data point to each cluster is estimated based on Eq. (9):

$$\mu_j(x_i) = \frac{\left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{p}\left(\frac{1}{d_{ki}}\right)^{\frac{1}{m-1}}}, \tag{9}$$

where m is the fuzzification constraint with values in the interval [1.25, 2].[55,56] The values of m stipulate the degree of overlapping among the clusters. The defaulting value of m is equal to 1.2. The process has the succeeding direct constraint in the DOM of each point (see Eq. (10))[14,52]:

$$\sum_{j=1}^{p} \mu_j(x_i) = 1, \quad i = 1, 2, 3, \ldots, k, \tag{10}$$

where p is the amount of the clusters, k is the amount of data points, x_i is the ith point, and $\mu_j(x_i)$ is a function that proceeds the degree of membership of point x_i in the jth cluster $i = 1, 2, \ldots, k$. Then the centers are estimated again.[53]

The subsequent equation (10) is used for the re-calculate of the values of new cluster centers[57]:

$$c_j = \frac{\sum_i [\mu_j(x_i)]^m x_i}{\Sigma_i [\mu_j(x_i)]^m}, \tag{11}$$

where c_j is the center of the jth cluster with ($j = 1, 2, \ldots, p$), and x_i is the ith point.[55] This is an iterative system and the whole procedure is repeated till the centers are stabilized.

The OMM is an advanced hybrid method based on the amalgamation of soft computing tactics. Let us deliberate a supervised learning situation with a training set of size $N\{X, Y\} = \{x_i, y_i\}_{i=1}^{N}$, where $x_i \in R^{n_i}$ and y_i is a binary vector of size n_o. It must be clarified that i and n_o are the dimensions of the input and output, respectively.[46,58]

The OMM primarily achieves semi-supervised clustering (SSC). These earnings that cluster assignments may already be known for some data subsets. The final aim is the classification of the unlabeled observations to the appropriate clusters, using

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the known tasks for this subset of the data. At the same time, the procedure produces the degree of membership of, respectively, record to its cluster.[4,52]

The clustering validation procedure is accomplished by engaging the "classes to clusters" (CL_A_U) technique that accepts SSC. Formerly a minimum data sample has used the covering clusters resulting from the SSC development (labeled data). The residual unlabeled data are dynamically used to arrange and regulate the classes based on their DOM. Essentially, the CL_A_U method consigns classes to the clusters

Algorithm 1. The OMM algorithm

Inputs: Input labeled data $\mathbf{D_l}$, clusters of the labeled data $\mathbf{L_l}$, and a set of unlabeled data $\mathbf{D_u}$

Stage 1: % Initialization of clusters

Recognize the separate number of clusters based on $\mathbf{L_l}$

For each cluster, produce matrices with the mean and standard deviation of all $\mathbf{D_l}$

Stage 2: % Estimate the new centers of the clusters

For every cluster, reconstruct these matrices, based on the testing data $\mathbf{D_u}$

Estimate a variable, based on the formula below:

$$x = (1./(2 * \mathrm{pi} * \mathrm{ns}. \wedge 2)). * \exp(-((\mathrm{test} - \mathrm{nm}). \wedge 2)./(2. * \mathrm{sn}. \wedge 2)),$$

where ns is the new standard deviation matrix, nm is the new mean matrix, and test $\mathbf{D_u}$

Sum all these variables for each cluster

Stage 3: % Estimate the winner cluster for each record

For every testing data $\mathbf{D_u}$, find the minimum value of the summary calculated beforehand.

% Estimate the fuzzy membership values for every cluster for every record

For every testing data $\mathbf{D_u}$ and for every class, divide the mean matrix with the sum of the values intended before (normalization probability − membership value)

Outputs: Winner cluster for each testing data $\mathbf{D_u}$, $\mathbf{C_u}$, and fuzzy membership values for every cluster

for every testing data $\mathbf{D_u}$, $\mathbf{F\_M\_V_{u,j}}$ (j the number of clusters)

Stage 5: % Validation of the clustering process

Repeat Stages 1–3 from the previous portion, only this time from $\mathbf{D_u} \rightarrow \mathbf{D_l}$, using $\mathbf{C_u}$ as labels

Output: Winner cluster for each testing data $\mathbf{D_l}$, $\mathbf{L2_l}$

Stage 6:

For every primarily labeled data $\mathbf{D_l}$:

Compare the preliminary label $\mathbf{L_l}$ with $\mathbf{L2_l}$

Create confusion matrix based on these comparisons

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Stage 7:
Repeat Stages 5 and 6 for every $\mathbf{D_w}$ of $\mathbf{D_u}$
% Generalization of the amount of the extreme suitcases, based on the fuzzy membership values
Inputs: The winner class for every record ($\mathbf{C_u}$) and the fuzzy membership values for each record ($\mathbf{F\_M\_V_{u,j}}$)
Stage 8:
For every record:
If max($\mathrm{F\_M\_V}_{u,j}$) = A AND $\mathrm{F\_M\_V}_{u,A}$- max2($\mathrm{F\_M\_V}_{u,j}$) <= threshold, then
% max2($\mathrm{F\_M\_V}_{u,k}$) = k, the second biggest membership value
Modification the winner class for this record to k ($\mathbf{C_u} = \mathbf{k}$)
Outputs: Updated winner cluster for each record $\mathbf{C_u}$

based on the overall value of the class quality within each group. The class quality is preserved like any other feature, and it is a part of the input to the clustering procedure.[4,22,53]

The objective is the valuation as to whether the designated clusters match the quantified class data. In the CL_A_U evaluation, you tell the scheme whose characteristic is a prearranged "class".[14,25,26,59]

Then this is detached from the data before transient to the SSC procedure. The CL_A_U evaluation finds the minimum error of mapping CL_A_U (where only the class labels that match the examples in a group are measured) with the restriction that a course can only be mapped to one collection. The arisen classes are fuzzified by conveying appropriate linguistics to get an accurate consistency among the related standards of the dataset under study.[5,14,26,53] The whole procedure is obtained in Algorithm 1.

In conclusion, the proposed algorithm initially performs clustering using a small number of labeled data to categorize several records in clusters. Typically, every group is assigned a characteristic center of gravity value. During iterations, the importance of the centers is adjusted, and when the center stabilizes, the iterations are terminated. Initially, a minimum data sample related to the obtained clusters (labeled data) is used. The remaining unlabeled data which ignore the class attribute are used to provide helpful information related to the structure of the overall dataset, as they dynamically modulate and adjust the classes based on the values that belong to each cluster.

3.2. *Recommendation mechanism*

The RMm is a machine learning method[60] in the AEeLS to create intelligent rules for intervention decisions and offer personalized real-time information for the student's educational needs with CF[61] technique.[3,62] CF is a machine learning method of filtering the conception by accumulating preferences or unique information from several users (collaborating).[63] In a more general sense, CF is the method of filtering for data or outlines using procedures affecting collaboration between various agents, opinions, information resources, etc. Usually, a workflow of a CF can be defined as follows[3]:

(1) A user extracts the predilections by ranking objects of the structure. These grades can be considered an estimated description of the user's importance in the related area.
(2) The scheme matches up this user's rankings compared to other users' and discovers the individuals with the most "related" preferences.
(3) With similar individuals, the method endorses substances where the comparable operators have ranked highly but have not yet been indexed by this individual.

Traditional CF methods[3] face two significant challenges: data sparsity and scalability. In the RMm, we use a hybrid technique from neighborhood-based CF and content-based filtering that addresses these challenges and improves the recommendations' quality. This mixed method aims to attain more tailored intellectual directions for intervention decisions and personalized recommendations in real-time information for the student's educational needs based on skills. This mixed technique is more adaptable because it can be applied to heterogeneous ontologies and, with some care, could also provide cross-domain recommendations. Also, it works most excellently when the operator space is enormous, it is easy to implement, and it scales well with no-correlated substances and does not need multifarious modification of parameters.[3,26,64]

Specifically, the recommendations are produced through a graph where the correlations of the stakeholders correspond to nodes in the graph, and two nodes are adjacent if the edges joining the respective recommendations do not join the third recommendation. So, from this point of view, the problem is reduced to the following graph-theoretical problem: in a coherent graph G, find a minimum closed walk containing all the edges of the graph's G (Eulerian walk).

To solve this procedure, we consider the coherent graph G that models the problem to be an Euler graph, so we immediately have a solution algorithm. To find an Euler circuit of G, construct the Euler walk starting and ending the starting and destination node w. If G is not an Euler graph, we resort to an alternative solution method described below.

A two-partition set $V_{\mathrm{odd}}(G) = \{u_1, u_2, \ldots, u_{2k}\}, k \geq 1$ (the set of nodes of odd degree G) is a partition of k into subsets of the two elements. For a two-member partitioning:

$$\pi = \{(x_1, y_1), (x_2, y_2), \ldots, (x_k, y_k)\}. \tag{12}$$

We define the distance $d(\pi)$ of π as the sum of the distances of its members in the graph G, i.e.,

$$d(\pi) = \sum_{i=1}^{k} d(x_i, y_i). \tag{13}$$

Let $\mu(G) = \min\{d(\pi)\}$, for each π of G (the minimum is calculated on all two-partition π of the set $V_{\mathrm{odd}}(G) = \{u_1, u_2, \ldots, u_{2k}\}, k \geq 1$, it is evident that if G is an Euler graph, $V_{\mathrm{odd}}(G) = \emptyset$ holds, and then we define $m(G) = 0$.

We recommend the use of weighted matrix factorization to decompose the target in the following structure of the two sums:

$$\min_{U \in \mathbb{R}^{m\times d}, V \in \mathbb{R}^{n\times d}} \sum_{(i,j)\in \mathrm{obs}} (A_{ij} - \langle U_i, V_j \rangle)^2 + w_0 \sum_{(i,j)\notin \mathrm{obs}} (\langle U_i, V_j \rangle)^2. \tag{14}$$

It should be emphasized that w_0 is the overbalancing parameter of the two terms so that the target is not dominated by one or the other term.

The above general formulation is corrected by weighting specialized training examples, considering the frequency of optimal recommendations, to replace the objective function with the following:

$$\sum_{(i,j)\in \mathrm{obs}} w_{i,j}(A_{i,j} - \langle U_i, V_j \rangle)^2 + w_0 \sum_{i,j \notin \mathrm{obs}} \langle U_i, V_j \rangle^2 \tag{15}$$

where $w_{i,j}$ is a function of the frequency of query i and item j.

More generally, the recommender problem can be interpreted as determining the mapping $(c, i) \to R$, where c denotes a user, i denotes an education item, and R is the utility of the user being recommended with the item. The utility sorts items and the top N items are presented to the user as recommendations.

3.3. *Performance metrics*

In this research, the classification performance is valued by the usual evaluation procedures: precision (PRE), recall (REC), and F-score indices that are well-defined as in calculations 16, 17, and 18 correspondingly[52,53,65]:

$$\mathrm{PRE} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \tag{16}$$

$$\mathrm{REC} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{17}$$

$$\text{F-Score} = 2 \times \frac{\mathrm{PRE} \times \mathrm{REC}}{\mathrm{PRE} + \mathrm{REC}}. \tag{18}$$

Also, the validation method used the 10-fold cross-validation method because the quantity of available examples is relatively more significant, which bargains statistically sound performance capacities. The testing hardware and software conditions for all simulations are as follows: PC Intel Core I7-10700K 3.80 GHz CPU, 64 GB DDR4-2933 RAM, Ubuntu 18.04 LTS, Anaconda TensorFlow (Python).

4. Dataset and Results

The suggested hybrid model was certified through examinations, which were done on datasets engaged from the ontology alignment evaluation initiative (OAEI) 2014 operation, as well as on data occupied from two well-known educative content repositories: ADRIADNE[66] and MERLOT.[67] Thus, two datasets were constructed, covering patterns representative of the relations among pairs of learning objects engaged from two different ontologies absorbed in the open and distance learning context. The Fig. 3 is an illustration of an instance-based solution for education environment.

For the first experimental test rendered by Cerón-Figueroa *et al.*,[68] the OAEI 2014 dataset was used for responsibility for the problem of instance matching track, more accurately for the identity recognition task, and specifically to find an appropriate similarity function to build pairs of objects which are close in significance. The ontologies matching problem transformed into a binary pattern classification problem through the acceptable use of a given resemblance purpose.

Animations, case studies, collections, questionnaires, and simulators are the learning assets and educational resources available. The subsequent trial contains a match among two diverse educative content repositories (ADRIADNE and MERLOT) in the learning objects metadata arrangement based on a sample of 100 from each repository associated with the computer sciences subject. The ADRIADNE foundation obtained a provision, which is the ability to convert the metadata of the substances into well-known stipulations, such as learning objects metadata and Dublin Core. MERLOT is one of the central open access repositories for educative topics and is shaped for use by research communities. In this experimentation, according to Cerón-Figueroa *et al.*,[68] a total of 100 1:1 matching instances were created from both ontologies.

The features extraction takes into account the pattern structure: title, description, keywords, and type of resource.

Also, Fig. 4 shows two examples of five attributes (four strings and one integer) taken from specific ontologies by ADRIADNE and MERLOT datasets.

Table 1 presents a comprehensive evaluation of the OAEI 2014 data bank dataset by engaging competitive methods, namely radial basis function neural network (RBFNN), group method of data handling (GMDH), polynomial neural networks

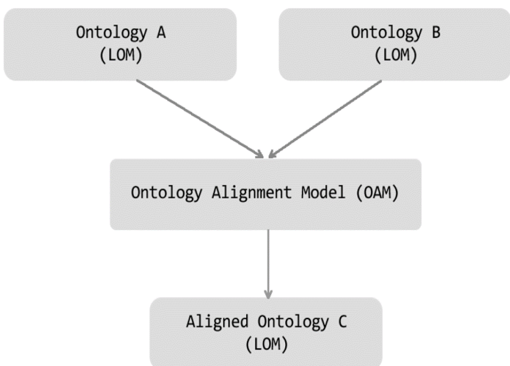

Fig. 3. Illustration of an instance-based solution for education environment.

Attribute	**Value**
Identifier	A4189051B
Title	Polynesian Bay
Description	A photograph of a bay near Raietia, Polynesia.
Keywords	Arts: Travel and Tourism: Polynesia
Learning Resource Type	0 (Book)

Attribute	**Value**
Identifier	C10750GL3
Title	World War II
Description	Events related to military weapons of World War 2.
Keywords	war: military: german: tank: guns
Learning Resource Type	1 (Quiz)

Fig. 4. Five attributes (four strings and one integer) by ADRIADNE and MERLOT datasets.

Table 1. Comparison between algorithms (first experimental test).

OAEI 2014 data bank					
Classifier	PRE	REC	F-score	Time/s	Match time/s
OMM	0.904	0.908	0.906	18.11	0.696
RBFNN	0.710	0.700	0.709	14.46	0.382
GMDH	0.845	0.846	0.848	16.32	0.521
PANN	0.813	0.818	0.817	17.38	0.620
FFNN-GA	0.887	0.888	0.889	25.12	0.933
FFNN-PSO	0.891	0.889	0.892	25.07	0.906
SVM	0.895	0.897	0.897	16.17	0.499
RF	0.900	0.900	0.901	11.33	0.205

(PNNs), feedforward neural networks using genetic algorithms (FFNN-GAs), feedforward neural networks using particle swarm optimization (FFNN-PSOs), SVM, and random forest (RF).[4,53,69,70] Also, there is an analysis of the efficiency of the methods based on training time and the operation time about the matching time in the same query.

As seen from the above comparison table, the proposed method has achieved excellent results, which confirms the method's reliability. Specifically, in the PRE, which is a particular metric related to the model's generalization, the proposed OMM is superior to 0.194 by RBFNN and 0.004 by RF. Respectively, in the REC, which is a particular measure to correctly identify the true positives, the proposed OMM is superior to 0.208 by RBFNN and 0.008 by RF. In addition, the F-score is used for information retrieval for measuring search, document classification, and query classification performance. The proposed OMM has the highest value with 0.05 from the second RF algorithm. It must be noted that the F-measure does not consider true negatives, which means that it is the most accurate index for classification problems.

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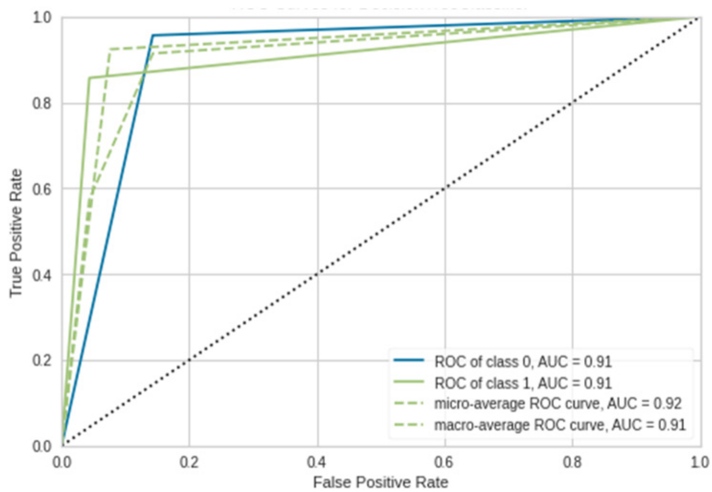

Fig. 5. ROC curve is the plot of the false-positive rate (x-axis) versus the true positive rate (y-axis) for a number of different candidate threshold values between 0.0 and 1.0.

Figure 5 shows visual assessments that give clear explanations about the performance of the proposed method.

Receiver operating characteristic (ROC) curves typically feature an actual positive rate on the y-axis and a false-positive rate on the x-axis. This means that the top left corner of the plot is the ideal point — a false-positive rate of zero and an actual positive rate of one. This is not very realistic, but it does mean that a larger area under the curve (AUC) is usually better.

A severe drawback of ontologies matching methodology regards synonymy and its representation in ontologies. Currently, two different ways of representing synonyms are observed: first, by a logical relation representing an exact match; and second, by denominative variants. In the first case, both synonyms are considered different concepts; thus, both are included in the ontology. Still, in the second case, both units considered one concept with two or more related terms (language-dependent), two graphical representations at the terminological level but only one at the conceptual level. This lack of agreement about synonymy prompts disorganization in knowledge representation, which hampers the re-utilization and interchangeability of ontologies. The specific ROC analysis offers a valuable tool to evaluate ontologies matching problems transformed into a binary pattern classification problem. It is used to assess quantitatively and compare the predictive models' accuracy. In addition, in the ontology matching case, continuous measures are converted to dichotomous tests. So, the above ROC analysis was used to select the optimal threshold under various circumstances, balancing the inherent tradeoffs between sensitivity and specificity.

A severe second drawback is the difficulty of transferring specialized knowledge from texts or domain experts to abstract and practical concept representations. At first sight, this action seems easy to attain as the required expertise is reachable,

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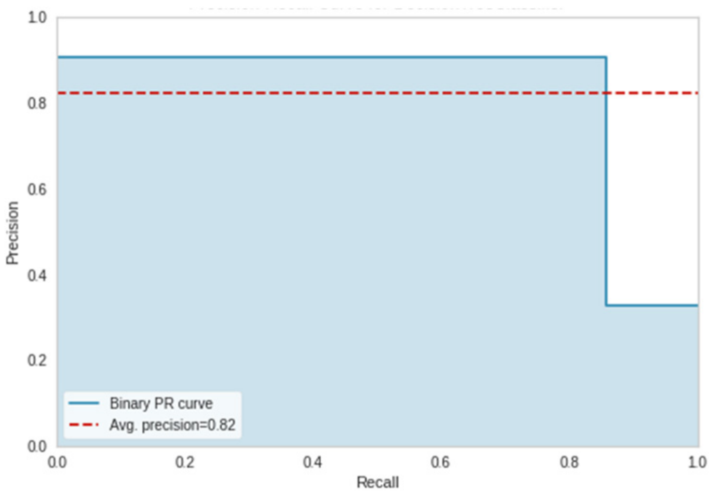

Fig. 6. Precision versus recall plot.

either by experts or texts as information sources, but these sources are not always clearly understood, contradictions or misinterpretations between them can occur, and problems in explaining concepts or phenomena can arise, etc. Consequently, ontologies matching methodology could be hindered in case the relationship between them and domain experts was not close, constant, and bidirectional throughout the process. To solve this issue, a precision–recall analysis was made to evaluate classifier output quality. Precision–recall (as depicted in the Fig. 6) is a valuable measure of prediction success when there is uncertainty. In information retrieval, precision measures result in relevancy, while recall actions how many truly relevant results are returned.

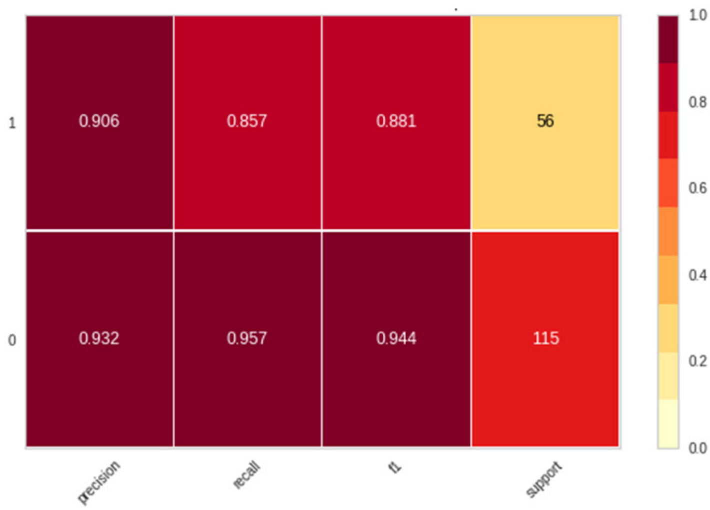

Fig. 7. Summary plot of the precision, recall, and F1-score of the proposed methodology.

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The precision–recall curve shows the tradeoff between precision and recall for different thresholds. A high AUC represents both high recall and high precision, where high precision relates to a low false-positive rate, and high recall relates to a low false-negative rate.

High scores for precision–recall–F1-score show that the classifier is returning accurate results (high precision) and a majority of all positive results (high recall). A system with high recall but low precision returns many results, but most of its predicted labels are incorrect compared to the training labels. A system with high precision but low recall is just the opposite, returning very few results, but most of its predicted labels are correct compared to the training labels. The real difficulty of this process occurs in the automated training process when using grid search for ontology matching. The system is ideal in the proposed approach because it achieves high precision and recall, and all results are correctly labelled. The F1-score can be interpreted as a harmonic mean of the precision and recall, where an F1-score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1-score is equal.

An additional advantage of the high precision–recall–F1-score is in encountering the semi-automatic linguistic enriching of ontologies (adding linguistic information to concepts, such as designations and definitions), which allows the model to identify different linguistic resources and use their data to enrich the formal content of ontologies. These accurate results also improve the model's features, which allow the precise searching for term definitions and synonyms, separating different senses of the same term, and exploring resource-specific concept relations. It also offers valuable functionality concerning informal information as it automatically provides equivalents when browsing resources. Figure 7 is a summary plot of the precision, recall, and F1-score of the proposed methodology.

Regarding the synchronic study of terminology of ontologies, concepts and terms evolve. These changes in concepts and terms are caused by several reasons, such as new realities to be named, new usages of words, and obsolescence of concepts/terms, among others. In this context, the ontology matching model needs to be prepared to deal with these changes and the new communicative situations that can occur. Accordingly, this dynamicity requires more flexible and specialized knowledge representation models that can better manage and integrate information from different sources and adapt the information to users' neusers'n order to overtake this issue. We made the actual lift plot which calculates the points on the lift curve by determining the ratio between the result predicted by our model and the result using the base model.

The lift chart (as depicted in Fig. 8) graphically represents the proposed model's when compared against a random guess and measures the change in terms of a lift score. Also, it determines the exact points at which the models become less valuable.

Bearing this in mind, the proposed model can work with ontologies representing knowledge domains and their evolution over time since they offer the possibility of employing a more comprehensive range of concept relations than the traditional

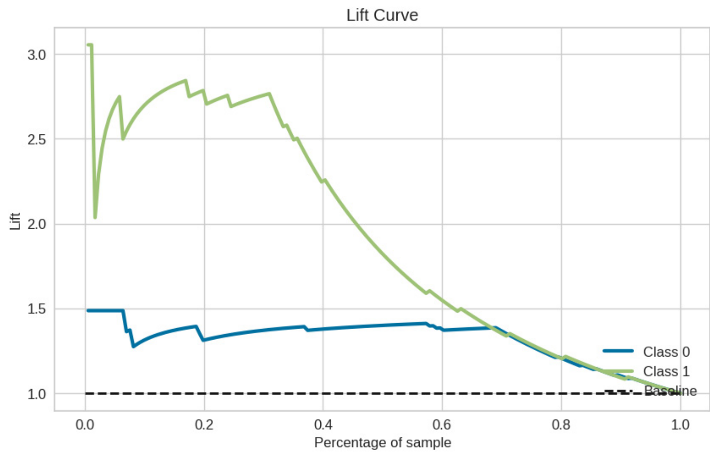

Fig. 8. The lift chart is derived from the cumulative gains chart; the values on the y-axis correspond to the ratio of the cumulative gain for each curve to the baseline.

generic specific and part-whole relations. Moreover, the proposed approach can effectively model the conceptualization in the human mind facilitating knowledge acquisition and adaptation to changes and new realities. Finally, it can be easily modified and further extended (if necessary).

Finally, the cumulative gains chart (as depicted in Fig. 9) shows the percentage of the overall number of cases in a given category gained by targeting a ratio of the total number of issues. There are gaps to be filled in, depending on the concept defined. This is the most appropriate way to identify mini-knowledge representations in establishing definitional templates for each hyperonym found in the domain ontology, which describes all of the concepts within that particular conceptual area, similar to a controlled language where the same patterns are repeated.

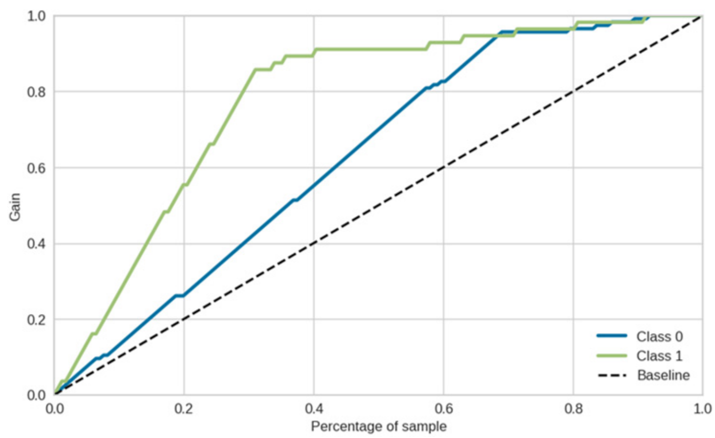

Fig. 9. The cumulative gains chart shows the percentage of the overall number of cases in a given category "gained" by targeting a percentage of the total number of cases.

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Table 2. Comparison between algorithms (second experimental test).

ADRIADNE and MERLOT					
Classifier	PRE	REC	F-score	Time/s	Match time/s
OMM	0.981	0.981	0.982	12.34	0.319
RBFNN	0.888	0.889	0.889	10.23	0.188
GMDH	0.940	0.942	0.946	13.12	0.354
PANN	0.901	0.902	0.902	12.09	0.236
FFNN-GA	0.963	0.962	0.962	19.55	0.697
FFNN-PSO	0.965	0.964	0.964	17.42	0.584
SVM	0.976	0.977	0.976	09.41	0.105
RF	0.975	0.976	0.978	03.10	0.028

Table 2 presents a wide evaluation for ADRIADNE and MERLOT dataset, and the analysis of the efficiency of the methods.

As seen from the above comparison table, the proposed method has achieved excellent results, which confirms the method's reliability.

As demonstrated experimentally, the proposed model has achieved remarkable results concerning the respective competing systems. One of the main advantages of the introduced method is its high reliability which is clearly shown by the high values of the F1-score. This can be considered the result of successful data processing that allows the retention of the most relevant data for upcoming forecasts. Also, the use of the ontologies matching technique in this work is related to the fact that very often, in multifactorial problems of high complexity, such as the one under consideration,

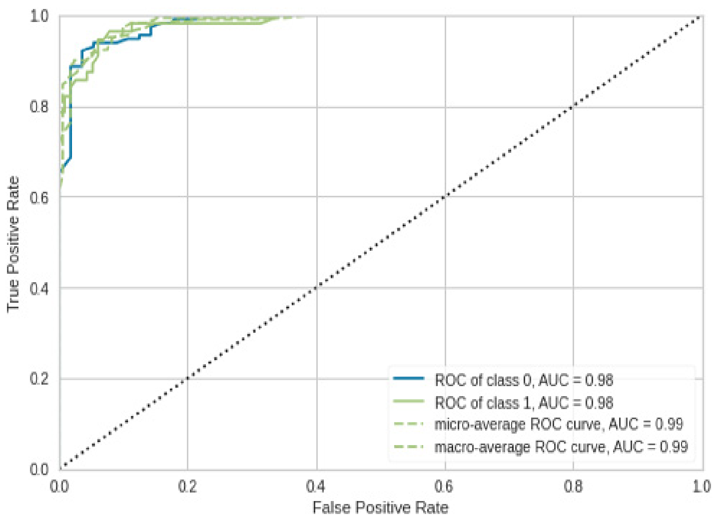

Fig. 10. ROC plot.

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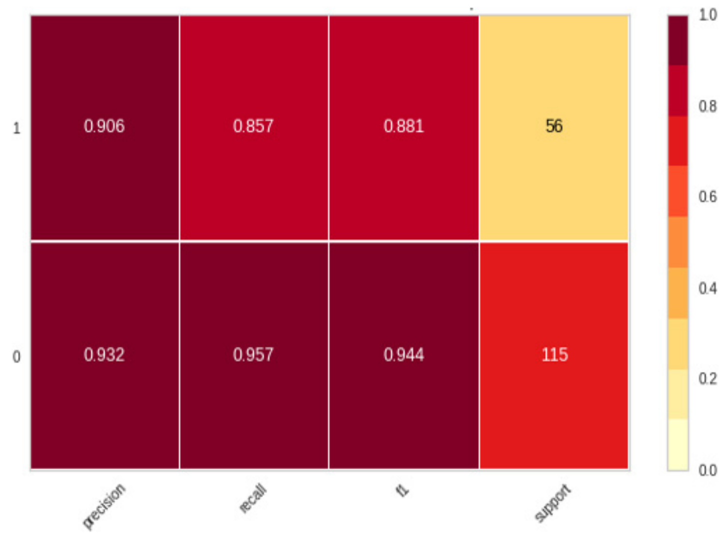

Fig. 11. Summary plot of the precision, recall, and F1-score.

the results of the prediction show variability as depicted in plots 10, 11, 12, 13 and 14. This can be attributed to the sensitivity of the correlational models to the data.

Tables 1 and 2, respectively, demonstrate that the suggested technique has more excellent performance for both datasets, which is relatively promising contemplating the complexities faced in this problem. It is crucial to say that evaluating several factors that can define a type of challenge discussed here is a partially individual nonlinear and dynamic process.[53]

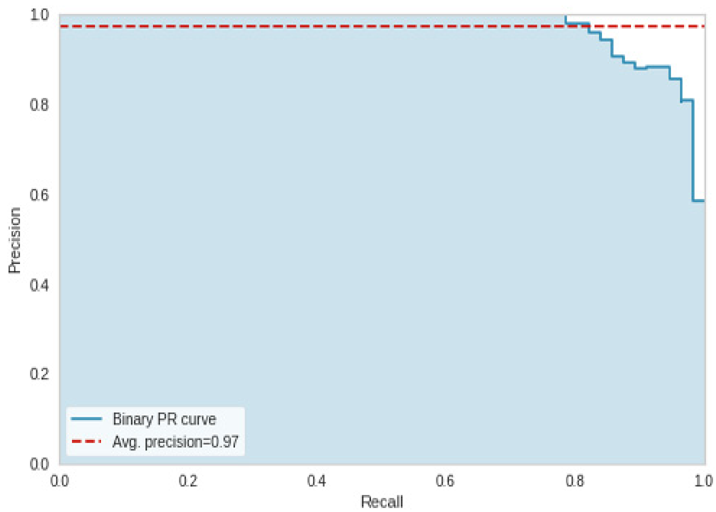

Fig. 12. Precision versus recall plot.

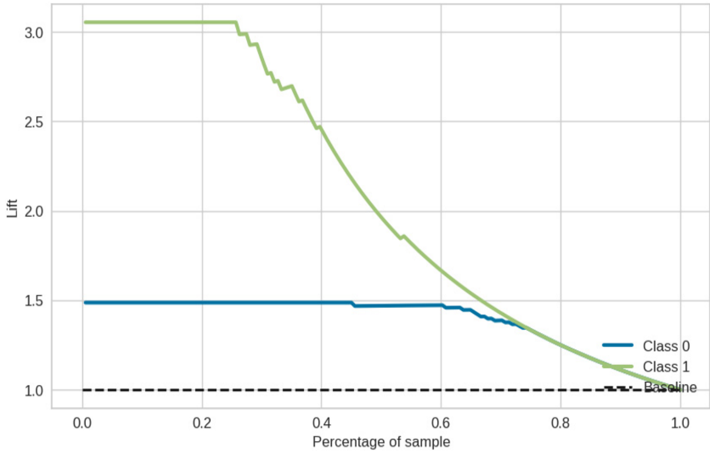

Fig. 13. Lift chart.

The two most important advantages of the proposed technique are the following: it offers better foresight and stability as the overall behavior of the model is less noisy. At the same time, it reduces the overall risk of a wrong choice that may result from subsampling.[71] The above view is also supported by the dispersion of the expected error, which is concentrated close to the mean value of the error. This fact categorically states the reliability of the system and its generalization capacity. Finally, as shown by the results, the innovative implementations proposed in the ontologies matching method dynamically balance latency throughput, resulting in fault-tolerance. At the same time, the intermediate representations are optimally utilized, producing stability, high generalization efficiency, and high classification accuracy.

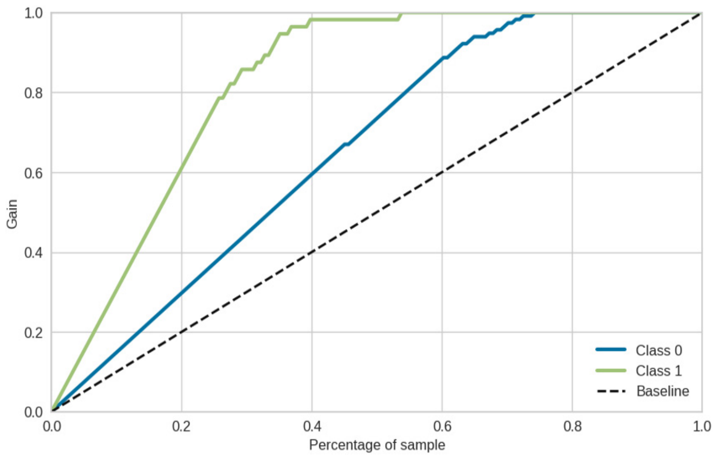

Fig. 14. Cumulative gains chart.

On the other hand, a serious point that needs to be improved is the operation time of the method, as, by the used hardware, the average time for training is about 18.11 s for OAEI 2014 data bank dataset and 12.34 s for the ARIADNE and MERLOT. In addition, the number of matching operations has an average time of 0.696 s and 0.319 s, respectively.

5. Conclusions

This paper proposed a hybrid,[1] sophisticated,[72] dependable,[73] and vastly effective eLearning system that can gather and analyze data from learning repositories and adapt these to the educational curriculum according to the student skills and experience, constructed on advanced machine learning methods. The implementation of the proposed method was tested on two sophisticated datasets of high complexity. The accuracy of the built models was compared to one another. It was discovered that the proposed OMM model accurately predicts the testing subset; hence, it can be inferred that this strategy is appropriate to forecast the goal of the research question. Also, the slightest greatest accuracy determines how different independent variable values affect a specific dependent variable under a given set of assumptions. In other words, the suggested model generates generic resources and can handle diverse sources of uncertainty in a mathematical model, which contribute to the overall uncertainty of the model. This determines that the proposed technique can be employed without any restrictions imposed by one or more input variables. The results have demonstrated the effectiveness of the proposed hybrid method.

Forthcoming exploration will require concentration on additional optimization of the parameters that the hybrid system uses to achieve faster and more precise results. Also, further, the expansion will be performed by combining novel self-improvement and auto-machine learning methods that can fully automate the identification of relevant educational content. Additionally, it would be necessary for a comparison study of the performances of the state-of-the-art models to investigate further improvements in our methodology. Finally, a very vital future enhancement is the upgrading of the method with natural language processing (NLP) capabilities, with recurrent neural network (RNN), and specifically with deep architectures such as long short-term memory (LSTM), to model the time sequences and their dependences with more superior precision and effectiveness.

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