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Hybrid intelligent framework for automated medical learning

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Abstract

This paper investigates the automated medical learning and proposes hybrid intelligent framework, called Hybrid Automated Medical Learning (HAML). The goal is the efficient combination of several intelligent components in order to automatically learn the medical data. Multi agents system is proposed by using distributed deep learning, and knowledge graph for learning medical data. The distributed deep learning is used for efficient learning of the different agents in the system, where the knowledge graph is used for dealing with heterogeneous medical data. To demonstrate the usefulness and accuracy of the HAML framework, intensive simulations on medical data were conducted. A wide range of experiments were conducted to verify the efficiency of the proposed system. Three case studies are discussed in this research, the first case study is related to process mining, and more precisely on the ability of HAML to detect relevant patterns from event medical data. The second case study is related to smart building, and the ability of HAML to recognize the different activities of the patients. The third one is related to medical image retrieval, and the ability of HAML to find the most relevant medical images according to the image query. The results show that the developed HAML achieves good performance compared to the most up-to-date medical learning models regarding both the computational and cost the quality of returned solutions.

KEYWORDS
automated medical learning, distributed learning, multi-agent systems, ontology matching

1 | INTRODUCTION

Deep learning Ahmedet al. (2020); Lin et al. (2021) is the set of automatic models for describing, learning, and extracting features from data. One of the excited topic in deep learning is exploring medical data, where the aim is to perform automated medical learning for helping doctors and medical teams to get a good decisions in diagnosing the different patients López-Martínez et al. (2020); López-Martínezet al. (2020); López-Martínez et al. (2018). The automated medical learning currently suffers from different bottlenecks such as the data heterogeneity, and the complex medical learning tasks, which led the whole process inaccurate. In order to mitigate these bottlenecks, this research works explores different intelligent approaches based on distributed deep learning, multi-agent systems, and ontology matching.

Distributed deep learning is the process of exploring the different deep learning models in a distributed environment. Dai et al. (2019) investigated the use of the reinforcement learning for processing distributed data in the next generation wireless sensors. It proposed a function for

maximizing the utility of the data sharing in the platform. Weng et al. (2019) developed a distributed federated learning framework to solve conflicts generated from the different behaviours in the crowdsourcing platforms. Liu et al. (2019) suggested the use of the intelligent learning approach for ensuring the evaluation of the distributed platforms in terms of several factors such as latency, scalability, and accuracy. Dai et al. (2020) mapped the online offloading problem to a Markov decision process, while proposing a hybrid combination between the deep learning, and the genetic algorithm for maximizing the long-term offloading performance in distributed platforms. Luo et al. (2020) developed advanced technology by taking the hidden features of the sensors data, as well as the environmental constraints into account in order to reduce the computational resources.

In order to achieve better learning in a distributed environment, multi agent systems are developed which are computerized systems composed of multiple interacting intelligent agents. Cicirelli et al. (2019) developed an intelligent framework based on cognitive agents for making autonomous behaviours in distributed models. It also exploits the different properties of intelligent agents such as reactivity, proactivity, and cognition for boosting the performances. Casado-Vara et al. (2018) proposed an intelligent system in order to process the supply chain. It also integrates blockchain technology for ensuring privacy. Ciatto et al. (2019) enhanced the autonomy of the intelligent agents by analysing independently the sociality features of each agent in the framework. Alqahtani et al. (2020) implemented and designed a multi agents framework that can be used to improve the security mechanism in distributed platforms. It builds an intermediate layer between the application, and the hardware layers to solve the conflicts among the different users. Alsboui et al. (2020) improved the scalability of data distribution for distributed mobile applications. It also introduced a smart mechanism in order to integrate the mobile intelligent agents in the communication level.

Another issue of automated medical learning, the heterogeneous problem, where the medical data can be collected into various representations such as texts, times series, trajectories, and images. Ontology matching is the process of modelling different data representations in order to find the semantic interpretation of the different data entities. Bellini et al. (2014) introduced a system for the handling with big amount of data from distributed and heterogeneous sources. It used static and dynamic properties in order to create the concepts of the ontologies. Qiu et al. (2018) introduced a semantic graph-based approach by investigating the both structural and contextual information for identifying the non-taxonomic relations in distributed settings. Le-Phuoc et al. (2016) handled billions of training rows data to unify the different views captured from the heterogeneous information. Qiu et al. (2019) extended the graph method for semantic knowledge for explaining distributed and heterogeneous information. First, the whole data are calculated with the word co-occurrence similarity values. Second, a semantic knowledge graph is built according to the similarities among the data. Third, a community detection model based on adopted modularity function is then executed in order to partition the data into several communities, each of which is considered as a concept.

Our understanding is that as of the present, to the best of our knowledge, this is the first work that explores the combination of distributed learning, the multi-agent systems, and the ontology matching in order to solve the automated medical learning problems. There are the key conclusions that can be summarized as follows:

1. We present a new framework, called Hybrid Automated Medical Learning (HAML), which adopts distributed deep learning, multi agents systems, and knowledge graph for automated medical learning. Each agent is responsible to locally learn patterns from the medical data. The communication among the different agents is performed to share the relevant patterns with all agents. The communication is ensured by the knowledge graph process, where the best alignments among the ontologies of the agents are captured in each communication.
2. We present a new adaptation of the ontology matching process for learning medical data. This adaptation is ensured by integrating the decomposition mechanism in the matching process. The ontology of each agent is decomposed into similar clusters. Instead of exploring the whole instances, only the centres of the clusters are compared during the ontology matching process.
3. Several experiments were extensively studied and tested to demonstrate the usefulness of the implemented and designed framework. Three case studies are discussed in this research, the first case study is related to process mining, and more precisely on the ability of HAML to detect relevant patterns from event medical data. For the secondary case study, it is associated to smart building, and the ability of HAML to recognize the different activities of the patients. The third one is related to medical image retrieval, and the ability of HAML to find the most relevant medical images according to the image query. The results reveal that HAM outperformed the present studies regarding automated medical learning algorithms in terms of both runtime and solution quality.

The remaining sections of this paper are laid out as follows. The topic in Section 2 relates the automated learning problem, thus some works are then discussed and surveyed as the literature review. For more information on the developed HAML, please refer to Section 4 for more details and see the results for further evaluation. Finally, Section 5 concludes the works on automated medical learning and discuss further opportunities of the studied topic in this paper.

2 | RELATED WORK

In this section, we include a discussion of the vast majority of the literatures relevant to learning automation.
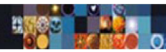
Nicolau et al. (2011) analysed and reviewed various interactive medical learning based solutions for surgical oncology development by explaining the merit and the limit of each system. It also opened discussions and future directions for using computer vision technologies in the surgical oncology areas. Wu et al. (2018) developed an extended alignment strategy applied to image surgery data. It used both the RGB-Depth data, and the point clouds for making the head surface knowledge. The optimal alignment is captured by the Hololens which allows the visualization of head surface and the surgery medical image together in a virtual reality setting. González Izard et al. (2020) proposed 3D reconstruction and visualization of medical images. It developed an end-to-end automated based solution for visualizing medical data by considering both the virtual and augmented reality. The process is fully automated without any involvement of the medical teams. The project was reviewed with medical professionals to verify the first version of the designed platform, then worked on to get feedback for the further improvement.

Ma et al. (2021) provided a deep understanding of adversarial attacks of the medical image in order to generate and detect these attacks. Medical images are processed and trained by the deep neural networks for the classification task. The perturbation features are extracted using the gradient operator. These perturbation features are integrated to the testing images, in order to able identify and detect these perturbations. Müller and Kramer (2021) proposed a python framework for medical image segmentation using the deep learning. The framework implemented different data augmentation techniques such as spatial and colour augmentations, and implemented an efficient U-Net algorithm for medical image segmentation. Taghanaki et al. (2021) reviewed the medical image segmentation solutions, and proposed a new taxonomy of the existing image segmentation solutions. The taxonomy includes the architecture level, kind of data used, the loss functions employed, the sequence models adopted, the supervision level of the method. It also provided an intensive review of the contributions in each category of algorithms.

Fang et al. (2021) developed an attention-based triplet hashing network for learning low-dimensional hash codes from images database. The spatial-attention module is integrated into the network structure to understand, and learn the region of interest information. The max-pooling, element-wise maximum, and element-wise mean operators are used to aggregate the features maps of the spatial information of the images database. Gupta et al. (2021) developed a hierarchical deep multi-modal network which groups the end-user queries, and integrated it for answer prediction problem. The authors proposed a question segregation for visual question answering. The question answering model is then integrated to the hierarchical deep multi-modal neural network in order to predict the correct answers. Wang et al. (2021) proposed an intelligent model to automatically analyse medical images, and estimate the infection rate of COVID-19. It considers both classification and segmentation tasks, and allows from 30% to 40% of the benefit in terms of detection time.

To handle multiple medical data sources of uncertainty, a deep probabilistic model was proposed by Chai et al. (2021). The multisource learning problem is first formulated, the Bayesian deep learning is adopted to extract the uncertainty medical features, which will be useful for the glaucoma detection. Hirano et al. (2021) developed a deep learning classification models for medical data. There was an effort to standardize the classification of three different types of medical images: pneumonia classification, referable diabetic retinopathy classification, and photographic images according to the chest X-ray images. The deep neural network models are derived from different medical image diagnosis models using the transfer learning. In addition, adversarial defence is considered by determining the increased robustness of deep neural network to both non-targeted and targeted attacks.

As can be inferred from the above literature works, which can be ascertained from the analysis, these authors', plenty of excited research have been proposed in the context of the augmented reality distributed deep learning applications. Some research explore learning mechanism to created automated models, some methods explores the multi-agents system to deal with smart sensors medical data in a distributed environment, other methods explore semantic modelling for medical data sharing in distributed environment. However, these methods are far to be used in the medical setting, where much efforts are needed in several directions. For the first time, we propose a system which fully incorporates augmented reality, the deep learning, the multi-agents system and the ontology matching, in order to achieve mature solutions for solving medical data in the context of distributed environment.

3 | HAML: HYBRID AUTOMATED MEDICAL LEARNING

3.1 | Principle

HAML target robotics applications, which provides fully automated system for learning from medical data. Each robot in the system has the ability to learn, intelligently interact with the other robots in the system, and update its knowledge base by using information and knowledge of the other robots. To achieve this scenario, our framework builds upon several intelligent components such as deep learning, multi-agents system, ontology matching, and evolutionary computation for automatically dealing the medical data. Each robot in the system is considered as an agent, provides its local knowledge base and inference system represented by the deep learning, and the ontology matching module. Let us begin by focusing on the most critical and important components of Hybrid Automated Medical Learning (HAML). As illustrated in Figure 1, we use the deep learning in order to create automated models from the medical data. The multi-agents system is used to deal with distributed and heterogeneous medical data, where the communication is realized using the knowledge graph techniques. The proposed framework provides different parameters to be tuned. In order to do such task efficiently, the evolutionary computation process is integrated on HAML. The following subsections are then used to explain the detailed components of HAML.
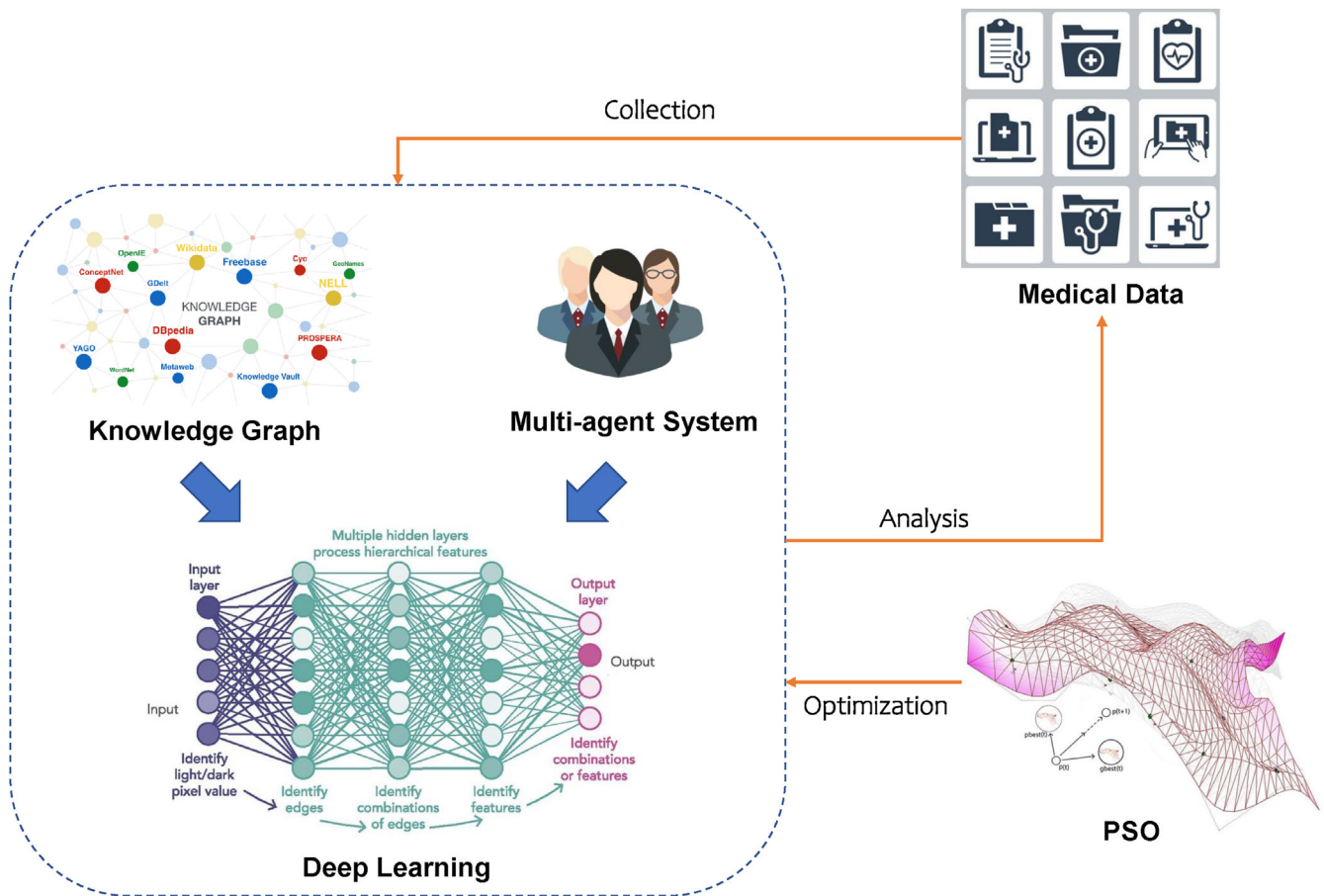
FIGURE 1   HAML framework

3.2 | Deep learning

We used three deep learning architectures in order to train the medical data. The models are combined in the HAML framework in order to handle heterogeneous medical data (images, texts, time series and so on), for each representation, we used a specific model for accurately training the medical data and reach high accuracy. The explanation of the models used in this research work are given as follows:

1. Long Short-Term Memory Network (LSTM): To efficiently handle the medial data regarding the time series data format, we propose the LSTM-based network architecture. The input consists of medical data represented by a time series. The network is composed of multiple layers each of which contains high number of neurons. The neurons in the layers are fully connected, where all neurons of the ith layer shared weights with all neurons of the $i+1^{th}$ layer. The time series medical data are connected to the neurons of the input layer, where each point value in the time series is linked with each neuron of the input layer. The output data share weights with the neurons of the output layer. The primary object of this paper to figure out the minimal error between the output of the network and the ground truth data. We note O_j^i the value of the ith neuron in the jth layer, computed using the activation function. A normalization procedure should be performed in order to obtain 1, when we sum all outputs of all neurons in the given layer. The algorithm starts by initializing weight values for all neurons of the successive layers in the network. For each time series medical data, injected, the output data is estimated, and the error is calculated. The adjustment of weights is performed for all layers of the network. The procedure is run through several times before all the medical series have been processed.

2. Entity-Embedding Deep Learning: To deal with structured medical data, we propose the entity-embedding deep learning architecture. Embeddings are first created in order to represent the structured in a vector of features. The feature vectors created will be connected to two fully connected layers, and then to output layer. We used bag of words solution in order to compress the structured data into a feature vectors. The number of visual words are first created from the data in order to represent the data space. The intersection of words and each row data is calculated, this yield a matrix called DW. It contains d rows, and w columns, where d is the number of all samples, and w is the number of words. Each element (i, j) in DW describes the presence/absence of the ith data in the jth word.

3. Convolution Neural Network: To deal with image medical data, we propose the convolution neural network architecture. Convolutional Neural Networks (CNNs) are a class of deep architectures that are highly applied to computer vision applications such object detection, and visual

recognition. However, it recently applied to other type of data representation such as time series, and textual data. The main idea of CNNs is the features extraction from matrix data using the convolutional filters. Convolutional filters are a set of weights that are applied to each element in the matrix data pixel. These weights are learned and adjusted using the traditional back-propagation methods.

3.3 | Multi-agents systems

We define a multi-agents system by a tuple $< \mathcal{A}, \mathcal{S}, \mathcal{U}, \mathcal{R} >$. $\mathcal{A}$ is considered as the set of agents, each of which is a Markov decision process, $\mathcal{S}$ is the considered as the finite set of environment states, $\mathcal{U}$ is considered as the set of actions and finally, $\mathcal{R}$ is then considered as the reward function in the designed system. The behaviour of each agent in $\mathcal{A}$ is represented by its policy, which specifies how the agent chooses its actions given the state. The purpose of each agent is to discover a policy that can be used to maximize the given objective function, for instance, in case of prediction, a policy of each agent is to maximize the number of predicted objects. Further to the local deep learning used by each agent, the reinforcement learning is used to learn from the environment and the other agents in the system. In the following the description the different components of our multi-agents system is explained:

1. State: The next action of each agent is dependent to the decisions of the previous states. Therefore, the state each agent is composed into two parts, the set of the previous actions, and the current data to be handled. The size of the state space $\mathcal{S}$ is measured by the number of observations in the database.
2. Action: It is the assignment of the decision behaviour of each observation in the database. For instance, in case of prediction task, it is the assignment of the class of each object.
3. Reward: It is crucial to determine an appropriate reward function. It allows a better learning process of each agent in $\mathcal{A}$. We used data with ground-truth to make reward to the actions of the agent. The following is the definition of the reward function as:

$$R\left(\mathcal{A}_i, \mathcal{U}_j\right) = \begin{pmatrix} 1, & \text{if } \mathcal{A}_i\left(\mathcal{U}_j, O_j\right) = \mathcal{G}\left(O_j\right) \\ 0, & \text{otherwise,} \end{pmatrix} \tag{1}$$

where $\mathcal{A}_i\left(\mathcal{U}_j, O_j\right)$ is the decision of the agent $\mathcal{A}_i$, whether the observation O_j has correct action or not.

$\mathcal{L}(O_j)$ is the ground-truth of the observation O_j.

4. Environment: The environment is a set of databases which contains a large population of smart senor data. This allows to the environment to generate particular states for training the agent and estimate the best actions to be taken.

Each agent $\mathcal{A}_i$ starts by scanning the observations of the ith smart sensor, it then computes of the first observation, and the remaining observations of the ith smart sensor. A reward function is computed for this decision based on the ground truth of the first observation. This process is repeated for all observations of the ith smart sensor. As result, a set of local decisions noted LD_i is derived for each agent $\mathcal{A}_i$.

3.4 | Ontology matching

HAML handles heterogeneous data retrieved from texts, time series, and images. Each agent provides its proper description of the local data that it perceived. In order to accurately merge the local decisions of the agents in $\mathcal{A}$, intelligent communication may be investigated using the ontology matching. Ontology is created for describing the knowledge of each agent. To make the matching of the ontologies of the agents in $\mathcal{A}$ in real time, a robust ontology matching solution is needed.

Definition 1. Consider the set of l ontologies $\mathcal{O} = \{\mathcal{O}_1, ..., \mathcal{O}_l\}$, each ontology $\mathcal{O}_i$ shows the set of m_i instances of the agent $\mathcal{A}_i$ such that $\mathcal{I}^i = \left\{\mathcal{I}^i_1, ..., \mathcal{I}^i_{m_i}\right\}$, and n_i properties or attributes $\mathcal{P} = \left\{\mathcal{P}^i_1, ..., \mathcal{P}^i_{n_i}\right\}$. The purpose and problem statement of the ontology matching problem among the agents in $\mathcal{A}$ is to determine the common properties among ontologies, that is, to determine the function $\mathcal{M}$ such that:

$$\mathcal{M}\left(\mathcal{O}_i, \mathcal{O}_j\right) = \left| \left\{ \bigcup_{l \le m_i, s \le m_j} \mathcal{M}_{ij}\left(I^i_l, I^j_s\right) \right\} \right|, \tag{2}$$

where

$$\mathcal{M}_{ij}\left(I^i_l, I^j_s\right) = \left\{ p \mid p \in I^i_l \wedge p \in I^j_s \right\}. \tag{3}$$

The naive limitation regarding the ontology matching is to scan all values of the instances among the ontologies and make comparisons. The process of matching determines the outcome of the alignment. Each matching may lead to different alignment instances. These different alignment instances are evaluated against to the optimal alignment. The optimal alignment is annotated by an expert of particular domain. The alignment of references includes all the common ontology instances. The naive approach is high time consuming in particular for smart sensors which are generally collect huge amount of data. To solve the above limitations and problems, we then implement and design a novel algorithm for ontology matching in smart sensors environment. It divides is the whole set of instances of each ontology into several dependent clusters. Each cluster then contains highly correlated instances to be processed later. Next, it explores the instances of the clusters to find the common features. It mainly includes the clustering and matching processes. In the clustering process, the instance set is divided into several collections of sub-instances (clusters) using data-mining techniques. This step is considered to be a pre-processing phase in the designed model. The set of instances is then grouped into different clusters with a small number of instances. Each cluster of instances shares the maximum number of common properties; thus, the instances of a cluster are highly correlated. During the matching process, it explores the instances of the clusters to find the alignments. Instead of performing the alignment operation between the instances of ontologies one by one, the alignment is established between the instances of the two ontologies and their representative clusters.

3.5 | Hyper-parameters optimization

To ensure better performance, we use a Particle Swarm Optimization (PSO) for hyper-parameter optimization. PSO was chosen for this task due to its known balance between intensification and diversification, which are both important in this setting. In addition, PSO proved its efficiency in hyper-parameter optimization task for deep learning models compared to the other evolutionary computation Singh et al. (2021). Next, the main parts of PSO are utilized and implemented in our developed model that can be used to solve the problem in hyper-parameters optimization.

- **Initialize population:** The particles in the initialized population is randomly generated using the solution space. The solution space is defined by the possible combinations of all hyper-parameters used in the proposed framework. Number of epochs, activation function, number of batches are just examples of the hyper-parameters of the proposed framework.
- **Update particles:** Let us consider a swarm P of particles, then there exists a vector X for position such that $X_{ti} = (x_{i1}x_{i2}x_{i3}...x_{in})^T$ and we say that the velocity vector is $Vti = (v_{i1}v_{i2}v_{i3}...v_{in})^T$ at iteration t for each particle i that it is composed of. The particles themselves are able to update their own positions using velocity formula given in Equations (4) and (5).

$$V_i^{t+1} = w \times V_i^t + c1 \times (p^t - X_i^t) + c2 \times (p^* - X_i^t), \tag{4}$$

and

$$X_i^{t+1} = X_i^t + V_i^{t+1}, \tag{5}$$

where $i = 1, 2, ..., P$.

The particles can update their positions using Equation (4), where two factors are shown, namely c_1, and c_2, that respectively contribute to particle movement in each and every iteration. Let p^t be defined as the position for the best particle iteration t, and let p^* be the position for the best particle iteration overall. Moreover, Equation (5) can be used for particle position updates. We also can let parameter w be constant and positive. w is the parameter that can be applied and utilized to balance the global search. Thus, it is considered as the exploration. The local search is known as exploitation in the evolutionary computation.

- **Fitness computing:** Is used for the evaluation function for solution S set as the accuracy of the proposed framework by setting the values of the hyper-parameters in S. The aim is to maximize this value. The fitness function is given as follows:

$$Fitness(S) = Accuracy_{HAML}(S_i), \forall S_i \in S. \tag{6}$$

Moreover, Algorithm 1 presents the pseudo-code of the HAML framework. It takes as input the set of agents in A, and produce the training model M, which the combination of all models learned by the agents using the deep learning, the knowledge graph, and the particle swarm optimization as explained in the previous parts. Each agent A_i use the deep learning to train its model M_i. It also construct its knowledge graph from the training data. The communication among agents is done by transferring the knowledge learned during the training process using the ontology matching. The particle swarm optimization is finally involved to identify the best parameters of each model of the agents.
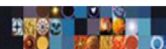
Algorithm 1

HAML: Hybrid automated medical learning

1. **Input**: $\mathcal{A} = \{\mathcal{A}_1, \mathcal{A}_2 \ldots \mathcal{A}_l\}$: the set of l agents.
2. **Output**: $\mathcal{M}$: The set of the models learned by the agents.
3. **for** each agent $\in A$ **do**
4. $M_i \leftarrow \text{Training}(A_i)$;
5. **end for**
6. **for** each agent $\in A$ **do**
7. $O_i \leftarrow$ **Construct**(A_i);
8. **end for**
9. **for** each agent $A_i \in A$ **do**
10.   **for** each agent $A_j \in A$ **do**
11. $M_i \leftarrow$ **Improve Training** (A_i, O_i, O_j);
12.   **end for**
13. **end for**
14. **for** each model $\in M$ **do**
15. $M_i \leftarrow$ **PSO**(M_i);
16. **end for**
17.   **return** $\cup M_i$.

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4 | PERFORMANCE EVALUATION

Extensive experiments were conducted on well-known medical databases to validate the usefulness of proposed HAML framework. The experiments were carried out on a desktop with an Intel *i7* processor. 16GB main memory is then equipped with the provided PC. Python language was used for all the implemented algorithms.

4.1 | Case study on event-based medical data

The good running of the medical process allows a better quality of hospital services. The different medical interaction in the hospital can be considered as a set of events, each of which are represented by the set of activities (disease recognition, diagnosis, prevention). This drastically improves the patient health and allows a better hospital management. Process mining is the process of analysing data from events log. The data in this context are structured in rows and attributes, therefore, we used the entity-embedding deep learning as deep learning architecture. Several approaches have been developed to solve the limitation of process mining. Heuristic miner Kabir et al. (2021); Weijters and Ribeiro (2011); Weijters et al. (2006) is one of the powerful method, well-known used in the process mining. The graph explaining the dependencies among activities of the corresponding trace is first deduced. The dependency relations are then retrieved from the above graph. In this case study, we will compare HAML with the recent implementation of Heuristic Miner Kabir et al. (2021). We used a hospital real-life event log,[1] produced in 2011 by a Dutch academic hospital. It depicted real activities and traces of the clinical process. It is first played for in the first business process intelligence contrast held in 2011. It enclosed 1143 of traces arranged in 150,291 events. It shaped as a Spaghetti process, one of the most complex models in process mining. It is hard to discover knowledge from the activity graph of such events log because traces are dense and involved large number of events per trace. The runtime is computed in seconds, while the quality of discovered models are evaluated by maximizing the following function Leemans et al. (2018):

$$Accuracy(M, P) = \frac{|m \in M, m \vDash P|}{|M|}, \tag{7}$$

where M is the medical event log, P is the process mining model discovered, and $m \vDash P$ is the set of events in M covered by the model P.

Figure 2 presents both the runtime, and the accuracy of HAML compared to the Heuristic-Miner Weijters et al. (2006). By varying the percentage of events from 20% to 100%, HAML increases in terms of accuracy, and reach 97% of covered events, however, Heuristic-Miner is very sensitive in terms of number of evens, where its accuracy decreases from 85% to 81%. In addition, HAML is very fast compared to the Heuristic-
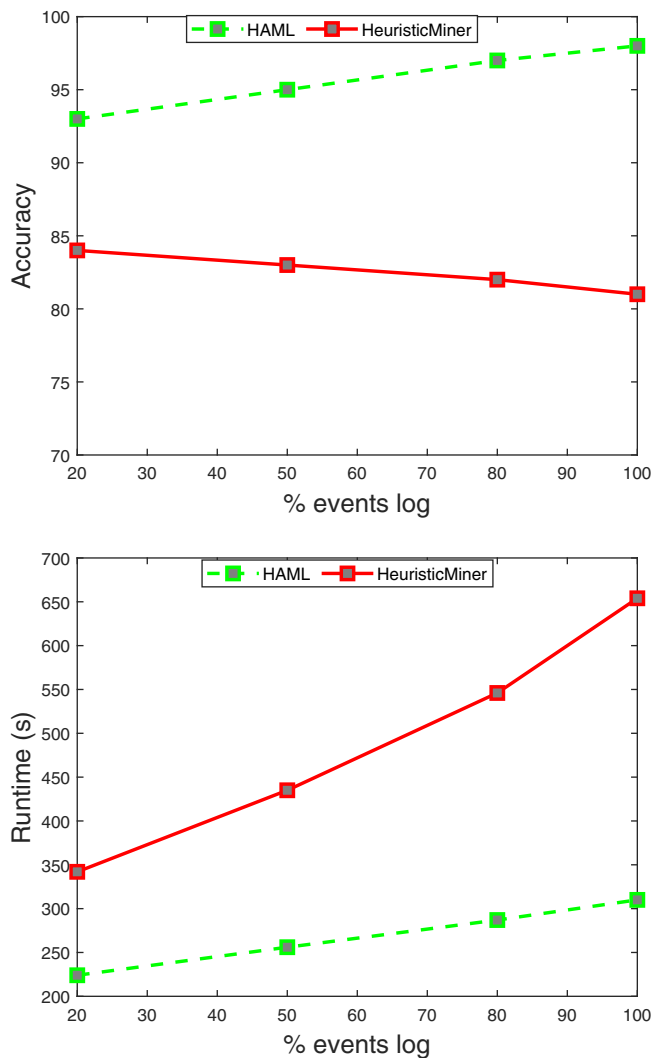
Miner. Thus, HAML needs less than 310 seconds to handle the whole events log, whereas, Heuristic-Miner needs more than 650 seconds to handle the same events log. This result is reached thanks to the efficient embedding learning for compressing the events log into compact features vectors. As what we understand, this is the first paper focusing on exploring the Bag of Words in process mining problems. Furthermore, our solution is a deep learning based solution, where only a simple propagation is performed in the inference step. However, Heuristic-Miner is an iterative based strategy which need high computational and memory resources.

4.2 | Case study on medical activity recognition

Medical activity recognition aims to determine the current activity of the patients from medical sensors data. It is crucial procedure for various operations in an old-age assistance. The data in this context is represented as time series, collected from sensors, therefore, we used the long short-term memory network as deep learning architecture. Several algorithms have been proposed for solving the medical activity recognition problem Djenouri, Laidi, et al. (2019a); Hossain et al. (2017); Tao et al. (2021); Zhou et al. (2020). The work of Hossain et al.is one of the most successful method for activity recognition Hossain et al. (2017). It used the decomposition paradigm Djenouri et al. (2018); Djenouri, Chun-Wei Lin, et al. (2019c) f for diagnosis activities. The kmeans algorithm is dynamically behaved for arranging the unlabelled activities. The derived clusters are consolidated with the variety of human activities in the residential building to avoid the need of aggregated data. In this case study, we will compare HAML with the recent implementation of Hossain et al. (2017). We used an activity recognition with healthy older people data.[2] The runtime is computed in seconds, where the accuracy is determined by the ratio between the number of recognized activities by the system, and the number of all activities.

Figure 3 presents both the runtime, and the accuracy of HAML compared to the Dynamic-Kmeans Laccetti et al. (2020). By varying the percentage of time series data from 20% to 100%, HAML increases in terms of accuracy, and reach 95% of correct recognized activities, however,
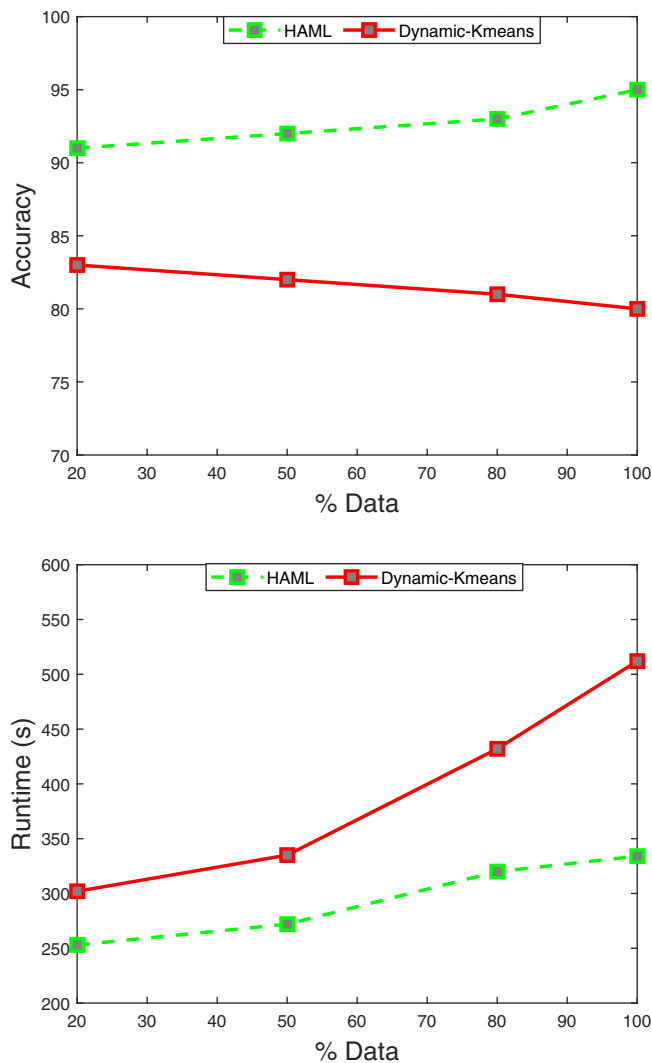
Dynamic-Kmeans is very sensitive in terms of number of time series data, where its accuracy decreases from 83% to 80%. In addition, HAML is very fast compared to the Dynamic-Kmeans. Thus, HAML needs less than 300 s to handle the whole time series data, whereas, Dynamic-Kmeans needs more than 500 s to handle the same time series data. This result is reached thanks to the both the LSTM algorithm handled by each agent in the system. Furthermore, our solution is a deep learning based solution, where only a simple propagation is performed in the inference step. However, in a Dynamic-Kmeans, each data need to be compared with the centers of the clusters, which is high time consuming, in particular for high number of clusters, and high number of samples in the time series data.

4.3 | Case study on medical image retrieval

Medical information retrieval aims to identify the relevant images from the medical images database according to the image query. It is crucial procedure for many applications such symptoms identification, and diagnosis. The data in this context is represented as images, collected from sensors, and ultrasounds. Therefore, we used the convolution neural network as deep learning architecture for feature extraction. We used the BoW (Bag of Words) Mukherjee et al. (2020) as an image search algorithm. Several algorithms have been proposed for solving the medical image retrieval problem Chen et al. (2021); Goeuriot et al. (2016); Sengan et al. (2020); Tao et al. (2021). ML-eHCR (Machine Learning for electric Health-Care Records) is one of the most successful method for medical information retrieval Sengan et al. (2020). It proposed a end-to-end pipeline for medical information retrieval. In this case study, we will compare HAML with the ML-eHCR. We used the COVID-19 Open Research dataset.[3] The runtime is computed in seconds, where the accuracy is determined by the mean average precision Djenouri et al. (2018).

Figure 4 presents both the runtime, and the accuracy of HAML compared to the ML-eHCR Sengan et al. (2020). By varying the percentage of images from 20% to 100%, HAML increases in terms of accuracy, and reach 96% of precision in terms of relevant images to the image queries,
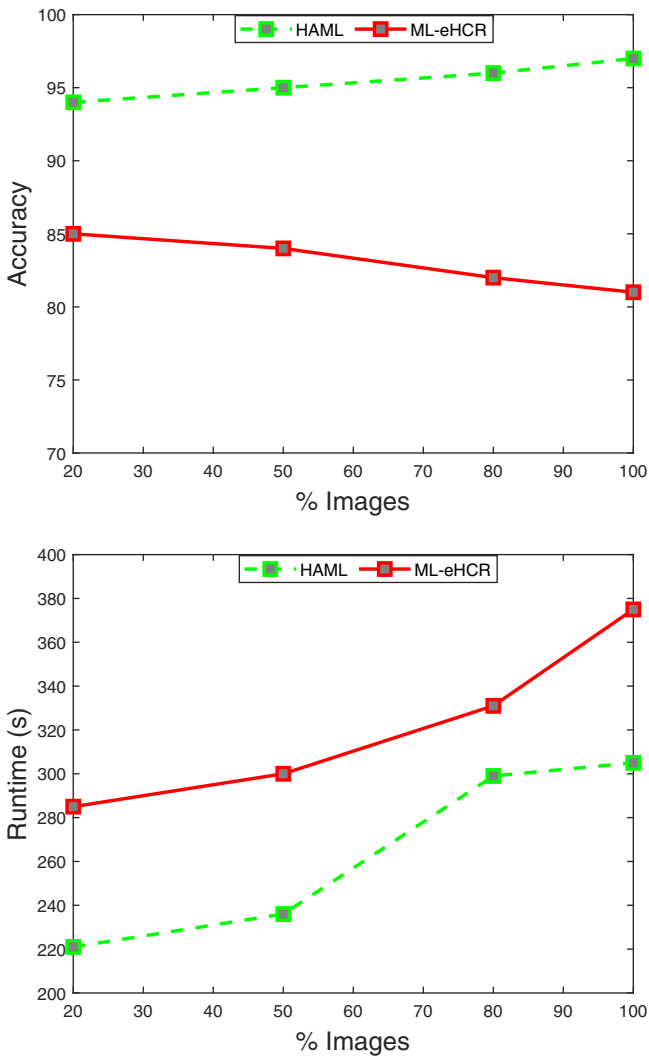
however, ML-eHCR is very sensitive in terms of number of images, where its accuracy decreases from 85% to 81%. In addition, HAML is very fast compared to the ML-eHCR. Thus, HAML needs less than 300 s to handle the whole medical images database whereas, Dynamic-Kmeans needs 380 s to handle the same images database. This result is reached thanks to the efficient combination of the convolution neural network with the existing image retrieval algorithms, which it is missing in the ML-eHCR. In terms of runtime, HAML is fast compared to the ML-eHCR due to the hybrid combination between the evolutionary, and the deep learning architectures.

In addition, the HAML outperforms the existing baseline solutions in medical setting, also thanks to the following reasons:

1. The efficient combination between the intelligent agents, and the deep learning, solutions, where each agent learns locally the data, and it shared the knowledge learned with the other agents.
2. The efficient communication strategy used during the learning process, where the ontology matching is used in order to extract the common concepts among agents, and therefore increase the sharing of knowledge among them.
3. The efficient optimization represented by the particle swarm optimization in order to increase in both the quality and the runtime performances.

4.4 | Discussions

From our extensive experiments dealing with automated medical learning, some perspectives remain to be studied:

1. Outlier Detection: Many medical data outliers were found in the experiments. These outliers reduced the overall performance of the automated medical learning process. It would be beneficial to remove them in the pre-processing step. An alternative method to solve this

limitation is to apply the existing outlier detection approaches Belhadi et al. (2020); Belhadi, Djenouri, Djenouri, et al. (2021a); Belhadi, Djenouri, Srivastava, et al. (2021b); Djenouri, Belhadi, et al. (2019b) for automated medical learning. In this context, several questions may be answered such as how to build the training data for the otulier detection process? how to compute the reachability density function for the set of the medical data, and how to determine the k nearest neighbours of the given medical data point?

2. Crowdsourcing: Automated medical learning solutions are apt to pinpoint distinct patterns from the same medical data. An open question is how can we determine which patterns are interesting and useful for the medical teams. The use of the crowdsourcing mechanism lift to enhance the importance of the detected patterns, where different deep learning approaches will be collaborated for finding the best, and the optimal patterns delivered to the medical teams.

3. Missing of ground truth: The lack of the data, and in particular the annotated data is a standard problem in medical learning applications. Indeed, data annotation is extravagant, where the need of both human and material resources is crucial for effective annotation process. The future challenges for medical research community is the quality assessment of the variety of patterns derived by the medical learning tasks. Two important issues hover to be discussed:

- It would be interesting to define the publicly, available and useful benchmark data for medical related issues; it thus becomes very helpful and beneficial to analyse the automated medical learning situations.
- It is very important to define the critical criteria for analysing the issues regarding medical information in the internal evaluation. An alternative progress aims to determine the challenges and provide the unified ranking-function scores that can be used to rank the outputs. Once an output has been identified, the functions should be distinct from one another and be maintained independent of that output.

5 | CONCLUSIONS

This paper presented a new framework, called HAML, which combines the distributed deep learning, the multi-agent systems, and the ontology matching to solve the medical data related problems. HAML explores the distributed deep learning to improve the learning process from medical data, it also investigates the knowledge graph for the data heterogeneity issue, and to increase the communication among the different agents in the system. To evaluate the performance of HAML, several experiments were carried out on the medical data. Several experiments are then extensively tested to demonstrate the usefulness of the designed and implemented framework. Three case studies are discussed in this research, the first case study is regarding as the process mining, and more precisely on the ability of HAML to detect relevant patterns from event medical data. The second case study is associated with the smart building, and the ability of HAML to recognize the different activities of the patients. The third one is related to medical image retrieval, and the ability of HAML to find the most relevant medical images according to the image query. The experimental results showed that HAML is much faster than the baseline algorithms regarding the solution quality and the execution time. For the further extensions of the current study as the future works, other intelligent techniques, such as pruning strategies and high-utility pattern mining, could be used for extracting more relevant knowledge for guiding the automated medical learning algorithms. Using emergent high-performance computing, such as GPU, to handle the very large-scale medical data will also be considered in our agenda.

ENDNOTES
[1] https://data.4tu.nl/articles/dataset/

[2] https://www.kaggle.com/marklvl/activity-recognition-with-healthy-older-people

[3] https://www.kaggle.com/koljabailly/covid19-extmetadatastatementsnerumls-cattree

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