Algorithm Selection in Multimodal Medical Image Registration

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ABSTRACT

Over the past few decades, fast-growth has occurred in the area of medical image acquisition devices, and physicians now rely on the utilization of medical images for the diagnosis, treatment plans, and surgical guidance. Researchers have classified medical images according to two structures: anatomical and functional structures. Due to this classification, the data obtained from two or more images of the same object frequently provide complementary and more abundant information through a process known as multimodal medical model registration. Image registration is spatially mapping the coordinate system of the two images obtained from a different viewpoint and utilizing various sensors. Several automatic multimodal medical image registration algorithms have been introduced based on types of medical images and their applications to increase the reliability, robustness, and accuracy. Due to the diversity in imaging and the different demands for applications, there is no single registration algorithm that can do that. This paper introduces a novel method for developing a multimodal medical image registration system that can select the most accepted registration algorithm from a group of registration algorithms for a variety of input datasets. The method described here is based on a machine learning technique that selects the most promising candidate. Several experiments have been conducted, and the results reveal that the novel approach leads to considerably faster reliability, accuracy, and more robustness registration algorithm selection.

Introduction

In the medical field, it is often that images of the same organs are captured using different imaging modalities. Examples of these modalities includePositron Emission Tomography (PET), (MRI)and (SPECT)[1]. These modalities possess different properties, making them capable of providing spectra of views and insights about the human body. For example, the CT and MRI modalities are frequently utilized in exposing anatomical structural ideas about the imaged area. In contrast, the PET and SPECT modalities are being used in revealing functional insights about the area [2].

Researchers have classified medical images according to two structures: anatomical and functional. Structuralmodality, for instance, (MRI), (US), and other systems, enable medical personnel to examine a body internally with high accuracy, thereby avoiding the risks associated with exploratory surgery. Functional (or physiological) imaging, for instance, Positron Emission Tomography (PET), Ultrasound (US), and further modality refer to a medical imaging system for discovering or evaluating variations in absorption, blood flow, metabolism, and regional chemical composition [3].

To derive a meaningful and comprehensive multi-modality insight into a given area of the body, images of this area obtained by a set of imaging modalities must be registered. This registration process ensures these modalities are geometrically consistent- at the pixel level and the voxel level [4]. Furthermore, the registration process is a necessary step before information obtained from different patterns can be fused or integrated. Although the early usage of medical image registration primarily occurred in the analysis of brain imaging, it has now become a core analysis tool in several other medical imaging applications, including cardiology, neurology, oncology, dentistry, and orthopedics [5]. Two categories of registration are used: visual registration and registration that utilizes a computer system. The visual version of medical image registration is a manual process performed by the radiologist /physician to analyze the content of multiple images. It has typically undertaken by radiologists, which can result in serious problems. For example, studies of breast cancer patients conducted at the University of Michigan have revealed that the treatment given to more than fifty percent of the patients was changed following a second opinion about their diagnosis. In a study conducted at Johns Hopkins University, researchers discovered that one or two of every one hundred patients who requested a second opinion following a tumor biopsy had been given an incorrect diagnosis. The outcomes of visual alignment are, therefore, doubtful and unreliable [6].

Because of these difficulties with visual registration as well as the diversity and variety of types of deterioration associated with medical images, several automatic multimodal medical image registration algorithms have been introduced according to standards of medical images and diverse kinds of applications [7].
Rapid developments in medical imaging knowledge have directed to an exponential increase in the number of images acquired for each patient using CT, MRI, PET, US, etc. Specialists cannot quickly arrive at accurate visual interpretations of such many different images, and individual registration algorithms are unable to provide effective

results for all these images. Because no single algorithm can perform well for every dataset, creating a novel approach to solve this problem is thus a vital and critical requirement.

Several types of multimodal registration algorithms have been established for medical image registration, each with its method of performing the registration process [8]. Current individual registration algorithms are characterized by both advantages and disadvantages that affect their efficiency. For example, any individual registration algorithm can produce optimal results for some datasets (medical images) while simultaneously providing poor results for others. Even though some registration algorithms are doing well than others typically, no single algorithm is recognized as the superlative for all input datasets. It is, therefore, unclear how the optimum existing registration algorithm can be identified for a given dataset.

Based on the literature review, most researchers have concentrated on developing a new registration algorithm, and while this focus might solve problems related to several medical images, it will not be appropriate for universal employment. Consequently, rather than finding a new registration algorithm, determining an existing system that can select the best registration algorithm for an input dataset could increase reliability, accuracy, and robustness while decreasing the search time required.

According to the issues listed previously, it is of paramount importance that we find a universal medical image registration system that can produce an optimum result for all input datasets. This paper introduces a novel method for developing a multimodal medical image registration system that can select the most accepted registration algorithm from a group of registration algorithms for a variety of input datasets. The method described here is based on a machine learning technique that selects the most promising candidate. Several experiments have been conducted, and the results reveal that the novel approach leads to considerably faster reliability, accuracy, and more robustness registration algorithm selection.

Background and Literature Review
In imaging processing, methods that provide the ability to view objects within the human body are of interest. Advances in computer technology have led to the advance of accurate and operative image processing systems, which are helpful in the medical field for diagnosis, treatment, planning, and research [9]. Incorporation of valuable data received from distinct images is frequently desirable for clinical diagnosis. For enhanced observation and information acquisition, these images must be geometrically aligned [10]. With the introduction of magnetic resonance (MR) imaging into numerous hospitals, along with increased use of computed tomography (CT) and functional modalities, for example,single-photon emission computed tomography (SPECT) it has become more usual for patients to be imaged using several techniques during their diagnosis or treatment planning[11].

The challenges associated with aligning two images from different modalities with different fields of view, slice orientation, and resolution can be addressed through intermodal image registration[12]. Image registration is the term used to refer to the process of mapping equivalent points in both modalities, which is described as a spatial transform [13]. This procedure involves aligning two images (known as the reference and the target) into one coordinate system, thereby aligning them to observe subtle differences between them. Target and reference images may differ for the following reasons: (a) they were taken at different times; (b) they were taken with various devices, such as CT, magnetic resonance imaging (MRI), PET, SPECT, and other devices (multi-model); (c) they were taken from different points of view to obtain a two or three-dimensional image[14].

Image registration has several potential applications in clinical diagnosis and treatment of the following illnesses: abdominal, cardiac, liver, pelvic, renal, retinal, tissue, and others [15].

The registration process by combining the structural images, such as CT or MRI images, with functional images, such as PET or SPECTis used in different applications such as disease diagnosis and computer-aided surgery [16-19].
Combined information from the variability of images, for instance, Computer tomography (CT), is applied to obtain more comprehensive data about the patient. At this time, the assignment of image alignment registration has been demonstrated using several techniques, which can be categorized according to a few criteria [20].
An early approach used for registering medical images is the shifting method, which involves taking one picture and shifting it gradually over a second image, with the similarity measured at each shift and the highest similarity finally chosen for registering the two models[21].

The various registration techniques can be categorized in several ways. Several researchers advocate a nine-dimensional method that supplies high-quality classification.

Table 1
Criteria for classifying registration methods.

Dimensionality	Registration Basis	Transformation	Interaction	Modalities	Subject	Object
2D-to-2D	Feature-based Method	Rigid	Interactive	Mono-Modal	Intra-subject	Brain
3D-to-3D	Intensity-based method	Non-Rigid	Semi-Interactive	Multimodal	Inter-Subject	Kidney
2D-t0-3D			Auto-interactive		Atlas-Subject	Liver

A substantial number of registration approaches have been advanced, and several standards have been provided for classifying them, as summarized in Table 1. Reference[22] ranked them according to several criteria: the dimension of the dataset (2D, 3D)[12]; the registration base (intensity-based/feature-based)[18]; the transformation domain (local or global); the nature of the transformation (rigid, non-rigid); the modality (monomodal, multi-modal); the subject (intrasubject, inter-subject, atlas subject); and the interaction (interactive, semi-automatic, automatic).
. In this research, the medical images described in the following sections have been used for several registration experiments because they represent the imaging commonly used for several purposes.

Table 2
Medical Image Categorization

Anatomical Structure	Functional Structure
Magnetic Resonance Image (MRI)	Electrical Impedance Tomography (EIT)
Computer Tomography (CT)	Single Photon Emission Computed Tomography (SPECT
X-Ray	Positron Emission Tomography (PET)
Ultrasound	Electroencephalography (EEG)

Table 2 lists examples of these two categories of medical image structure: anatomical and functional.
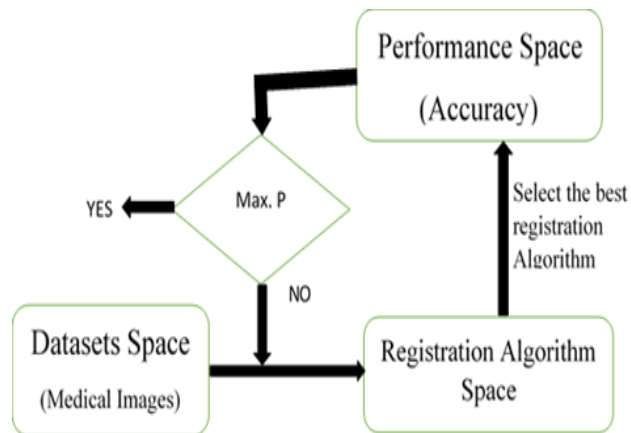
Algorithm Selection Problem
The Algorithm Selection Problem involves the selection of the optimal algorithm for a given issue may be resolved in detail [19]. In the past decade, this has become particularly relevant since researches are applying increasing effort into examining the means of recognizing the most suitable existing algorithm to solve an issue rather than by developing new algorithms.

For some time, researchers have accepted that an individual registration algorithm will not provide the best performance about every problem that requires a solution and that the selection of the most suitable technique will probably enhance the overall performance.

As in [22]Sharma el. they defined a method to tackle the selection algorithm problem by estimating the computation time of Concorde and LKH on problem instances. Komal et al.[20] represent that they solved the selection problem using some ranking techniques to select the best process based on its ranking.

Rice published the initial explanation of the Algorithm Selection. The primary type outlined in this part is somewhat simplistic; a space of inputs and area of process combines each input-algorithm couple based on its results. This process can be followed to select the most appropriate algorithm when faced with a problem.

The algorithm selection framework, as shown in Figure 1, was represented by [23].

Fig. 1. Algorithm Selection Framework

The schematic block diagram in Figure 1 explains the main stages that used as a framework to solve algorithm selection problems where:
Datasets space as (D), Registration Algorithms space (A), and (Y) as a performance space.
The required is the best algorithm that maximizes performance (y). The task is finding the best registration algorithm (α), with input dataset (x), that maximize $y(\alpha(x))$ as shown in this equation
$$\alpha = S(f(x)) \quad (1)$$
Where:
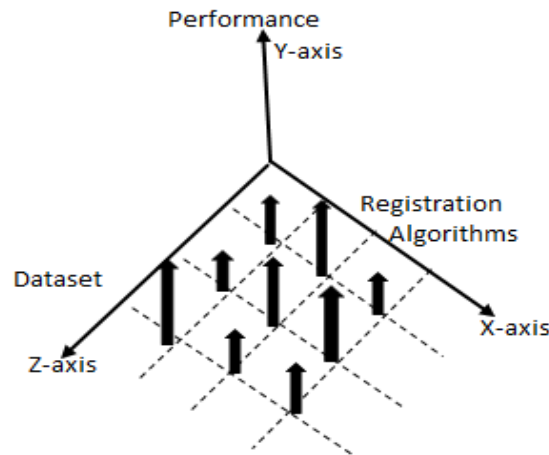$\alpha \in A$, Registration Algorithm Space
S is Selection mapping
P, Performance Space

Problem Definition
According to the literature review, several registration algorithms have been developed for registering medical images of the same objects using different datasets, including CT, PET, SPET, and MRI. Registration algorithms are designed for two main reasons: first, because of the diversity of medical images that exist for distinct types of organs and, second, the variety of medical applications for which they can be used. As well, the diversity of medical images and differences in the degradation of the same object create problems concerning registering the performance of an algorithm, such as increased processing time and decreased accuracy.

However, none of the single registration algorithms outperform the others across all datasets, which makes individual registration algorithms unreliable. Therefore, Image diversity and application diversity present a significant challenge for any single registration algorithm-based solution: reliability and accuracy.

Consequently, selecting the best-performing registration algorithm can optimize the results and enhance the performances of the registration system.

Fig. 2. Algorithm selection problem in three-dimensional space

The selection of a registration algorithm can be seen as a problem in three-dimensional space, as depicted in Figure 2, where the x-axis expresses a set of registration algorithms (A); the z-axis denotes multiple different datasets (D), and the performance (P) of the registration algorithms is defined on the y-axis.
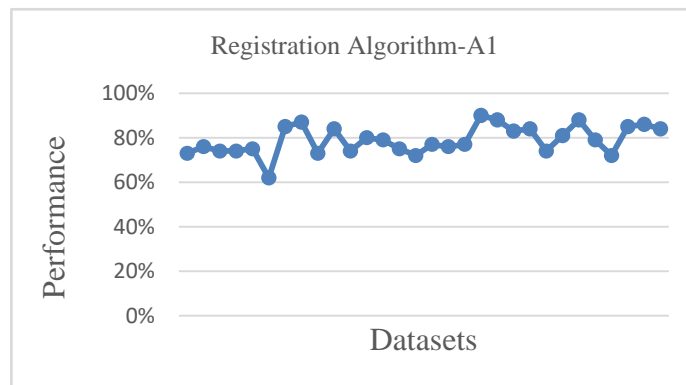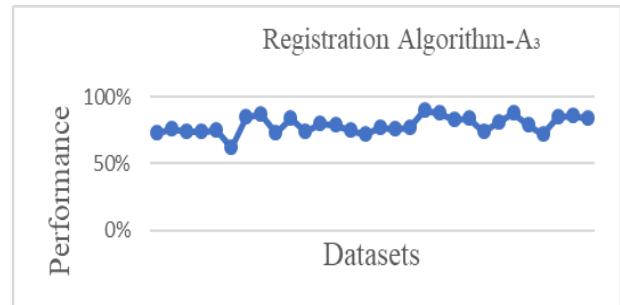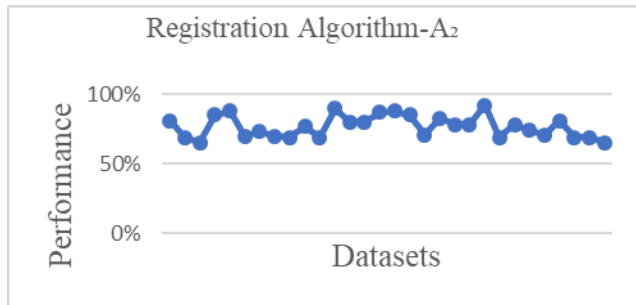

Fig. 3. Relationship between Registration Algorithm A1 and dataset

For example, as shown in Figure 3, the registration algorithm A_1 gives the best performance with dataset d_3, and the registration algorithm A_2 produces the highest accuracy with d_1. Therefore, if dataset d1 is selected and mapped to several registration algorithms, such as A_1, A_2, and A_3, the results will be dissimilar. Moreover, if the same procedure is repeated with the d_2 dataset, the results will once again be different. On the other hand, if a registration algorithm such as A_1 is used with different datasets (d_1, d_2, d_3..., d_m), the outcome performance is different, as shown in Figures 4 and 5. A final observation is that no superior registration algorithm produces optimal performance with all datasets, and no datasets outperform all others across all registration algorithms. Consequently, the question that arises is how to select a registration algorithm that will produce high-performance results for all datasets.

The registration algorithm A_n is selected to be the one that presents the best performance P with dataset d_j.
$$P = S (A_n, d_j) \quad (2)$$

The problem statement defined that no single registration algorithm outperforms for all registration algorithms for all input datasets and that selecting the most suitable technique is likely to advance the performance. For this reason,

they are choosing the best registration algorithm to tackle the issue rather than evolving new processes that become especially relevant.

Fig. 4. Relationship between Registration Algorithm A2 and dataset

Fig. 5. Relationship between Registration Algorithm A3 and dataset

The prime determination of this research paper is to create a selection strategy that will choose the best registration algorithm for the given registration dataset based on the machine learning technique.

Solution Strategy

The goal is to investigate the performance of a wide range of image registration algorithms under various modalities and situations, to come up with an automatic system that can optimize the selection of a registration algorithm that can address a set of registration situations.
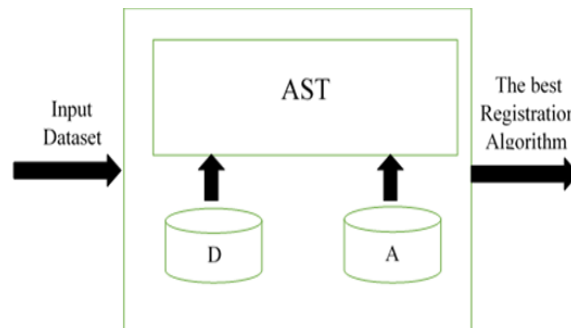
Fig. 6. Proposed selection system

The automatic registration system is a multimodal medical image registration selection system, as illustrated in Figure 6, where the input consists of dataset space (D), and the output is the selected registration algorithm that produces the best result with the input dataset as expressed in equation (1).

If the best registration algorithm can be identified for a given dataset, it becomes possible to achieve the best of both worlds and improve overall performance.

Machine learning based on algorithm selection

To build the algorithm selection technique, there are three steps, as indicated in Figure 7:

  1- Dataset labeling based registration algorithms
  2- Creating a learning algorithm-based machine-learning technique (MLP)
  3- Labeling performance analysis

Dataset Labelling based Registration Algorithms

1- Dataset Division

The benchmarks dataset utilized in this paper is an open-source dataset. A total of 100 MRI/PET/CT datasets were Chosen: one pair of images for each patient. The datasets were divided into two groups: 75% for training, 25% for testing.
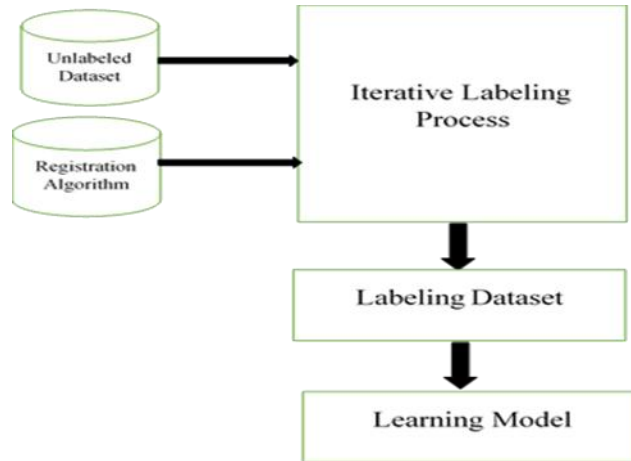
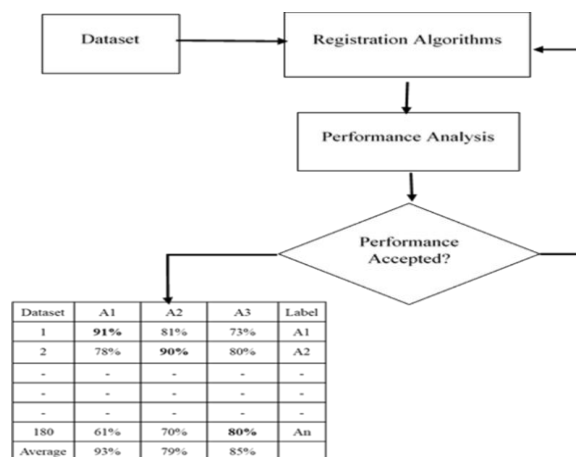**Fig. 7. Schematic diagram of the proposed solution**

2- Dataset Labeling

Supervised machine learning techniques rely on labeled datasets during the training stage.

The novel method presented in this article includes the advancement of a labeling system by evaluating the performance of dataset-based registration algorithms, as outlined in Figure 8. The labeling scheme comprises of three stages:

1- Dataset Space: A set of benchmarked datasets (a pair of medical images)
2- Registration Algorithm Space: A collection of registration algorithms
3- Performance Space: This is an accurate measurement.

The ultimate objective is thus to determine the registration algorithm that provides the highest accuracy, and that will be chosen as a label for the input dataset dm.

| Dataset	A1	A2	A3	Label
1	**91%**	81%	73%	A1
2	78%	**90%**	80%	A2
-	-	-	-	-
-	-	-	-	-
-	-	-	-	-
180	61%	70%	**80%**	An
Average	93%	79%	85%	

Fig. 8. Dataset labeling

In work conducted thus far, for the creation of a labeled dataset, 100 benchmark datasets (pairs of images) were selected. The process began with the mapping of all dataset in the dataset space to all registration algorithms in the

registration algorithm space. For this purpose, three registration algorithms were selected: a points-based registration algorithm, a distinct points registration algorithm that uses alignment, and an iterative closest point registration algorithm. The registration algorithms were designated A_1, A_2, and A_3, respectively.
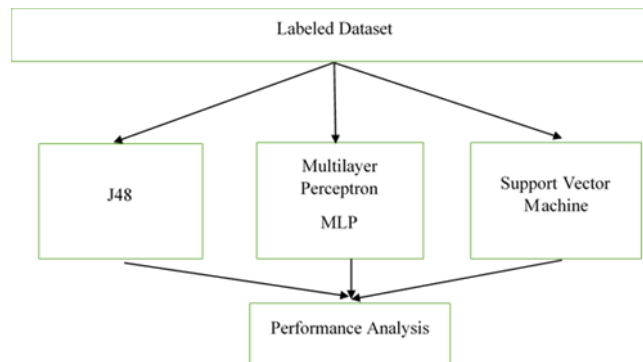
Fig. 9. Classifier selection based on performance

The registration algorithm performance space is then used as a measure for evaluating the accuracy of each registration algorithm based on the input dataset. The registration algorithm that provided the highest degree of certainty concerning the input dataset was selected as a label for that dataset, as indicated in Table 3. The same procedure is then applied to all unlabeled datasets, and the registration algorithm based on the labeled dataset is then produced. Three classes of registration algorithms are then created: A_1, A_2, and A_3. The final output of the first stage is that of the labeled-dataset-based registration algorithms (training dataset). The training dataset is then ready for the next step.

Creating a Learning Model

Table 3
Classifier selection based on performance

Performances	MLP	J48	SVM
TP Rate	0.967	0.918	0934
FP Rate	0.016	0.032	0.027
Precision	0.970	0.921	0.934
Recall	0.967	0.918	0.934
F-Measure	0.967	0.919	0.934
ROC Area	0.987	0.943	0.964

As explained above, registration algorithm selection is considered as a simple classification problem. As shown in Table 3, the labels of the input datasets are the registration algorithms, which are three A_1, A_2, and A_3. To create a learning model, three classifiers are chosen, which are a support vector machine (SVM), J48, and multilayer perceptron (MLP). A set of experiments was conducted on the three selected classifiers, as displayed in figure 9, and finally, the (MLP) was designated based on their results, as depicted in table 3. Therefore, the MLP classifier is used to create a learning model.

For this purpose, as viewed in figure 10, the MLP classifier used 100 labeled datasets: 75% of the training dataset for training and 25% for testing.
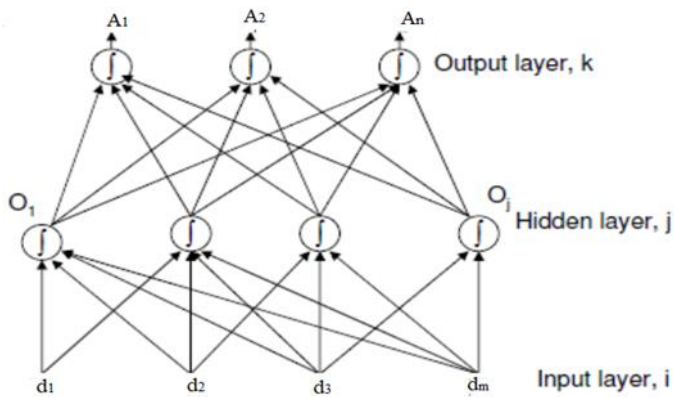
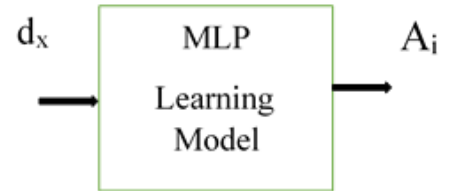Fig. 10. Multilayer perceptron classifier   Fig. 11. Learning Model

As presented in Figure 11, the outcome of this stage is a learned model, whose learning was achieved based on a labeled dataset and which is ready to classify an unknown (unlabeled) dataset.

Where:
dx ϵ (Pairs dataset): is the unseen dataset
Ai ϵ (A1, A2 ...An): is the selected registration algorithm.
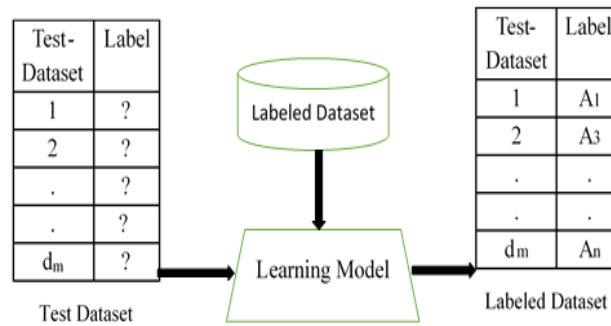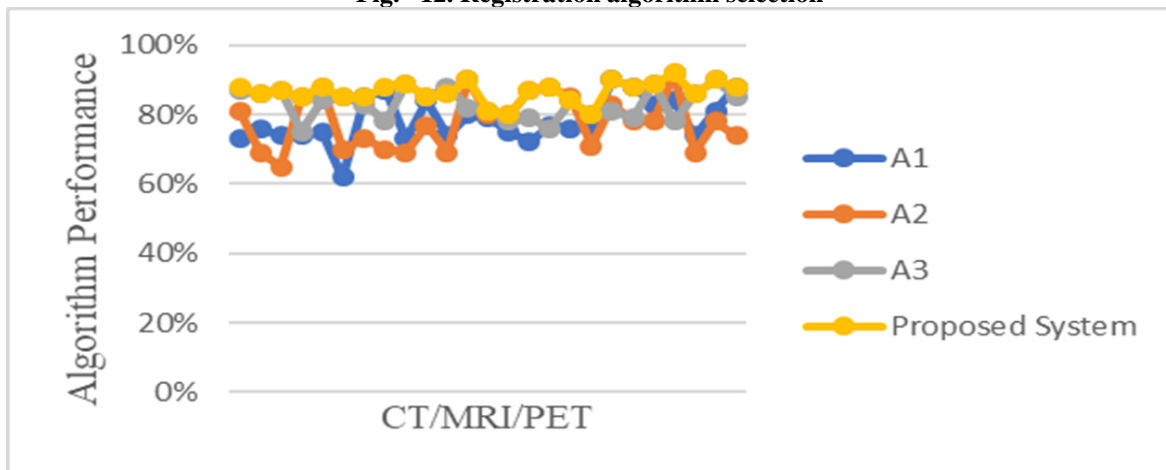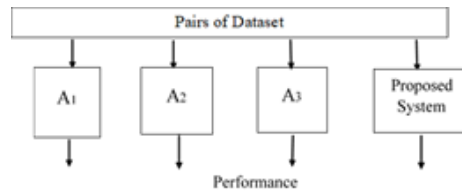

Fig. 12. Registration algorithm selection

Fig. 13. System Performance: Learning Dataset

Labeling Performance Analysis

The final stage is the selection of the best registration algorithm based on the learned model, as shown in Figure 13. The learned model that was created during the late-stage applied for labeling the test dataset, which is unlabeled. The primary function of the learned model is to assign a label to the unseen input dataset. When the test datasets, which are 100 unlabeled datasets (CT/MRI/PET), are mapped to the learned model, the classifier matches the test datasets with the data points, and the best-match result is selected as a label for the test dataset. The output of the learned model is, therefore, the labeled dataset, whose label represents the registration algorithm, which is one of the three registration algorithms A1, A2, or A3. The chosen algorithm will thus be the best registration algorithm for the unknown input dataset. In this way, the best registration algorithm for the learning input dataset has been selected, as shown in Figure 13. Therefore, the final stage involves mapping that dataset to the registration algorithm chosen to implement the registration process.

Discussion

According to the issues listed previously, it is of paramount importance that we find a universal medical image registration system that can produce an optimum result for all input datasets. This paper introduces a novel method for developing a multimodal medical image registration system that can select the most accepted registration algorithm from a group of registration algorithms for a variety of input datasets.

Registration algorithms are developed for two main reasons: first, because of the diversity of medical images that exist for distinct types of organs and, second, since the variety of medical applications for which they can be used. As well, the diversity of medical images and differences in the degradation of the same object creates problems in registering the performance of an algorithm, such as increased processing time and decreased accuracy.

However, none of the single registration algorithms outperform the others across all datasets, as shown in figures 3,4,5, which makes individual registration algorithms unreliable.

As shown in the 3,4,5,6,7, the results show that the registration algorithms that used provide promos results with a limited number of datasets. In this research, the proposed method outperforms for all datasets, as shown in figure 13. For future work, the performance of the created technique is a function of the similarity between the new dataset and the learned dataset.

Conclusion

The most crucial aim of this research paper is to create a selection strategy that will choose the best registration algorithm for the given registration dataset based on the machine learning technique.

Therefore, Image diversity and application diversity present a significant challenge for any single registration algorithm-based solution: reliability and accuracy.

Consequently, selecting the best-performing registration algorithm can optimize the results and enhance the performances of the registration system.

Depending on the results from the proposed system, the decision produced is more reliable and accurate than those obtained using the current registration algorithm.

The proposed system will provide much accurate and reliable decisions than obtained using visualization.

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