Algorithm Selection in Multimodal Medical Image Registration

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Medical image acquisition technology has improved significantly throughout the last several decades, and clinicians now rely on medical images to diagnose illnesses, and to determine treatment protocols, and surgical planning. Medical images have been divided by researchers into two types of structures: functional and anatomical. Anatomical imaging, such as magnetic resonance imaging (MRI), computed tomography imaging (C.T.), ultrasound, and other systems, enables medical personnel to examine a body internally with great accuracy, thereby avoiding the risks associated with exploratory surgery. Functional (or physiological) imaging systems contain single-photon emission computed tomography (SPECT), positron emission tomography (PET), and other methods, which refer to a medical imaging system for discovering or evaluating variations in absorption, blood flow, metabolism, and regional chemical composition. Notably, one of these medical imaging models alone cannot usually supply doctors with adequate information. Additionally, data obtained from several images of the same subject generally provide complementary information via a process called medical image registration. Image registration may be defined as the process of geometrically mapping one -image's coordinate system to the coordinate system of another image acquired from a different perspective and with a different sensor. Registration performs a crucial role in medical image assessment because it helps clinicians observe the developing trend of the disease and make proper measures accordingly. Medical image registration (MIR) has several applications: radiation therapy, tumour diagnosis and recognition, template atlas application, and surgical guidance system. There are two types of registration: manual registration and registration-based computer system. Manual registration is when the radiologist /physician completes all registration tasks interactively with visual feedback provided by the computer system, which can result in serious problems. For instance, investigations conducted by two experts are not identical, and registration correctness is determined by the user's assessment of the relationship between anatomical features. Furthermore, it may take a long time for the user to achieve proper alignment, and the outcomes vary according to the user. As a result, the outcomes of manual alignment are

doubtful and unreliable. The second registration approach is computer-based multimodal medical image registration that targets various medical images, and an arraof application types. . Additionally, automatic registration in medical pictures matches the standard recognized characteristics or voxels in pre- and intra-operative imaging without user input. Registration of multimodal pictures is the initial step in integrating data from several images. Automatic image processing has emerged to mitigate (Husein, do you mean "mitigate" or "improve"?) the manual image registration reliability, robustness, accuracy, and processing time. While such registration algorithms offer advantages when applied to some medical images, their use with others is accompanied by disadvantages. No registration technique can outperform all input datasets due to the changeability of medical imaging and the diverse demands of applications. However, no algorithm is preferable under all possible conditions; given many available algorithms, choosing the one that adapts the best to the task is vital. The essential factor is to choose which method is most appropriate for the situation. The Algorithm Selection Problem has emerged in numerous research disciplines, including medical diagnosis, machine learning, optimization, and computations. The choice of the most powerful strategy for a particular issue seeks to minimize these issues. This study delivers a universal and practical framework for multimodal registration algorithm choice. The primary goal of this study is to introduce a generic structure for constructing a medical image registration system capable of selecting the best registration process from a range of registration algorithms for various used datasets. Three strategies were constructed to examine the framework that was created. The first strategy is based on transforming the problem of algorithm selection into a classification problem. The second strategy investigates the effect of various parameters, such as optimization control points, on the optimal selection. The third strategy establishes a framework for choosing the optimal registration algorithm for a delivered dataset based on two primary criteria: registration algorithm applicability, and performance measures. The approach mentioned in this section has relied on machine learning methods and artificial neural networks to determine which candidate is most promising. Several experiments and scenarios have been conducted, and the results reveal that the novel

Framework strategy leads to achieving the best performance, such as high accuracy, reliability, robustness, efficiency, and low processing time.

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I would like to convey my heartfelt appreciation to my parents, who have shown me unconditional love and encouragement throughout my life. Last but not least, I would like to express my gratitude to my wife, Allam, and my children. Their unwavering love and support motivated me to make my spontaneous inspirations a reality.

Dedication

To sole of my mother and father.

TO my wife and my children, Yones, Yasmen, Yaqin, Yomna.

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List of Acronyms

2D-2D	Tow Dimensions
3D-3D	Three Dimension
A1, A2, A3	Registration Algorithms
ANN	Artificial Neural Networks
CT	Computed Tomography
CT-t1	Computed Tomography with Various times
CAT	Computed Axial Tomography
CC	Cross-Correlation
FR	Feature-Based Registration
FP	Fuls Positive
FN	Fuls Negative
PET	Positron Emission Tomography
U.S.	Ultrasound
X-ray	X-Ray
CNN	Convolution Nural Network

List of Abbreviations

MLP	Multilayer Perceptron Classifier
MITK	Medical Imaging Interaction Toolkit
MRI.	Magnetic Resonance Imaging
MSD.	Mean Squared Difference
NMI	Normalized Mutual Information
MIR	Medical Image Registration
MI	Mutual Information
NC	Normalized Correlation
NFL	No Free Lunch Term
IR	Intensity-Based Registration
Im	Medical Image
SPECT	Single-Photon Emission Computed Tomography
SSD.	The Sum of Squared Grey value differences
T.N.	True Negative
T.P.	True Positive
O.P.T.	Ortho Pan Tomography

Chapter 1
Thesis Introduction

1.1 Introduction

The study domains associated with algorithm selection methods are numerous and highly distinguished. Numerous selection algorithm strategies, or variable adjustment procedures, are adapted to a particular algorithm and frequently result in comparable exciting answers across other research domains [83]. Numerous efforts have been made in other disciplines, using different categorizations, and neglecting technical commonalities, while all of these disciplines will gain from a better understanding of the successes in various algorithm selection projects. Algorithm selection is the process of determining the optimal solution for a specific problem instance, and it has appeared in numerous forms and under various names in various domains over the previous few decades [84]. Historically, algorithm selection has been used to resolve classification difficulties in the area of machine learning. Smith-Miles extended this System to include regression, classification, and optimization [7]. Most researchers have focused on novel approaches to address and solve this problem in practice. When applied in several search problems, for instance, algorithm selection approaches have preceded considerable improvements in performing that leverage the variety of systems and techniques that have been recently developed. In computer science, the algorithm selection can be asserted as follows: Which method, among several viable choices, is most likely to perform optimally on that excellent problem? The generic paradigm for this problem is described in Figure 1-1. In this diagram, f(x) features are extracted to define a given problem x and then algorithm A selected to resolve the dilemma. The algorithm's output is then quantified (P(f(x); A). In the literature, algorithm selection has been used to solve various optimization issues, including model selection, estimation and data reduction. Kotthoff [94] specified four conditions that a problem must satisfy in order to be amenable to algorithm selection analysis: (1) There are several examples of the issue, each with a somewhat different degree of complexity.; (2) There are several algorithms that may be used to solve the issue, each with a different degree of complication and performance;(3) There are generic and well-defined measures for measuring the performance of algorithms on a particular task; and (4) There is a collection of available features that define complex problems that can be calculated in the background and coexist with the problem.

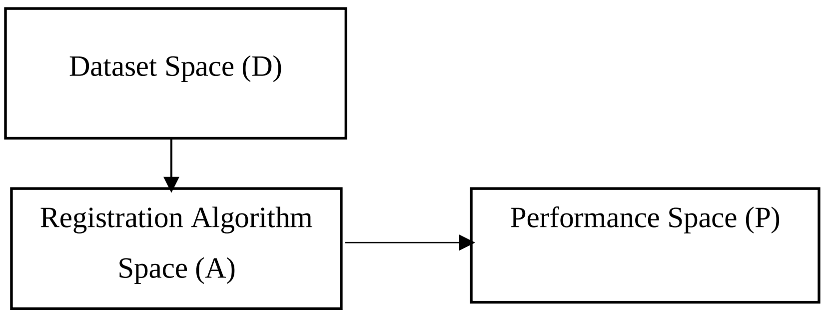


Figure 1-1:Algorithm selection Model

Rice then provided realistic examples to illustrate the model's applicability. Next, he improved the original model by including characteristics correlated with issues used to classify the selection mapping. Figure 1-2 depicts the initial illustration of the refined model. The illustrated model, or a variant thereof, is the most frequently used in most functional approaches. The incorporation of features is often the deciding factor in determining the viability of an approach.

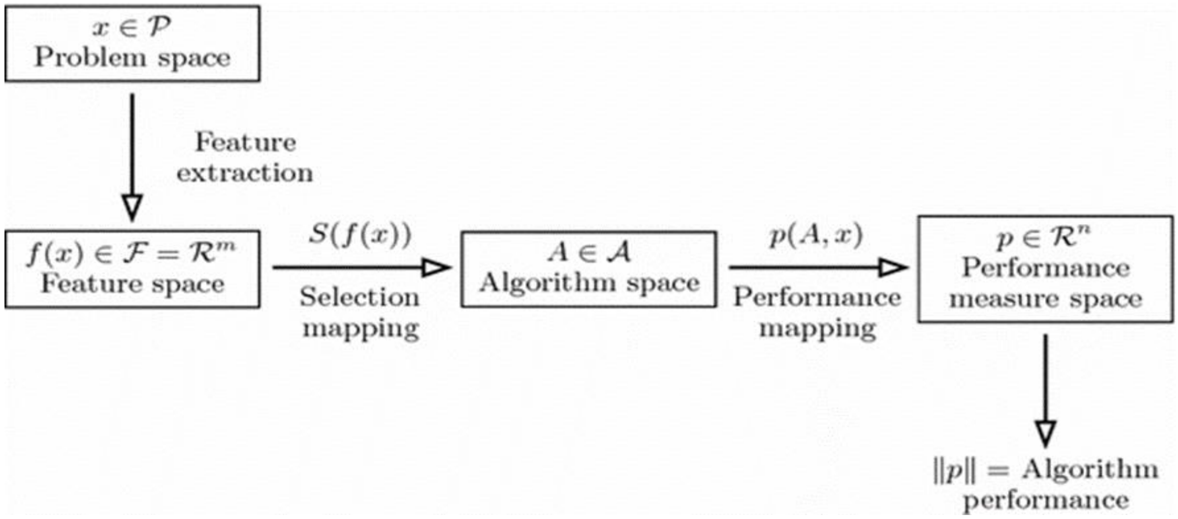


Figure 1-2:Algorithm Selection Problem

The feature extraction is carried out for every instance in each set. These characteristics generate a mapping that enables the optimal algorithm for each instance to be selected [34]. Determining the precise output mapping for every issue algorithm pairing is necessary if the best algorithm can be found. Rice enquired further about feature recognition [91]. Which characteristics are most predictive of the performance of a specific algorithm, a class of algorithms, or a subset of selection mappings?

Additionally, he stated that determining the optimal (or even adequate) characteristics is a fundamental but imprecise component of the algorithm selection dilemma. He alluded to the difficulties inherent in comprehending the problem space. Multiple problems are challenging to understand, but a set of challenges is often used to conduct an empirical assessment of a specific algorithm category. If this sample does not appropriately reflect the problem of the features and does not allow for a sufficient distinction of the issue categories in the feature space, there seems to be little likelihood of obtaining an optimal or maybe even a useful selection mapping. Bradley stated, "Although it may appear that limiting a heuristic to a particular situation would lower its efficiency, we believe that the ability of efficient pickers to split the solution space of specific NP-hard problems is fairly surprising[27].Numerous scholars have permitted this viewpoint, and the critical importance of Algorithm Selection systems, particularly for problems requiring combinatorial assistance, arises primarily from their surprising functionality. Machine Learning is used in most techniques to learn output mappings from problems to algorithms using problem-specific features. The training data generated can be utilized to develop a performance standard that can estimate new, unobserved problems. In medicine, images of the same organs are frequently acquired utilizing various imaging modalities, including structural and functional modalities. The structural modalities contain MRI and C.T., but the functional modalities encompass SPECT and PET. These modalities possess different properties, allowing them to provide spectra of views and insights about the human body [1]. For example, the C.T. and MRI modalities are frequently utilized to expose anatomical structural insights about the imaged area, whereas the PET and SPECT modalities expose functional insights [2]. In image processing, searching for the relation between two or more images is crucial to combine the images' details. If a similarity between the images is established, the analysis of this relationship becomes manageable. The process of establishing this correspondence is referred to as image registration [3].The term "image registration" refers to the process of aligning two or more partially overlapping images obtained at various times or from separate observation locations. It is an essential technique for image processing that enables the aggregation of data from various sensors. In addition, it assists in identifying variations in images taken at various time moments. Image registration is a critical essential of a wide variety of systems, including aligning a fixed image to a moving image for target recognition, property use observation using satellite pictures, stereo image matching to obtain a figure for automatic navigation, and disease detection using multi-modality images [4].Registration of images is the first step in various remote sensing and multi-sensor fusion-based object recognition applications. It is necessary before image fusion or mosaic. The strategy for visualization imaging is depicted in Figure 1-3. First, the pictures from the several scans are co-registered to the precise geometric location; then, all of these photos are combined into a single image via image fusion. A computer graphic system is used to visualize the generated composite image. This technique offers physicians comprehensive information derived from all available modalities. Manual or automatic registration is possible. The optical version of medical image registration is a manual process performed by the radiologist /physician to analyze the content of multiple images [5]. It is normally undertaken by radiologists, which can result in serious problems. For example, studies of breast cancer patients undertaken at the University of Michigan have revealed that the treatment given to more than 50% of the patients was changed following a second opinion about their diagnosis [6]. In a study conducted at Johns Hopkins University, researchers discovered that one or two of every 100 patients requested a second [7]. As a result, it is critical to develop automated methods that need slight or no operator supervision. The registration of multimodal images is a critical feature of medical image processing. Various modalities such as MRI, CT, and PET reveal distinct tissue features [8]. The registration effectively combines data from disparate images into a shared frame of reference, such as when images are registered for single and multi-patents. In addition, the datasets registration can be used to provide information about the organ or individual being image's structure, function, and pathology [9]. Consider alignment as the optimizing of a similarity measure across a range of possible transformations. [10]. These terms may have various meanings depending on the degree of robustness and accuracy needed in the registration output. The transition model can be rigid or non-rigid. If the registration process is produced from images (unbending distortions), then the transformation model consisting of translation, rotation, and scaling, named Multimodal Image Registration, will suffice. Non-rigid models define the deformations of objects between images in a more general way [11]. The most utilized similarity metrics in medical image registration is normalized cross-correlation [12]. correlation ratio [13], and mutual information [14]. The normalized cross-correlation and correlation ratio implies a functional relationship among the two images' strength values, with the former assuming a direct correlation and the final allows for any functional connection. On the other hand, mutual information is an information-theoretic metric. It is a statistical measurement of the quantity of data included in a random variable (image) about another random variable (image) [15].Combining spatial information such as gradient magnitudes and orientations, as well as other statistical spatial dependencies, has been suggested as a way to improve the mutual information measure [16]. A method for searching the variables space for a set of transformation variables that best match the two images that use provided similarity measure must be chosen. On-derivative and derivative-based optimization techniques that select parameters iteratively to minimize the similarity metric error [17]. Normalized cross-correlation and mutual knowledge minimize the negative value of their functional meanings [18]. Because the similarity metric's hypersurface is frequently multidimensional and is not necessarily a convex function, optimization approaches converge on local extrema [19]. As a result, effective registration requires early estimates or approximate alignment when employing non-global optimization algorithms. Equally critical is the interpolation technique utilized. When transforming a target image to a fixed image, it is frequently necessary to specify grid points for the moving image. As a result, interpolation is necessary to assess the value of the moving image at the no integer places specified. Netsch et al. found that quadratic interpolators outperform linear interpolators much more than higher-order interpolators. Due to the widespread use of medical imaging, considerable research has been performed on multimodal image registration [21]. Despite this important study, all current registration techniques have limitations that restrict their practical use in a comprehensive variety of medical submissions. There is no single technique widely recognized as the best; each method has pros and cons. Registration algorithms must be accurate, robust, and reliable to the various biases present in medical imaging to be useful in clinical practise. Due to the no-free-lunch principle, it is unreasonable to assume that existing registration techniques will succeed in any medical image collection.

The thesis examines the problems and concerns associated with medical image registration and proposes various ways to address them. The research establishes a general and efficient algorithm selection algorithm for multimodal registration using machine learning and ANN. The creative technique was established to determine the most universally accepted registration algorithm for various input datasets from many available registration algorithms. The developed system was evaluated in various states, involving a unique registration algorithm and associated performance procedures. The ANN-based learning model was validated using N-fold cross-validation. The System achieved an average accuracy of approximately 95 percent while predicting the best registration algorithm that maximizes registration accuracy while minimizing processing time for testing datasets.

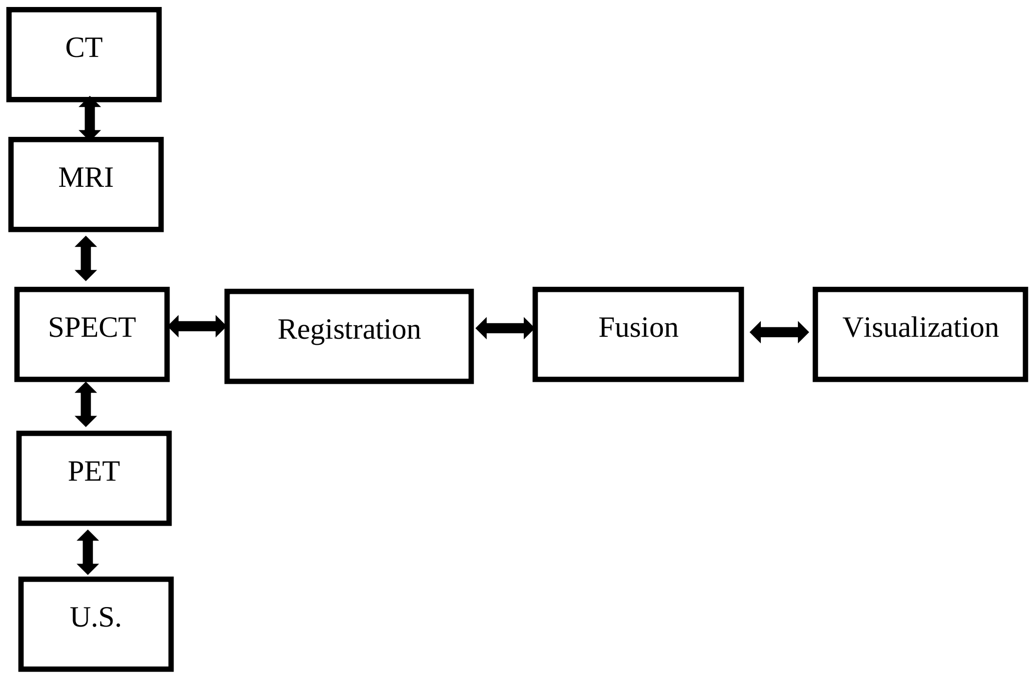


Figure 1-3:The Visualization Imaging System

1.2 Research Motivation

Over the last few decades, medical image acquisition equipment has advanced rapidly, to the point that physicians now rely on medical imaging for diagnostics, diagnostic testing, follow-up, and surgical guiding. Medical pictures are classified into two categories according to research: anatomical and functional structures. Anatomical imaging, such as C.T., MRI, ultrasound images, and other systems, enables medical personnel to internally examine a body with great accuracy, thereby avoiding the risks associated with exploratory surgery. Functional imaging, such as PET, SPECT and other methods, refers to a medical imaging system for discovering or evaluating variations in absorption, blood flow, metabolism, and regional chemical composition. In most cases, one of these medical imaging models is insufficient to provide doctors with necessary information. Importantly, through a process known as medical image registration, data gathered from two or more pictures of the same object typically provide complimentary information. Thus, image registration could be explained as the process of spatially mapping an image's coordinate system to the coordinate system of another picture collected from a different viewpoint and using separate sensors. Registration is essential in medical image analysis because it helps physicians track the course of a condition and take necessary action. Medical image registration (MIR) has various applications, including radiation therapy, cancer detection and diagnostics, template atlas applications, and surgical guidance systems. There are two forms of registration: manual registration and computer-based registration. Manual registration is a technique in which the radiologist/physician does all registration activities interactively while receiving visual feedback from the computer system, which might cause significant difficulties. For example, two specialists' studies are not identical, and the registration accuracy is determined by the user's judgement of the relationship between anatomical elements. Moreover, it may take an extended period for the user to acquire perfect alignment, and the results may vary depending on the user. As a result, manual alignment results are ambiguous and unreliable. The second registration technique is computer-based multimodal medical image registration, directed toward a variety of medical pictures. (ii) Numerous application types. (?) Without user intervention, automated registration in medical pictures matches the standard recognized characteristics or voxels in pre-operative and intra-operative images. The first step in integrating data from two or more photos is called multimodal image registration. Automatic image registration has emerged to address and advance the reliability, robustness, accuracy, and processing time associated with manual image registration. While such registration algorithms have advantages when used with certain types of medical images, they have drawbacks when used with others. No registration technique can surpass all input datasets due to the variability of medical imaging and the diverse demands of applications. However, no algorithm is superior in all potential cases; given many available solutions, choosing the one that adapts the best to the problem is most important. The essential factor is to choose which method is most appropriate for the situation. Numerous scientific disciplines have encountered the Algorithm Selection Problem, including medical diagnosis, machine learning, optimization, and computing. (Please rewrite this sentence as it is not 100% clear.) The automatic selection of the ideal solution for completing the registration task within the constraints of the registration problem demonstrates the Meta-Learning difficulty that drove this research.

The following considerations motivated the study discussed in this thesis:

1- Each modality has distinct properties. For example, C.T. and MRI are utilized for structural modality, while PET and SPECT are utilized for functional imaging. Aligning different features in multiple-input images is critical for the registration's performance. However, , alignment is a challenge because images obtained from multiple modalities have a different high spatial resolution. In multimodal medical picture registration, the relationship between the strength values of adjacent pixels is also complicated and unclear. Additionally, there is a doubt about the absence of features in one model and their presence in another. These problems directly impact the accuracy with which similarity measures are computed in medical image registration.
2- Manual registration is performed by the radiologist to analyze the contents of multiple images but has some drawbacks, such as being time-consuming, subjectivity to human error, and substantial consequences.
3- None of the state-of-the-art registration algorithms outperform others for all datasets, making individual registration algorithms unreliable.
4- Physicians face several complications when performing pre-and intra-operative measures in guidance surgery systems and radiotherapy.
5- The performance of medical image registration techniques relies on several considerations, including the modality, the impact on the image subjects, the similarity steps, the transformation, the optimization, and the implementation mechanisms. These sophisticated parameters are dependent and determining their effect on the registration

process is complicated. However, preliminary assessments of the effects of these criteria are necessary before registration.

6- Another challenge currently faced in image registration is the evaluation of algorithms. The evaluation is conducted to determine the performance level and implementation scope of a particular registration process. Furthermore, evaluating the outcomes of a registration process demonstrates the application's efficacy and scope for development. As a result, we need to understand how performance parameters and application types affect the registration process.

7- The task of correlating contrasting details in various sorts of medical images is difficult in multimodal image registration. In a surgical guidance system, the patient's organ is visualized several times with various imaging modalities, posing difficulties in identifying/fixing the patient's spot and orientation across several imaging techniques. Consequently, more complex registration algorithms are required to rapidly reduce inconsistencies in inpatient location and link data from diverse image categories.

8- 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 a novel system that can select the best registration algorithm for any input dataset could increase reliability, accuracy, and robustness while decreasing the search time required.

9- (Please rewrite this sentence. It does not make sense.) With various approaches, user interaction decreases exploration space and accelerates the progression of the optimization. On the other hand, human interaction might complicate the validation process since interaction levels can be neither measured nor controlled.

10- There is a need to design a universal selection system to choose the best registration algorithm for the given dataset.

1.3 Research Objectives

With reference to the problems listed in the research motivations, it is paramount to find a universal medical image registration system that can produce the best results for all input datasets and tackle all the issues defined in the motivation section. Clearly, what constitutes the best registration algorithm for the best applications and the best imaging modality? As a result, the following are the thesis's primary contributions:

1. Study the performance of image registration techniques under various image modalities, focusing upon reliability, accuracy, and robustness.
2. Investigate the effect of registration parameters on the registration algorithm performance.
3. Develop a generic framework that can transform the selection problem into the classification problem
4. Develop an understanding of how various assessment criteria affect the proposed framework's performance. The established framework was evaluated using various methodologies that included different performance indicators for registration algorithms and their applications.
5. Validate the created framework based on a comparison of its results with those of individual registration approaches.
6. Experimental work was conducted to validate designed system performance concerning accuracy and processing time.

The proposed framework was evaluated concerning various strategies using a variety of different registration algorithm performance measures. When applied to algorithm selection for medical image registration, promising results were obtained by employing a set of 400 datasets. Additionally, the System achieved great accuracy, reliability, and robustness by utilizing an artificial neural network and N-fold cross-validation as the assessment criterion and learning model.

1.4 Problem Statement

Algorithm selection is a critical aspect, mainly when the cost of implementing any algorithm is high -. Corresponding to the " No Free Lunch Theorem " (NFL), there is no single solution for all problem and output measures. The issue of algorithm selection has gained considerable interest in various research fields because it poses a general challenge applicable to various applications. Automatic algorithm selection becomes necessary when various algorithms are accessible and available to accomplish diverse tasks, each of which produces a slightly different outcome reliant on the algorithm selected. Choosing between all viable algorithms for a particular task becomes a challenging process - under such circumstances.

Given a set of different registration algorithms and a set of images from different modalities, these images must be registered to derive a comprehensive insight into the target area of the body.

- Manual registration is time-consuming, inaccurate, tedious, and entirely subjective.
- Automatic registration is more practical; however, there is no single registration algorithm that is guaranteed to achieve high performance for all input modalities at all times.

The question is: What is the best registration algorithm for a given dataset of multi-modal images?

In response, there are several related questions: :

- Should there be an investigation concerning whether an assembly of well-chosen algorithms can construct a group that offers the best registration performance possible as a function of the image set on hand?
- Is it possible to design a strategy to select the one candidate that delivered the best performance based on the images to be registered?

Further:

- How reliable is this selection strategy?
- How robust is this strategy?
- How accurate is the registration performance of the Selection compared to the average performance of the group?

The problem statement is described in this chapter based on the literature review, emphasizing the importance of developing a universal medical image registration framework capable of producing the optimal solution for all input datasets.

1.5 Thesis Outline

The following is the remains of the thesis: Chapter 2, The following is the remains of the thesis: Chapter 2the relevant background and literature study for the algorithm selection problem and medical picture registration is supplied and conducted in-depth to aid in comprehending the suggested framework. In Chapter 3, based on the issues represented in the motivation section, the main problem statement was determined, explained, and discussed in detail. Moreover, the solution of the persistent problem is provided, where three scenarios of solutions are provided with different assumptions. Chapter 4 explains and discusses the experimental works of all solutions scenarios conducted to validate the proposed solutions. Finally, Chapter 5 offers concluding thoughts and recommends future work to improve the existing framework and investigate alternative situations.

Chapter 2
Background and Literature Review

This chapter offers background material necessary to comprehend the work provided in this thesis. First, briefly describe the concept of medical picture registration: reviewing past work in this area: reviews on medical image registrations by studying previous work. Also, it explains some related topics such as medical image categories, registration framework and classification of medical image registration. Additionally, the first topic discussed evaluating the registration algorithm's performance and medical registration algorithm applications. Second, describe the primary notion of algorithm selection through presenting previous works in this field and provide a detailed explanation about algorithm selection approaches and machine learning.

2.1 Review of Literature

Image processing is an actively researched discipline due to its diverse applications, including medical imaging, geographic information systems (GIS) and mapping, satellite communications, biomedical engineering, robotics, and remote sensing [20]. Most research on medical image examination is already dedicated to image processing, and the literature contains several assessments of image registration methodologies. It cannot be overstated how critical medical imaging is a critical component of numerous medical applications and healthcare diagnoses. Integration of usable data gathered from various images is critical for conducting a thorough study of the information included in the observed images [21]. These images must be geometrically oriented for optimal viewing and information gathering. Patients are increasingly imaged using multiple techniques during diagnosis and treatment planning, including MRI, CT, and tomographic nuclear medicine modalities such as PET and EEG. Intermodal image registration can address the challenges of aligning two images from different modalities with different fields of view, slice orientation, and resolution [18]. As a result, image registration is required to ensure the integration process is successful. The word "image registration" refers to the process of mapping similar spots in two photographs, which is characterized as a spatial transform [21]. This process aligns two photographs (referred to as the reference and target) into a single coordinate system, allowing for observing tiny variations between them. The following reasons may account for discrepancies between the target and reference images: They were taken at various periods and with several devices, including C.T., MRI, PET, SPECT, and others (multi-model); and they were taken from various vantage points to generate a 2D) or 3D image [23]. Additionally, various research in image registration has been undertaken. The following is a synopsis of some of the journals. Zitova and Flusser provide an introduction to image registration techniques [22]. Also, Studies of overall image registration and reviews concentrate on specific structural parts, such as cardiac [23], retina [24], breast [27], and brain [28]. Other methods are based on non-rigid registration, in which a structure extracted from one modality is deformed to align with a second image [29]. The shifting method was an early method for registering medical images. It entails taking one image and gradually shifting it over a second image. The similarity between the two images was determined at each shift, and the most significant similarity was ultimately chosen for registration [30].In imaging processing, methods that can view objects within the human body are of particular interest. Computer technology advancements have developed precise and effective image processing systems that benefit the medical profession's diagnosis, treatment, planning, and research [31]. Suganya and Priyadharsini have the centre of gravity of the images to perform initial registration. Final registration was Linpeng, and Ping suggested a method for registering medical images called weighted mutual information (WMI), enabling physicians to weigh the image according to the sort of registration required [28]. I. Misra and R. Ramakrishnan present a method for automatically registering remotely sensed multispectral images [7]. The approach is applicable even when the float and reference images originate from different sensors. C.S.Qiao proposes a new corner point matching approach based on singular value decomposition using an image matching method based on feature extractors such as the Harris Operator [27]. Z.Su proposes rapidly registering medical images using multiscale transforms and contour lines [29]. G. Marchal and P. Suetens propose reciprocal information as the matching parameter and use it to quantify statistical dependence or redundant information in the grey values of corresponding pixels in couple images [28]. L. Ding presents a method for registration that involves selecting templates, or sub-images, from an image, locating them in another image of the same view, and using the templates' centroids as control points [27]. M.A. Viergever explains how to incorporate gradient information into a similarity measure to maximize the measure's information content [30].

[16] Proposed using a Normalized Mutual Information (NMI) metric to account for the rise in the significance of mutual information caused by mismatch, which occurs when the number of marginal entropies grows faster than the joint entropy. [31] Introduced a new approach for measuring MI between tiny patches in hierarchical segment registering approaches in 2018. Lu et al. [32] addressed getting trapped at the localized peak while evaluating MI in 2008 because these universal matching metrics ignore local structural characteristics. They devised a novel technique for calculating the joint histogram that applies to rigid and flexible multimodal registration. In 2009, to address the issue of MI-based similarity measures being insensitive to overlap during registration, researchers employed Accumulated Residual Entropy to advise normalized types of accumulated residual entropy-based normalized mutual information and ECC [10]. The writers demonstrated that the suggested similarity processes significantly surpass the CRE-based mutual information similarities test for stiff multimodal registration. Wachinger et al. [33] established a unique approach for multimodal image registration in 2010, built on the idea that images recorded via diverse modalities have identical structural features. They used Laplacian Eigenmaps, a manifold learning method, to describe multimodal images structurally and tested the proposed methodology utilizing virtual MRI scans [34]. Next that year, Wachinger et al. developed a lightweight CNN-based multimodal image registration metric and showed that it outperformed the previously utilized mutual information-based technique by a large side in aligning T1- MRI images [35]. In 2018, Cao et al. devised a strategy centred on a bi-directional image combination for resolving all CT-MRI pelvic image registration issues [3]. Cervenka et al. [36] recently evaluated in comparison various clinical image processing algorithms for multimodal whole-body MRI mosaicking. In contrast, Li et al. [28] used a hybrid (coarse & fine) registration technique to resolve concerns affected by modality-dependent resolution, brightness, and distinction across retina images.

2.2 Medical Imaging

Medical imaging is increasingly being used in the healthcare business to evaluate, plan and direct therapy, and monitor sickness progression [33]. Moreover, these images are used in medical research, namely brain research, to understand better disease processes and natural growth and degeneration [37]. The term "medical image" encompasses various image types based on various fundamental physical principles and is used for various purposes [38]. The images used in medical science and healthcare ranged from video modalities for remote consultation to microscopic images of histological parts and whole-body radioisotope imaging to fundus camera techniques [24].

2.2.1 Types of Medical Images

Primary radiological modalities such as ultrasound, C.T., SPECT, and PET focus on this research. The standard images, such as C.T., MRI, SPECT, and the U.S., are imaging modalities, and they are the simplest in many ways, including image registration [16]. The following discussion offers a concise overview of some of the most prevalent modalities. Various devices are utilized to obtain images of the activities and structures within the human body [12]. The choice of (imaging) procedure for capturing the image is dependent on doctor requirements [7]. Multiple registration tests were performed on the medical images described in the following sections since they represent imagery frequently used for several purposes.

- **X-rays:** The images provided by X-rays depict body parts in various shades of grey (Figure 2-1). Since the calcium in the bones quickly absorbs X-ray radiation, this method is preferred for imaging bones. In addition, today's use of X-rays [5].

- **Computed Tomography (C.T.):** This kind of imagining utilizes specialized X-ray

Figure 2-1: X-Ray of Human Hand [5]

equipment for obtaining cross-sectional images of the human body (Figure 2-2). Doctors employ C.T. scans to detect broken bones, blood clots, cancers, indications of heart disease, internal bleeding, and other conditions [18].

Figure 2-2:C.T. Scan of Human Brain [18]

- **Positron Emission Tomography:** This nuclear imaging system supplies doctors with data related to the functioning of organs and tissues [40]. Nuclear medicine imaging, which includes PET, involves swallowing and is frequently used to evaluate neurological diseases. Muscular dystrophy and Alzheimer's disease, cancer, and heart disease are experimental conditions [8]. Figure 2-3 shows an instance of a PET scan of lung cancer.

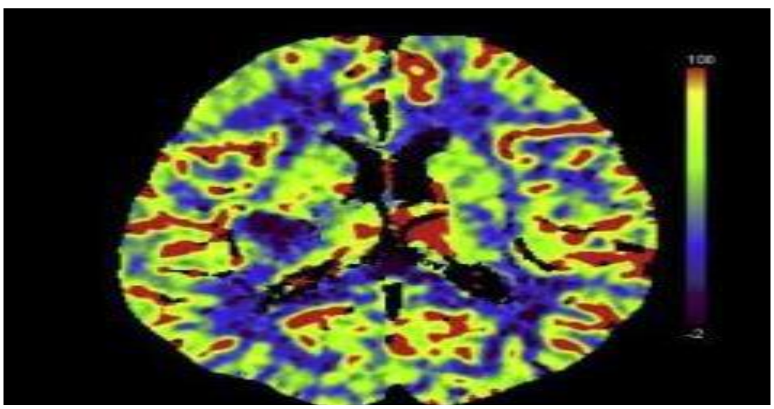


Figure 2-3:PET Image with Brain Cancer [44]

- **Magnetic Resonance Imaging**

An MRI scanner utilizes a solid magnetic field and radiofrequency pulses to create details. It produces cross-sectional images or slices of the body's interior architecture but does not release ionizing radiation [26]. MRI is utilized to identify brain tumours, slipped discs, and inflammation of the spine and assess heart functioning and blood flow, as explained in graph 2.

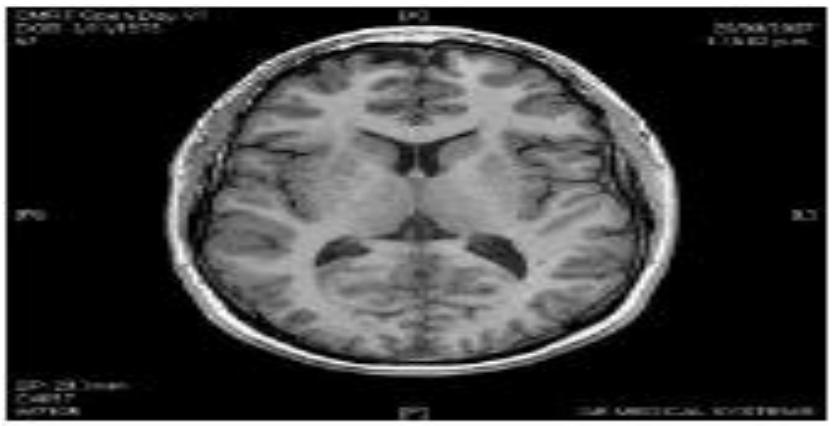


Figure 2-4:MRI Slice of a Human Brain [24]

2.2.2 Categorization of Medical Images

Medical images can be categorized according to several criteria, as shown in Table 2-1. As shown in Figure 2-6, a particular categorization is based on the structure examined by the medical imaging, such as MRI and C.T., to supply data concerning the anatomical issues.

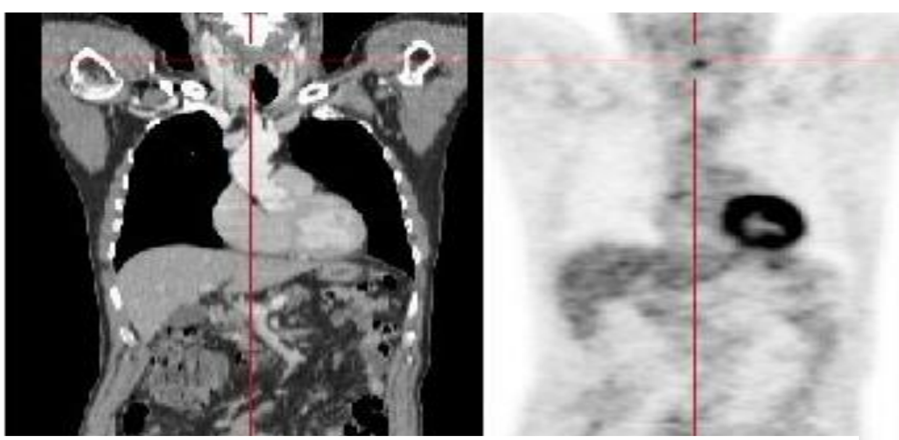


Figure 2-5:Anatomical and Functional Structure [41]

The structure of the organs enables visualization of the tissue of body parts, whereas other devices such as SPECT and PET supply operational data that reveal physiological activities within specific tissue or organs [12]. Table 2-1 lists examples of these two groupings of medical image structure: functional and anatomical.

Table 2-1:Medical Image Categorization

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

2.3 Registration Framework

Registration algorithms are divided into four sections, as shown in figure 2.7:

(1) Similarity metric: The MI among two images is employed to determine their statistical dependence. Furthermore, it is the optimization process's objective function.

(2) Optimization method: to find the target function's maximum value by adapting the conversion variables in a high dimensional space.

(3) Interpolation: the method of evaluating the strength at the interpolation point in the interior of the reference space following rigid transformation.

(4) Transformation: the rigid or Non-rigid move utilized to transport the image's pixels between subject and reference space. Most registration algorithms belong to one of two categories, which are feature or intensity-based.

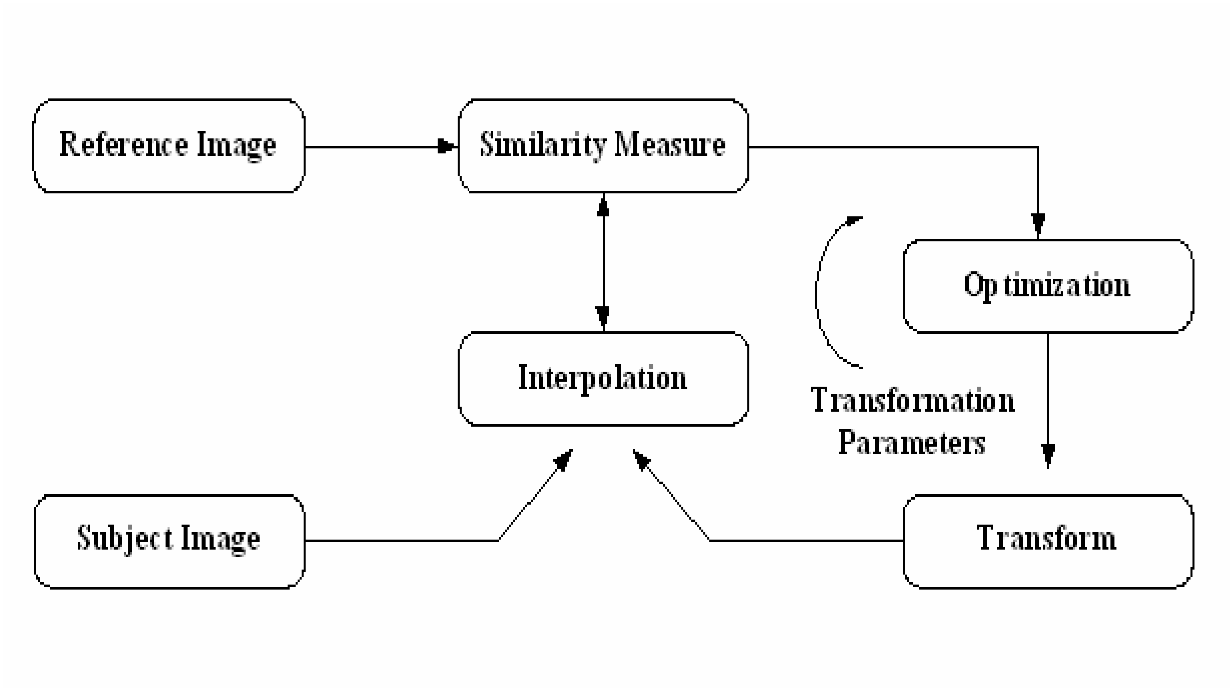


Figure 2-6: Registration Algorithm Stages

2.3.1 Algorithms for Registration Based on Intensity

Intensity-based registration algorithms are summarized in Figures 2.7. The predominant concept identifies the spatial transformation that maximizes or minimizes the cost function with a moving image [42]. The similarity calculation corresponds to the strength of the voxels and is measured concerning overlapping elements of the entered images. The role of the optimizer is to classify the search process [43]. The interpolator aims to resample the voxel's strength for input into the developing coordinate process by the spatial transformation indicated [3].

The registration algorithm's initial response is a pre-registration change, which connects the models more precisely to the reference image. Effective pre-registration speeds up the optimizer's convergence and minimizes the likelihood of a crossover with a local optimum.

2.3.2 Feature-Based Registration Algorithms

Two predominant search methods are employed for finding the best alteration following a feature segmentation approach for entering images [44]. First, similarity among elements is determined via several criteria, such as mathematical, physical, or data elements. Second, the geometric alteration is developed regarding the matches identified, as indicated in Figure 2-11. One instance of such a method is the extraction of features from the images entered. These comprise a range of points, with each point covering a different indicator. Therefore, the associated costs are the gaps between the indication of potential point combinations, and the similarities between entered data are typically expressed in terms of the associated costs. Thus, this method is appropriate when the indicators utilized are invariant concerning the spatial alteration to be reviewed. Generally, registration techniques can be categorized according to the following characteristics [26]:

- ❖ Feature space: The feature space extracts significant and distinctive image features that will be used for alignment.
- ❖ Search space (transformation): The search space refers to the transformations used for aligning the images.
- ❖ Optimization method (search strategy): The search strategy denotes the optimal transformation produced based on the optimizer used.
- ❖ Similarity metric (cost function): The similarity metric determines the cost function that produces the most satisfactory results.

It refers to the three critical aspects of image registration that must be defined: a transformation model, optimization method and a similarity metric. The type of medical images governs the Selection of each of these components. Matching can be conceived of as the optimization of a similarity measure over a range of transformation possibilities. Different meanings for these aspects can rely on the optimal performance, such as robustness and accuracy of the matching outcome. The transition model can be rigid or non-rigid. If the images to be registered result from a technique that incorporates only extreme distortions, a combination of translation, rotation, and scaling, referred to as Multimodal Image Registration, will suffice as a transformation model.

2.3.3 Similarity Measures

Similarity measures are statistical concepts used for the correct alignment of source and target images during registration. These measures determine the registration level of images through a given location. Based on picture intensities or features, similarity measurements among fixed and moving images are computed. Mutual information, correlation, and joint entropy are three strategies that are frequently used to build similarity measurements. The common utilized similarity metrics in medical picture registration are normalized cross-correlation (NCC) [10], correlation ratio(CR) [9], and mutual information(MI) [3][14]. Both the normalized cross-correlation and correlation ratio imply a beneficial relationship among the strength values of the two pictures, with the earlier implying a linear relationship while the end is permitting any beneficial relationship [2]. Mutual information (MI) is a strength-based similarity metric that calculates the similarity between multimodal images automatically also, is a statistic derived from information theory quantifying knowledge that one random variable (image) provides about another [13]. By integrating spatial information, such as gradient magnitudes and Enhancements to the mutual information assessed have been suggested by incorporating spatial information such as gradient magnitudes and orientations, as well as other statistical spatial dependencies [16].orientations, and other statistical spatial dependencies, enhancements to the mutual information measured have been suggested [16]. Joint entropy is a widely used knowledge metric in digital image processing. Both normalized cross-correlation and correlation ratio suggest a functional link between the two images' intensity levels, with the former assuming a linear relationship and the latter implying any functional relationship [2].

2.3.4 Convergence of Optimization Methods to Local Maxima

A strategy must be chosen for exploring the state space for a set of transformation variables that best match the two images using the supplied similarity measure [10]. There are both non-derivative and derivative-based optimization approaches that iteratively select parameters to minimize the similarity metric. In normalized cross-correlation and mutual knowledge, it minimizes the negative value of their functional meanings. Because the high-dimensional of the hypersurface defined by the similarity metric may not be a convex function, optimization approaches typically converge on local extrema [15]. As a result, effective registration requires early predictions or approximate alignment when employing non-global optimization algorithms. Equally critical is the technique employed for interpolation. When converting a floating image to a fixed image, it is essential to supply non-integer grid points for the floating image. Interpolation is necessary to determine the significance of the target image at the specific non-integer points. According to Netsch et al. [25], while quadratic and cubic interpolators outperform linear interpolators, larger interpolators do not. Numerous optimization techniques have been established for medical models registration to prevent local maxima and increase similarities, such as accumulated understanding and cross-correlation. However, additional research is necessary to enhance advanced image process optimization techniques.

2.4 Classification of Medical Image Registration Methods

Medical image matching research has been extensively documented in the literature, and several classification methods for categorizing clinical image processing algorithms have been examined. Presented here are categorizations that are dependent on which registration algorithm is employed. In general, as illustrated in Figure 2-8, registration processes can be split into two basic categories: Visual and computerized approaches.

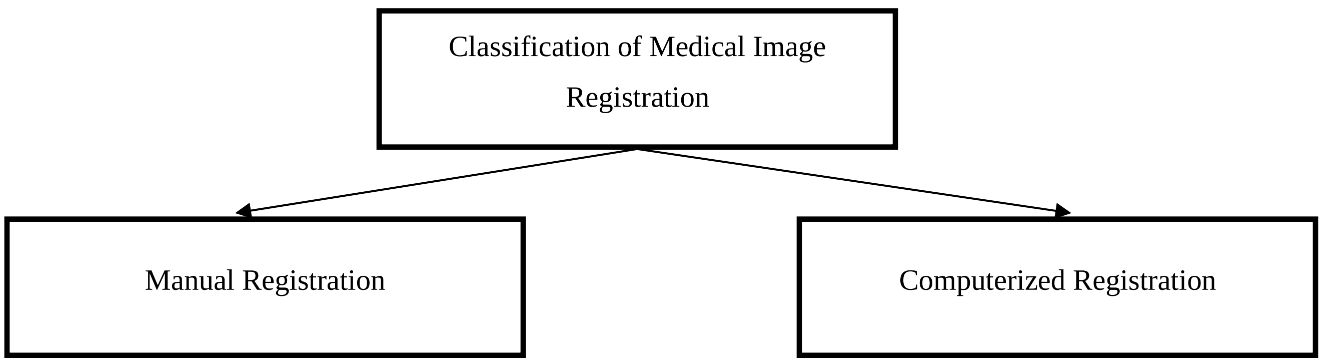


Figure 2-7: Classification of Registration Algorithms

2.4.1 Manual Registration

It is a manual process performed by the radiologist /physician to analyze the content of multiple images. Researchers occasionally must associate photos of numbers of patients rather than working with several images of a single person. The result is that, as part of their regular workload, specialists must visualize and interpret a vast number of medical images and radiology reports. Potential advantages are associated with enhancing how such images can be coordinated and compared visually. The usual clinical practice is printing these images on radiographic film and viewing them in a lightbox, as shown in Figure 2-9.

Figure 2-8:Manual Registration

The number of medical images has increased due to developments in medical imaging devices [14]. Visualizing and interpreting such many medical images is considered time-consuming. In addition, many recent research studies have been targeted at analyzing visual alignment issues and how such issues may result in differing diagnoses. For example, breast cancer research undertaken at the University of Michigan revealed that the treatment given to more than 50 % of patients was changed following a second opinion of the diagnosis provided by a "tumour board" of radiation experts, surgeons, and oncologists [45]. Furthermore, according to a Johns Hopkins University study, one to two patients out of every hundred who seek a second opinion following a tumour biopsy receive an incorrect diagnosis. As a result of these factors, the results of optical alignment are dubious and unreliable [47].

2.4.2 Medical Image Registration Based Computers

Computerized approaches may have advantages because they allow for accurate alignment within images and view the coordinated images. The registration or alignment of the medical images is a critical element in this procedure. Numerous classification schemes exist for the various registration techniques. Numerous researchers advocate for a nine-dimensional classification method that produces high-quality results [48]. Numerous approaches to medical picture registration are being established, and numerous classification criteria have been proposed, as shown in Table 2-2. Elsen, Pol, and Viergever classified them according to several criteria: the dimension of the dataset (2D, 3D); the registration base (intensity-based/feature-based); the transformation domain (local or global); the transformation's nature (rigid, non-rigid); the modality (monomodal, multimodal); the subject (intrasubject, intrasubject, atlas subject); and the interaction (interactive, semi-automatic, automatic).

Table 2-2:Registration Methods Classifying Criteria

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	Multi-Modal	Inter-Subject	Kidney
2D-t0-3D			Auto interactive		Atlas-Subject	Liver

- **Image Dimensionality**

The dimensionality criteria are classified using both time series and spatial dimensions. The spatial dimensions of a picture are proportional to the number of geometrical dimensions included within it. Medical applications are frequently several dimensional, and they might occasionally be two-dimensional [46]. Additionally, registration algorithms can calculate the appropriate transformations based on the images' coordinates and the input image. Additionally, registration can be accomplished using consistent point pairs or related surface couples [19]. The primary categories of image dimensionality are as follows:

2D-to-2D: Registration of the images can be accomplished rapidly and easily by rotation and orthogonal translations if the model capture process firmly controls the geometry of the images [46]. Additionally, it may be necessary to compensate for discrepancies in scaling between each image's real-world counterpart. Thus, picture acquisition control is frequently a highly taxing task.

3D-to-3D: In this case, the registration procedure depends on the presupposition that the patient's internal anatomy is not changed or distorted within the spatial interactions among any organs. In general, 3D-to-3D aligns tomography datasets or individual tomography images with spatially described data [47]. Scaling the scanned images needs a detailed study of each scanning device; understanding this constraint is critical. 2D-to-3D: The registration technique is used in this scenario to establish correspondence between 3D projection dimensions and projection images, such as optical images or X-rays.Time-series: The term "registration based on a time series" requires the alignment of clinical images of the same or different subject across time, which can aid in detecting illness progression and analyzing handling response [2]. This method can thus offer an opportunity for more extraordinary meticulousness and precision of treatment. The obtaining of temporal image sequences has been possible because of recent improvements in medical imaging. Compared with static images, these sequences provide further data concerning the movement of the body organs imaged, such as the liver. Ledesma, Preperiodic, Grau, and Peyrat explain the geometrical registration of liver images [48].

- **Basis of Registration**

Medical image registration is categorized as either extrinsic or intrinsic techniques according to the nature of the registration base [19].

1- Extrinsic Registration Techniques

This approach attaches apparent artificial objects to patients, requiring that they are detectable in every modality collected. The principal elements of these registration techniques are simplicity of automation and computational efficiency. However, these systems need no complicated optimization algorithms since the transformational parameters can be easily calculated. Extrinsic approaches do not incorporate patient picture information. Due to the complicated nature of the registration conversion, techniques are typically limited to inflexible ones, with only rotation and translations being used. Due to severe transformation limitations and various practical issues, employing these techniques to images with minimal spatial available data involves obtaining additional spatial data from another viewpoint [14].

The following are instances of related external items frequently used in medical imaging [49]:

a) A stereotactic frame emphasizes the patient's exterior brain table to the maximum extent possible [50].
b) Using screw mounting to obtain external markers [**15**].
c) Skin-attached markers [16].

2- Intrinsic Registration Techniques

This categorization uses patient-supplied data, such as conspicuous landmarks, partitioned decimal frameworks, or pixel image intensities [30]. In this example, any prominent and recognized elements in an image, such as points, curves, and surfaces, are coordinated with corresponding features in another image. [23].As a result, whereas a pair of landmarks corresponds exactly, interpolation is utilized to deduce the correspondences for the remainder of the image volume and the coordinating landmarks [51]. The used landmarks can be identified physically or geometrically by assessing differences in voxel intensity across the entire image. Of course, landmarks can be established manually, but the precision of the location measurements inside the registration operation is significant when using manual recognition.

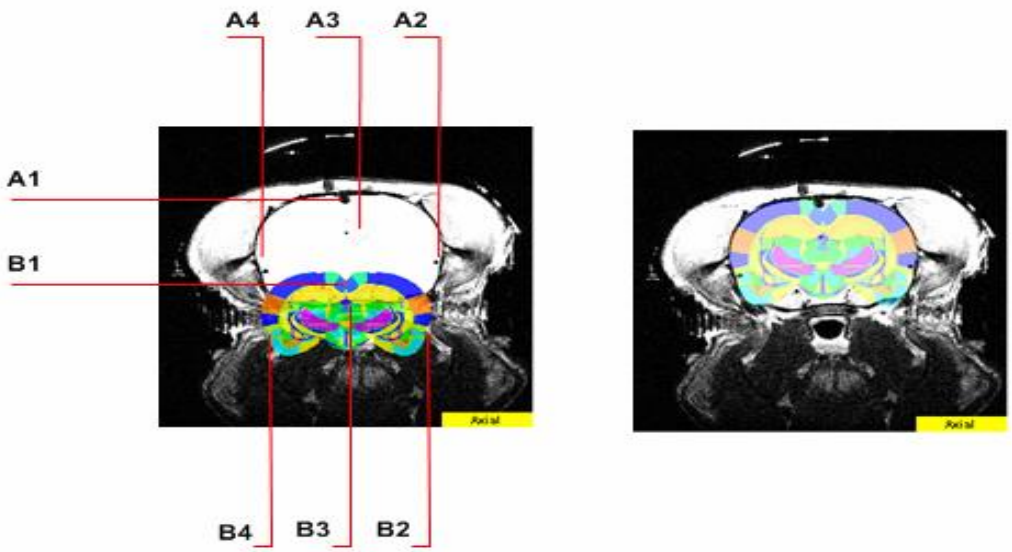


Figure 2-9:2D Landmark Registration

- ### Techniques for Registration Based on Segmentation

When segmentation-based techniques are applied, non-rigid or rigid paradigms form the basis of the registration procedure [3]. Furthermore, the surfaces are removed from both images in inflexible paradigms and utilized to input the registration procedure. In deformable paradigms, the curves or exteriors are removed from only one picture and used to match the other image through elastic deformation [24]. It is essential to be aware that inflexibility-based techniques are less complicated than deformation-based ones. The complexity of deformable techniques arises from specific regularization terms within the cost function; for this reason, inflexibility-based techniques have, for some time, proven to be the most popular choice for clinical applications. An additional factor is that undertaking a segmentation procedure is reasonably straightforward and entails a comparatively low degree of computational complexity, making this technique preferable. For this reason, much of the published literature discusses automatic segmentation as a means of improving optimization implementation of the extension of a technique [52].

- **Methods Based on Mutual Information**

Each image's intensity patterns are coordinated based on statistical or mathematical criteria [53]. These strategies are predicated on the premise that photographs with the precise register will have the most significant degree of resemblance. The similarity of the brightness of the input pictures is utilized to drive transformational changes until optimal similarity is achieved [3]. The main voxel-based similarity evaluation methods are mutual information (MI), normalized correlation (N.C.), the average squared difference (MSD), and normalized mutual information (NMI) [54]. For antra-modal matching, the sum of squared grey value differences (SSD) can be applied to distinguish among input images with the same grey-level framework. If no identical grey-level structures exist, but there is a linear dependency among the grey levels, cross-correlation (CC) can be used. Due to the lack of linear dependency in multimodal registration. Because they benefit from producing acceptably precise results, the similarity evaluations most frequently employed are MI and NMI. The authors utilized various approaches to obtain data related to image-based registration, including a Parzen window and spline pyramids [55]. Alternative techniques include a hierarchical search process and simulated annealing, Brent's approach, and Powell's multidimensional directional method [5]. The effectiveness of such processes and approaches concerning optimizing mutual data have been researched by scholars such as Vandermeulen, Suetens, and Maes [56]. Antoine, Viergever, and Josien also scrutinized image registration processes based on mutual data [30].

- **Hybrid-Based Registration Methods**

The intensity and geometric aspects can be coordinated with the use of hybrid-based methods [57]. The objective is to provide more robust techniques to establish more precise correspondences within problematic registration factors such as hybrid multiscale landmarks and deformable registration algorithms[14]. The disadvantage of this strategy is that it is effective only with a restricted number of certain sorts of medical photographs in specific circumstances. These techniques coordinate the intensity and geometric aspects; the objective is to present more robust techniques that institute more precise correspondences within problematic registration matters such as hybrid multiscale landmark and deformable registration algorithm. The drawback of this method works with limited medical images under specific conditions. In [49], moments are used with a classical method to classify stiff bodies according to their spatial breadth. The primary axes refer to the orthogonal axes by which the moments are reduced. If two objects are identically similar aside from a rotation and a translation, they can cause their principal axes to come into coincidence to register them precisely. If two objects have a likeness in shaping, a rough registration can be acquired via this method. Suk and Flusser obtained affine transform invariants and subsequently utilized them for registering Landsat and SPOT images [7]. Moment-based techniques are also used in hybrid registration processes, which accept segmented or normalized picture data as input. Pre-segmentation is required in various instances if moment-based techniques are to provide good outcomes [58].

- **Surface Methods:**

Within medical images, surfaces are significantly more distinguished than landmarks [19]. Therefore, they can be implemented for segmentation by utilizing suitably different surfaces. Algorithms are usually utilized to combine surfaces for stiff body registration [55]. Surface representation is a boundary-centred method for registering multi-modality brain images, as shown in Figures 2-11. An array of points taken from a cloud of points in one image is fitted into a boundary model and exported from the contours within the second image [59]. The image encompassing the more sizable patient's volume, or the image with a more enhanced resolution if the volume quantity can be compared, is utilized to acquire the boundary model**.** A further version of boundary combination gives the patent a navigation transformation application that permits the user to rotate and translate an image about the others [32]. Audette and Ferrie **[26]** have scrutinized the model-centred registration approaches within medical images. Pelizarri suggested a surface fitting approach to register head images, referred to as the 'Head and Hat Algorithm' (2). The registration algorithms that have been advanced latterly include the Iterative Closest Point algorithm [**29**] and Correspondence combination. Jack and Roux in [24]have suggested devising the difficulties with boundary registration as a multi-dimensional maximization issue, which can be resolved via a genetic algorithm.

Figure 2-10:Surface Registration Method

- **Curve Methods**

Several registration methods employ curve-matching approaches. In [60]**,** Butler reported using a curve-matching process for the registration of 2D images. He devised various related points for registration and attempted to find the corresponding curves for the subsequent registration of 2D projection models. Moreover, he tried to determine the best possible fit of local features and curvatures within both curves to combine associated open curves. Andre and Nicholas Pin [31] described a method for combining 2D and 3D medical pictures. In their method, fixed lines on organ boundaries relate to purposeful anatomical elements and are steady relative to stiff alterations. The author has utilized third-order derivatives of the strength of the image role with the suitable 3D sifting of the volumetric data. The combinations were then established based on a refreshed geometric hashing process. Final matching was achieved using a new geometric hashing approach. Wen [46] asserted that a medical image registration process implements points, suggesting contours and curves. This method combines the precision of feature-based registration with the stringency of line-based registration (such as contours and curves.).

- **Networks of Artificial Neural Systems**

A neural network, also known as a mathematical model of biological brain networks, is widely used in an artificial neural network (ANN) [61]. An ANN encompasses an interrelated set of artificial neurons and data through a connectionist computation method. A neural network is frequently an adaptive process that alters its structural foundation due to external or internal data available to the network during the learning or training stage**.** For example, an ANN incorporates alterations to the network construction and the connection weights during the training stage to learn about intricate nonlinear input-output associations [51]. Several methods involve the use of an ANN: radial basis functions [62], self-organizing maps[63], and Hopfield networks [64]. In image registration, these approaches can be employed with a variety of computational elements. Heng and David in [9]suggested a three-layer neural structure for identifying the registration matrix for a 3D image. Li and Tan described applying a pulse-coupled neural network for addressing the difficulties associated with multimodal model fusion based on image regions[65]. Zhang and Yi employed a principal component analysis (PCA) to register CT-MR and MR-MR medical images[66]. Zhang and Ong outlined a 2D boundary-centred stiff matching process that employed an ANN for surgery-guiding systems [67]. A genetic algorithm (GA) seems to be a search process employed in computations to seek precise or approximate answers to optimization and search problems. GAs have been used in medical picture registration [68]. They are classified as global search heuristics and are defined as a particular evolutionary method. Researchers Jean-Jose and Roux outlined a new approach that uses a canonical GA to register 3D MRI and PET images for volume-to-volume and surface-to-volume matching [69]. GA-based optimization has also been employed to produce the best solution for boundary registration issues and determine transformation parameters for rigid and deformation registration processes[70].

- **Nature of transformation**

According to the literature review, there are two sorts of transformations: rigid and non-rigid. A stiff transformation is most frequently used in two situations [13]. The first case is rigid structure registration, such as skeletons, and the second situation is pre-registration, which is used to speed the registration process [71]. The non-rigid transformations are not commonly used in the final registration stage but in some samples [27]. Each mapping approach is categorized into two broad classes: rigid transformations and deformation transformations. Each 2D and 3D image is modified rigidly; for example, by rotating, translating, sharing or scaling, or showing objects using the same methods that maintain angles, distances, and lines [3]. This transformation may be depicted mathematically as in Equation 2-1, with as many as two parameters [72].

$$\begin{pmatrix} x_1 \\ y_1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & Tx \\ 0 & 1 & Ty \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{2-1}$$

The rigid type transformation, including brain or bone registration during which neither the dura nor the skull has been opened, is found in medical image registration [73]. Furthermore, this may be utilized to line up those pictures that include minor alterations in the object's shape. Since many strict body limitations within several medical images result in an excellent approximation, rigid techniques are popular. Moreover, this classification of techniques includes some parameters to be established, and ultimately several registration methods are unprepared to apply further complicated transformations [74]. Even though rigid techniques have their uses for registration in fixed bodies, many body organs possess spatial geometric variations requiring more non-rigid techniques if the registration task is achieved. Non-rigid approaches provide adequate flexibility by integrating the input data via spatially distinct local warping [19]. Figure 2-12 illustrates a non-rigid (local) deformation methodology, illustrating how it is more flexible than rigid (global) approaches while also demonstrating the intricacy of such techniques [37]. Furthermore, Non-rigid techniques include affine transformation, perspective projections, and similarity transformation; As defined in Equation 2-2, affine transformation can be defined as a sharing, scaling, or rotation of the lines, or as an independent translation that retains the lines' intersection and parallelization qualities but not their lengths or angles [19].

$$\begin{pmatrix} x_1 \\ y_1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ \xi y & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & \xi x & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \alpha x & 0 & 0 \\ 0 & \alpha y & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{2-2}$$

This similarity transformation is regarded as a specific situation of non -rigid transformation that maintains the angle. When simply rotation, translation, or uniform scaling are utilized, the distances between the lines or the placements of the spots do not affect. To summarise, point of view projection is a sort of conversion that does not retain the characteristics of the lines as it maps from one to the other. [75] contains further information on these techniques. Most non-rigid registration methods are used in various applications, ranging from tissue malformations and anatomical structure differences to modelling. When managing flexible registration, it is critical to keep in mind that this is considered an open study topic due to the deformation procedure's significant degree of freedom and smoothness.

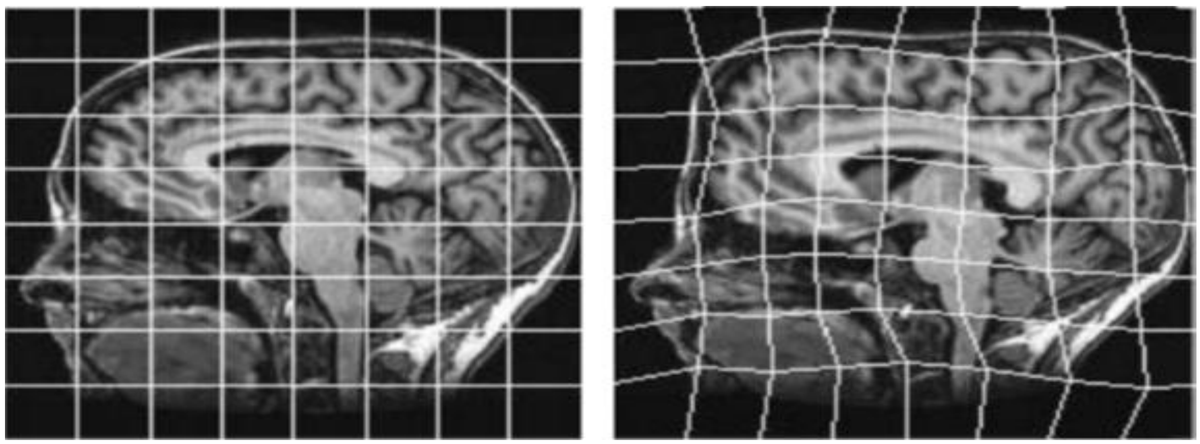


Figure 2-11:Non-Rigid (Local) Deformation [41]

- **The domain of Local or Global Transformation**

Images can be transformed in two ways: locally or globally, as illustrated in Figures 2-13. Global transformation is attained utilizing mapping frameworks that are valid for the whole image; feature-based registration is an example of a global transformation [67]. Local transformation entails modifying a tiny area of the image. When the dimensions of a local mapping are valid only for a small spot surrounding the location of the chosen control point, intensity-based registration is an example of local transformation [67].

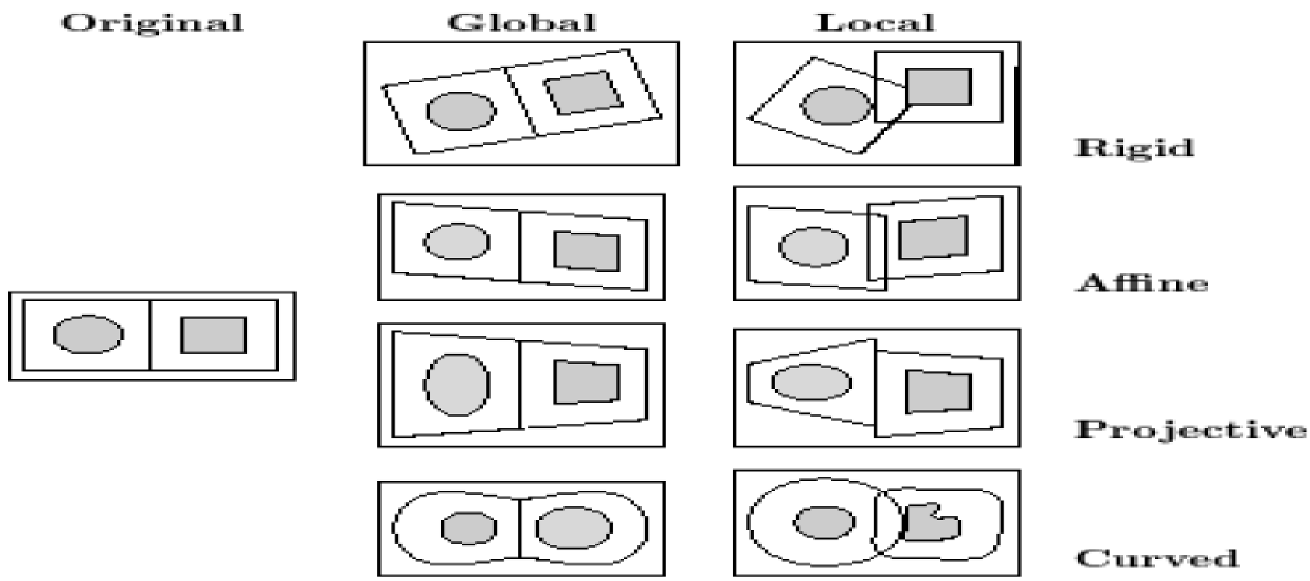


Figure 2-12:The Domain of Transformation [71]

Image registration techniques have three interaction levels founded on the relationship between the registration procedure and the user. Some software utilizes interactive algorithms to attain the registration task, employing the parameters' estimation of the initial transformation; contrastingly, automatic algorithms operate without interaction. Furthermore, semi-automatic algorithms start by categorizing the input or guiding it to the proper answer [24]. Recent developments have resulted in a trade-off between accuracy and power to maintain a minimal degree of contact. Interaction with the user constrains the search space, rejects mismatches, and accelerates optimization using specialized strategies. Additional human participation complicates the validation oppositely, as does the lack of quantification or control at the interaction level [36].

- **Modalities**

Four distinct sorts of registration missions are based on the various registration images used. In comparison with other types, the best-known kinds are the multimodal and mono-modal tasks. While registration happens between modalities of the identical medical modality in mono-modal missions, it occurs across images of distinct medical modalities in multimodal tasks [26]. Additional registration tasks include model-to-modality and modality-to-model registration, using one image or including the patient as an additional registration input. The model-to-model mission is repeatedly used in intra-operative process approaches [76], whereas the modality-to-model mission can assist in skin morphology by collecting statistics. Mono-modal tasks help in the application, which manages comparison of rest-stress, verification of intervention, monitoring growth, subtraction imaging, and a considerably more significant number of applications.

In contrast, multimodal tasks help in applications generally classified under the diagnosis concept and surgical guided system. Functional anatomical and anatomical–anatomical represent the principal classification in which the multimodal task can occur [38]. These classifications differ in that the anatomical registration aims to amalgamate images that demonstrate varying tissue morphology sides, whereas functional–anatomical registration aims to associate the tissue metabolism and its linked spatial position concerning the anatomical frameworks. Furthermore, despite the difficulty of the multimodal registration task, this can involve particularly intense mapping dissimilarity because the images are received from various modalities; this registration type presents images that demonstrate anatomical and physiological data. Subsequently, this can help in both clinical diagnosis and therapy [77].

- **Subject (same patient, different patients, atlases)**

The development of medical image registration has been applied to almost every organ or part of the human body [78]. This subject adds another dimension to image registration techniques by referring to the patients whose images are registered using this technique. As a result, these registration procedures can be separated into three classifications: atlas, inter, and intra-registration. This classification is determined by whether the relevant images depict the same or distinct patients, or if one image depicts the patient, another is from a database [2].

(a) Intra-subject registration techniques: These aid in achieving various clinical benefits by precisely aligning images obtained from the same subject but using a different modality and time. These can aid in identifying any differences in the form or intensity of the framework [42]. This classification technique is most frequently used in diagnostic and surgical procedures, as well as interventional procedures. These are most typically used to align repeated brain MRIs.

(b) Techniques for inter-subject registration: The photos used in the registration operation are of distinct patients in this classification. As a result, this registration type is frequently used to establish size and form changes and grosser topology changes [42].

(c) Atlas-based registration techniques: When applied, one input image is collected from one patient, while the other is built through an image database obtained through many subject images

[32]. Therefore, this registration classification displays assistance in gathering statistics regarding the shape and size of a specific framework.

- **Object**

Researchers have established medical image registration for major components (organs) of the human body: brain [47]; retina [24]; chest/lung [79]; breast [**28**]; liver, kidney, and spleen [32]; prostate [79]; the entire body [80]; vascular structures [81]; bones [12]; knee [82]; and spine [21].

2.4.3 Formation and architecture of a software

A significant amount of resolution software has been produced for medical image registration. Table 2-3 lists free, open-source programs that offer several registration techniques [**85**].

Table 2-3:Current Image Registration Systems Examples

Registration Tools	**Author**	**Year**	**Description**
FAIR	Modersitzki	2009	Stands for Flexible Algorithms for Image Registration
AIR	Woods,	1998	Automated Image Registration: A tool used for automated 3D and 2D image registration processes [83]
ITK	Ibáñez	2005	ITK toolkit is a fully accessible toolkit that facilitates registration by providing four distinct registration materials: similarity measurement, transform, optimize, and interpolation. [85]
FLIRT	Jenkinson	2010	Framework for Linear and Nonlinear Registration toolkit
Elastix		2008	This toolkit concentrates on medical pictures and assists with establishing, testing, and comparing various registration methods. [86]
ANTs		2009	Advanced Normalization Tools: Registration of images using variable transformations (rigid and non-rigid) and similarity metrics (landmarks, cross-correlation, mutual information); segmentation of images using various approaches. [87]
MITK		2006	The Medical Image Registration Tool Kit is an accessible toolkit for medical image registration based on the ITK toolkit.

MIPAV		2004	Image Analysis, Analysis, and Visualization deliver a comprehensive variety of medical image processing services. [88]
NITRC		2010	Neuroimaging Informatics Tools and Resources Clearinghouse, an innovative set of software services that provide free resolutions for revising medical images [89]

Free medical pictures are also accessible for research study from sources such as the Brain Web project's website, which contains a modelled head database incorporating three MRI phases (T2, T3, and proton density), and the website contains modelled PET data.

2.5 Algorithm Selection

2.5.1 Introduction

The research domains associated with algorithm selection methods are abundant and highly distinguished. Numerous algorithm choice techniques, or constraint tuning methods, are adapted to a particular process and frequently provide intriguing results throughout several research areas [83]. Several studies have been conducted in various disciplines, using different terminology and ignoring approach similarities, whereas "all of these fields will benefit from a deeper understanding of the successes across several cross-disciplinary projects for algorithm selection. The process of choosing the optimization technique for a particular problem instance is known as algorithm selection, and it has appeared in numerous forms and is under various names in various domains over the previous few decades [84]. Historically, algorithm selection has been used to resolve classification challenges in the area of machine learning. Smith-Miles extended this technique to include regression, classification, and optimization [7]. Most scholars have concentrated on novel techniques for addressing and resolving this issue in practice. When applied to a range of search problems, the emerging algorithm has significantly increased performance using various recently developed systems and techniques. This study summarizes the existing knowledge and describes the research process. Researchers have long understood that no single algorithm can give maximum efficiency in all instances of a problem that requires a solution and that selecting the best appropriate strategies will almost certainly improve overall performance [85]. The concept of Algorithm Selection is quite broad and has frequently been applied in various academic domains. Nonetheless, another terminology is frequently used. Borrett, for example, used the term algorithm chaining to describe the process through which switching algorithms are used to solve online algorithm selection problems [48]. Lobjois and Lemaitre [18] defined Algorithm Selection using the term selection by performance prediction. Vassilevska [86] used the tenure hybrid algorithm to denote the permutation of a collection of procedures using the Algorithm Choice model. Algorithm Variety is commonly defined as meta-learning in Machinery learning, as Mechanism selection models can teach when certain Machine learning approaches should be applied. Nevertheless, early attempts referred to hybrid strategies, such as. Utgoff. Aha [87] proposed principles for picking a Machine learning model that considers the attributes of a dataset. He coined the phrase "meta-learning." Bradley [74] coined the term "selective preeminence," meaning that a particular algorithm is best for some tasks but not others. Algorithm selection is classified as meta-heuristic or hyper-heuristic in the realm of heuristics. Cowling [21] coined the term hyper-heuristic for the first time. It has gotten ingrained in the folklore of Artificial Intelligence, and its actual roots are obscure. The phrase was probably first used in the paper that proposed Tabu search [85]. Along with the plethora of labels used to explain the Algorithm selection process, scholars have used various terms to describe the models of what Rice referred to as the achievement metric space. Allen and Minton [78] identified them as runtime performance indicators. The phrase Experimental Rigidity model was coined by Leyton-Brown et al. [88]. Nonetheless, the above-mentioned experimental hardness models analyze just processing time performance. In all situations, the method is chosen based on the anticipated measurements. This study summarized previous research on algorithm selection, focusing on challenges involving combinatorial search. Diverse techniques have been classified as fundamental elements that influence algorithmic choice in the subject. The introduced categorization is based on various low-level facts and additional criteria to clarify the underlying concepts. Furthermore, additional information is supplied regarding the different ways that can be used to solve the technical issue and the numerous strategies that have been used in practice to find solutions. The study is limited to providing a thorough and high-level overview of the area. The algorithmic space is the popular algorithm that is used to solve a particular issue. The algorithm space, in our arrangement, also contains alternative constraint sets for the machine learning algorithm. The program's creators created it to facilitate the deep learning algorithm changing behaviour [89]. Combinations of potential parameter values constitute an algorithm's parameter space or configuration. The key performance indicators space contains various metrics that describe an algorithm's behaviour concerning a particular challenge. It could include the precision with which instances are classified, the speed with which they are executed, and the amount of RAM used. Several studies on algorithm selection could be found in the area of machine-learning. “LLAMA [90] viewed algorithm choosing as a specified language and undertook an evaluation of different previously existing approaches,” L. Kotthoff. Indeed, it proved that the Algorithm Selected Structural is in general unsolvable. It may be desirable to choose a generalizable mapping over one that performs optimally. Additionally, various considerations can be considered. For instance, he examined many technique selection models and chose one that demonstrated acceptable performance while remaining easily intelligible [86]. [89] also picked a method based on the same premise. Similarly, [85] chose a model with low computation costs over one with optimal performance. They noted that "each of these approaches incurs a higher computing cost than ridge regression, and our earlier experimental findings indicate that the predictive performance is not substantially improved to justify these additional costs. The algorithm choosing problem can be phrased as follows in computer science: Which method, among several feasible alternatives, is most expected to do efficiently for different problems? A typical paradigm for this challenge is described in Figure 2-14. In this shape, the f(x) features can be extracted to identify a given problem x and then a solution algorithm A is chosen. The output of the algorithm is then quantified (p(f(x); A). Algorithm choice has been used to solve various optimization issues in the previous work, counting model selection, estimate, dimensionality reduction, and protein detection. L. Kotthoff [94] defined four requirements for a problem to be susceptible to method selection analysis, which is: (1) There are numerous versions of the major issue with different complexity; (2) There is a range of potential methodologies for fixing the issues with varying degrees of complication and efficiency; (3) There are generic, and specific measures for measuring the performance of algorithms on a particular topic, and (4) There is a collection of accessible characteristics that characterize issue cases that may be utilized to evaluate the performance of processes on the issue.

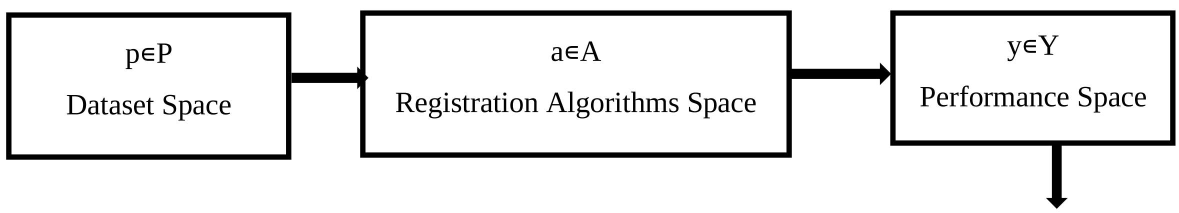


Figure 2-13: A Model Addressing the Problem of Algorithm Selection [11]

Rice then provided realistic examples to illustrate the model's applicability. Next, he improved the original model by including characteristics correlated with issues used to classify the selection mapping. Figure 2-15 depicts the initial illustration of the refined model. The illustrated model, or a variant thereof, is the most frequently used in most functional approaches. The incorporation of features is often the deciding factor in determining the viability of an approach. The feature extraction is carried out for each challenge in each setting. These features generate a matching that enables the optimal algorithm for each challenge to be selected [34]. Determining the exact output matching for each challenge algorithm pairing is less critical if the single best algorithm is detected. Rice inquired more about the recognition of features [91]. Which characteristics are most predictive of the performance of a specific algorithm, a category of procedures, or a set of selection transformations?

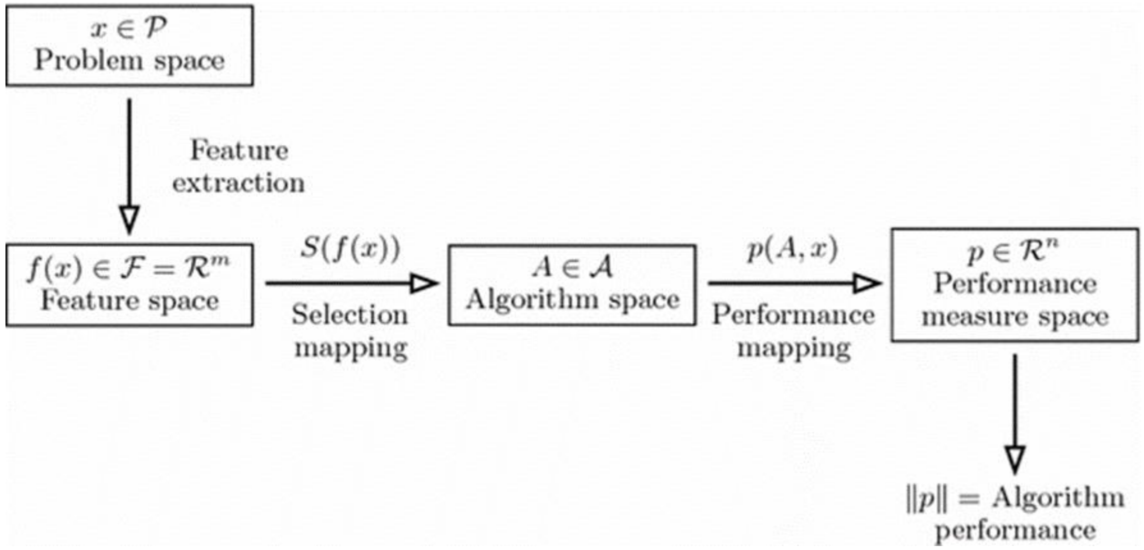


Figure 2-14:Algorithm Selection

Additionally, he stated that "determining the optimal (or even appropriate) characteristics is a fundamental, but poorly defined, component of the algorithm selection problem. He alluded to the difficulties inherent in comprehending the problem space. Multiple problems are challenging to comprehend, but a set of challenges is often used to conduct an empirical assessment of a specific algorithm category. If this sample does not accurately reflect the problem of the features and does not allow for a sufficient differentiation of the issue categories in the characteristic space, there is a bit probability of obtaining an optimal or helpful choice mapping. Bradley stated, "While it may appear that limiting an empirical to a particular situation would lower its efficiency, we believe that the capability of efficient pickers to split the optimal solution of specific NP-hard problems is somewhat surprising [27]. Many scholars have endorsed this perspective, and the crucial importance of Algorithm Selection systems, especially in the case of problems involving combinatorial help, is expected primarily to the surprising fact that they function. Machine Learning is used in most techniques to learn output mappings from problems to algorithms using problem-specific features. The training data generated can be applied to build a performance model that can estimate new, unobserved problems.

2.5.2 Algorithm Selection Approaches

This section discusses current enhancements in algorithm choice by offering an overview of the strategies developed throughout the last two periods to resolve algorithm selection difficulties.

1. Advisor for Statistics and Data Mining(DMA)

The Stat Log project's first large-scale meta-learning analysis[69] employed nineteen data features and ten procedures. This method identified algorithms as relevant or non-appropriate throughout the training process based on their closeness to the learning classification on provided data. A tree-based model was constructed for each method to forecast its application on unseen data. Finally, the scheme developed a set of learned regulations that needed to be physically verified. The Stat Log concept was extended upon [26] in the proposal: Meta-learning assistant for assisting users with data mining and machine learning tasks by investigating image classification and combination methodologies. The Data Mining Adviser (DMA) is an internet system that ranks categorization algorithms for users [25]. This strategy recorded the actual performance indicators for each algorithm and trained a k-Nearest Neighbor method to forecast how well the strategies will operate on the unseen dataset. As a result, a score of all processes is generated depending on the user-defined objectives.

2. The Electronic Assistant for Intelligent Discovery(IDEA)

Bernstein created the Intellectual Exploring Electronic Assistant (IDEA), the world's first to plan data analysis device capable of creating workflows [88]. This method considers pre-and post-treating operators and resumes all pertinent proposals (series of actions) for the specified difficulty. This framework comprises an ontology of operations that describes the prerequisites and consequences of each operator and physically specified criteria that enable it to rank all prepared plans corresponding to the user's purposes. Ultimately, built on this rating, the operator can choose multiple processes to process the given data. After implementing the method, the user will examine the findings and adjust the weights to acquire alternate grades. For example, the employer can trade specific velocities in compensation for a further precise model. Lastly, if realistically limited workflows are detected, the approach lets for their inclusion as additional operators in the ontology.

3. Intelligent Discovery Assistant e-Lico (eIDA)

The e-Lico Artificial Exploring Assistance (eIDA) developed from the e-Lico executes data mining procedures depending on the user's primary aim and input data specification [26]. It takes advantage of the Ontology for Data Mining Workflows (DMWF), which encodes operational inputs, outputs, prerequisites, and impacts as Domain-Specific Rule Language (SWRL) laws (which are stored as ontology annotations) [92]. Additionally, it makes use of such a Flora2 HTN planner [7]. A query is made against the DMWF ontology, and the resultant inputs, outputs, prerequisites, and impacts are converted into Flora3 for informational purposes. Following that, these plans are graded and use a second taxonomy, the Data Mining Optimizing Ontology (DMOP), which contains information on the detailed features of the operators [56].

Additionally, the framework contains a modelling approach, eProPlan, that enables the modelling of data mining operators and the design of the HTN language that drives the development process [92].

4. WEKA

Auto-WEKA is a method that assists learner machine learning employers by allowing them to search the combined area of WEKA's learning procedures and associated hyper-parameter locations to improve a specified performance metric, for example. This accuracy used a novel Bayesian optimization process [85]. As a result, this problem, dubbed Merged Algorithm Selection and Hyperparameter Optimization, is defined as a continuous hierarchical hyperparameter objective function, with algorithm selection acting as a hyperparameter [93]. Instead of creating a classifier, WEKA's three-characteristic search technique and eight feature assessors were used to preprocess the data. Auto-WEKA analyzed data using two different reference systems [92]. The first approach uses default parameter values and conducts tenfold cross-validation on the training set to get the classifier's minimal mean misclassification error. The second more robust baseline, dubbed random grid, employs grid searching for classifiers in each of the 28 base classifiers and behaviours are influenced by the randomized grid search over all 22 datasets, at an average cost of 420 CPU hours per dataset. The observed results are compared to a baseline of default parameters [94].

5. Auto-SK-Learn

Auto-WEKA uses cutting-edge Bayesian optimization methods to create a sophisticated machine learning pipeline based on sci-kit-learn. Auto-sklearn is used to generate a standardized search space with 110 hyperparameters in one experiment using a mix of 14 classifiers, 16 function classification methods, and five data preprocessing techniques. It outperforms previous AutoML systems such as Auto-WEKA by automatically preheating the Bayesian optimization technique with meta-learning, resulting in a significant performance improvement [96]. Auto-SK.learn adds a stage for automated ensemble construction, which permits all classifiers assessed primarily during the Bayesian optimization approach. By utilizing new Bayesian optimization, meta-learning, and ensemble creation techniques, Auto-SK-learn delivers an automated machine learning toolset [95].

6. Expert Systems

Algorithm Selection systems first emerged about what are known as expert systems [51]. The underlying concept of such systems was that they enabled non-expert users to access complex libraries' power. Consequently, the problem domain that such systems address generally needs a significant amount of specialized knowledge, like differential equations in mathematics. The user desired to solve this problem and could select appropriate methods by utilizing the expert system. In this regard, Algorithm Selection is employed to enhance a system's performance and make the problem solvable. Although the first description of the Algorithm Selection Problem was made several decades ago, its emergence as a separate research field is relatively new. The extent of user interaction when solving a problem can vary. Individual systems only provide user assistance, whereas other systems require that the user specify the problem.

7. Algorithm Portfolios

The fundamental concept of expert systems was further developed under the subject of algorithm portfolios [89]. The notion of having a portfolio was derived from the field of Economics, in which they are employed to maximize utility while reducing the connected risks, as Huberman et a1. [25]. In the context of algorithms, the utility being maximized is the algorithm's performance or the problem solution's quality. The aims of algorithm portfolios and expert systems coincide to a certain extent. In expert systems, increased emphasis is placed on helping users make complex decisions, whereas algorithm portfolios enhance overall problem-solving performance. In that regard, they can be considered two methods of viewing the same thing. For example, Hough and Williams investigated an optimization algorithm's selection from a more comprehensive portfolio [97].

8. Hierarchical Models

Various models within a hierarchical performance model in specific approaches, such as Sparse multinomial logistic regression was employed by Xu et al. [66]. The speed of each algorithm in the portfolios was then forecasted using a logistic regression model. Kaloudis adopted a similar approach using a portfolio of different kinds of algorithms [98]. However, Marius said that as the number of scenarios in which hierarchical models can be applied is limited, they have been relatively under-researched [99].

2.6 Selection of Model Learner: Machine Learning

As previously explained, different approaches can be adopted for learning performance models. In some of the studies reviewed, comparisons were made between the various approaches used to achieve this. For instance, in addition to lasso regression and the regression they picked for runtime prediction, they investigated and used support vector machine (SVM), Gaussian methods, and lasso regression [100]. Brazil compared different decision tree learning methods using a Bayesian classifier, the closest neighbour system [101]. Michie explored many types of linear and nonlinear regressions, also explored the application of naive rules and meta-learning methods [102]. Silverthorn discussed the differences between nearest neighbour classifiers, forest three, and numerical simulations [103].

Moreover, Hough and Polina employed support vector machines, whereas Pulina incorporated decision trees, logistic regression, and closest neighbour approaches [104]. Finally, Roberts predicted algorithm runtime and probability of success using 32 distinct Machine Learning algorithms [35]. Roberts then attempted to justify the strategies they had selected. Machine learning is a multidisciplinary study that integrates computer science, mathematics, statistics, operations analysis, cognitive science, and engineering to give machines intelligence [29]. Machine learning is a discipline of study concerned with automating the process of system learning. Automated learning systems come in a variety of configurations and levels of complexity. They range from simple learning systems based on memorizing, such as those that filter undesired emails (spam) built on a remembered table of undesirable transmitters, to more sophisticated systems that execute more subtle tasks in dynamic contexts utilizing inductive reasoning [34]. In latest years, machine learning has risen to prominence as the preferred technique for extracting valuable information from vast and complicated datasets. In recent years, machine learning has risen to prominence as the preferred technique for extracting valuable information from vast and complicated datasets. This part will discuss machine learning in further detail, emphasizing the available methodologies, as illustrated in Figures 2-16. Machine learning is categorized in a variety of ways. First, it may be categorized according to the learning method or the model (system) utilized to choose [83]. Second, a learning system could be classified based on the learning theory it employs or the degree of contact it has with its input. An interactive learner will interact with the environment (data) through experimentation to gain extra knowledge about the input, whereas a passive learner will watch the information provided by the input. The research on machine learning could be roughly split into three distinct strands. Supervised, unsupervised, and reinforcement learning are all forms of learning.

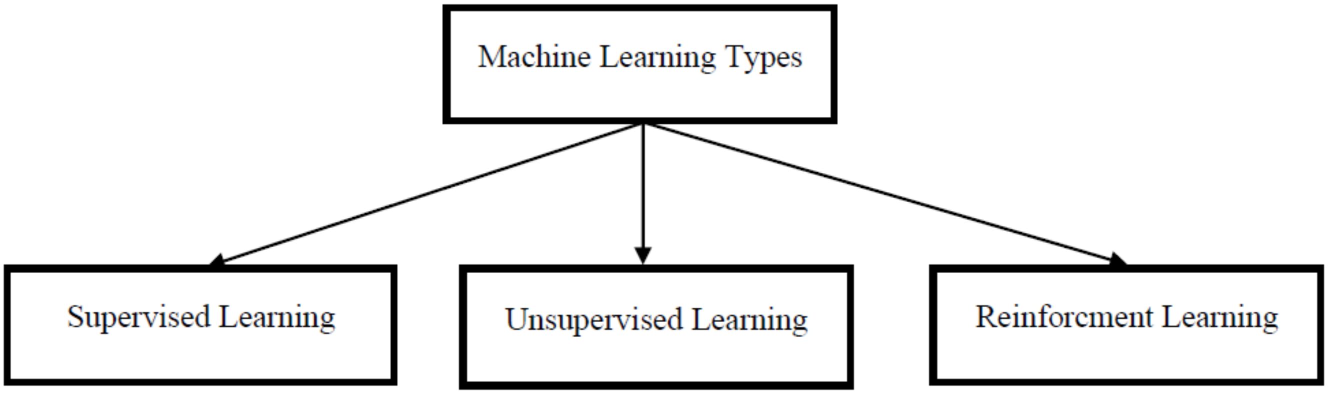


Figure 2-15:Machine Learning Types

2.6.1 Supervised Learning

The machine is presented with the optimum number of outputs for presented inputs (learning phase). Following that, the computer is commanded to generate an output in response to the newly arrived data. The desired result in machine learning systems used for classification could be a classmark [6]. In regression, optimal performance predicts machine learning approaches and creates a new value for predictor variables based on values computed from data attributes and initial training sets. Nevertheless, in categorization issues, the required result is classifying the input data into predetermined markers or groups utilizing a previously labelled data training set [85]. The following characteristics define supervised machine learning:

• A training method that takes into consideration both the input/ output data.

• The required outcome is already identified and is typically given to the estimation method during the learning process.

• When given input that does not contain the target output, the model will generalize the result.

2.6.2 Unsupervised Learning

Unsupervised learning does not provide the desired outcome to the system during the training process [31]. The machine's job is to discover how to develop a mechanism that groups the input data based on its statistical qualities. This grouping is not established during the learning phase by any supervisory process or consumer; instead, it is determined by the association discovered between the various properties of the input and the modelled groups. Unsupervised learning techniques must discover how to cluster inputs with shared properties into groups. Clustering is a technique for segmenting big datasets into subsets that have common properties. K-means clustering is a technique for unsupervised learning.

2.6.3 Reinforcement Learning

An excellent example of an immersive learning method is Reinforcement Learning. The computer (agent) performs specific activities in the world in reinforced machine-learning systems. Due to the input, this behaviour may produce a scalar reward signal or a scalar punishment signal [105]. The agent should be able to choose the right relationship with its surroundings autonomously. It is accomplished by rewarding positive actions and punishing negative ones. The agent's objective after its interaction with the world is to maximize the cumulative rewards. Several difficulties associated with reinforcement learning include associating current behaviour with future rewards (delayed rewards) [106]. This type of challenge allows the agent to experiment with a variety of different scenarios.

2.6.4 Artificial Neural Networks

The interconnected processing components (neurons) are primarily composed of the neural networks (ANNs) that perform vital functions [97]. Neurons can process information and respond to external stimuli with production. The human brain is represented by artificial neural networks composed of billions of neurons (nodes) linked in an extensive network. ANNs are frequently organized and built through the use of node layers [59]. The input layer is the first layer accountable for accumulating dataset from the outside world and incorporating it into the network. The output level of an ANN is the last; it generates output for the outer environment. The hidden layer is found between input/output levels, and its size might vary according to the network's required complexity. Additional layers, such as filtering and picture pooling, are included in specific neural networks, such as image processing [107].

The layers are connected via weighted, completely connected linkages between individual nodes, with the first level's output acting as the input for the subsequent level. The required output is obtained by adapting the nodes' weighted interconnections to the present and desired outputs. This intricate cycle of weight change is analogous to the learning cycle of an ANN. An ANN can comprehend various ways, including through backpropagation rules that use trivial errors from the output to modify the weighted inputs to the connections. ANNs are not sequential computing networks, in contrast to conventional computing networks. There is no central computing processor in an ANN; instead, it consists of numerous superficial processing nodes that receive the weighted aggregate of their inputs from other nodes. Thus, the information stored or acquired in an ANN is characterized by the network's weights, more significant than its components. While an ANN can take on various types and be trained in various methods, this research uses a supervised training variant defined as the MLP. MLP trains an ANN using the backpropagation method on a reasonably simple architecture (three levels: an input level, hidden levels, and an output level) [25]. Figure 2-17 is a simple one-hidden-layer MLP. The number of buried levels in an MLP differs according to the required level of sophistication.

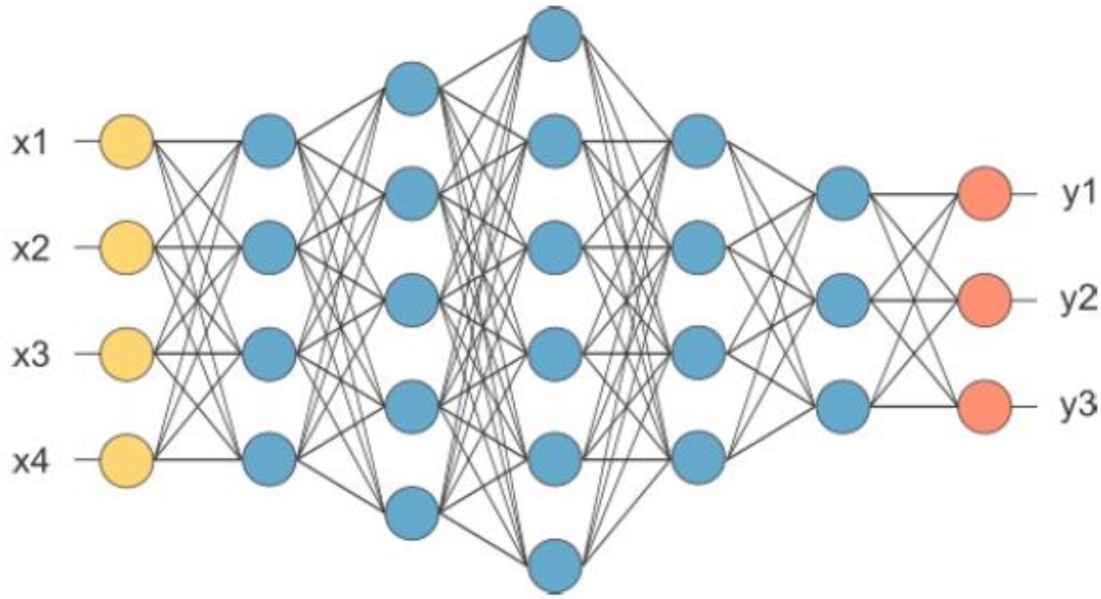


Figure 2-16:A Simple MLP Architecture

Additional hidden layers enable the MLP to learn more complicated visualizations, but overfitting occurs when the MLP becomes too complex. Excessive fitting of training data produces unsatisfactory output for the real-world situation. This trade-off is examined (experimentally) while deciding the number of utilizes in a network [108]. The hidden-layer neurons in the MLP network use nonlinear activation functions. This trade-off is examined (experimentally) while deciding the layers to use in a network [108]. The hidden-layer neurons in the MLP network use nonlinear activation functions. The sigmoid function or a Tanh function is the activation function and can be either a for each given input value (x) (Equations 2-4, 2-5). Both functions have their advantages and disadvantages; nevertheless, this study concentrated entirely on the sigmoid function.

$$f(t) = \frac{1}{1+e^{(-t)}} \tag{2-4}$$

$$f(t) = \frac{(e^{t} - e^{-t})}{(e^{t} + e^{-t})} \tag{2-5}$$

The type of function performed by MLP output neurons varies according to the task. For example, each output neuron represents a distinct problem class in classification tasks. The SoftMax function (a sigmoid function extension) can be used for this purpose [109]. These procedures return values for each neuro that are proportional to the total of all other output layers, essentially constraining them to sum to "1." Additionally, it provides a probabilistic model over neurons that belong to mutually exclusive distinct categories, which is used to represent the classification task [110]. The SoftMax function for a network with (n) output units may be determined using Equations 2-6. (refer to Figure 2.3). Additionally, for regression tasks, the output unit form is usually a normal sigmoid function.

$$yi = \frac{e^{Zi}}{\sum_{j=1}^{n} e^{Zj}} \tag{2-6}$$

2.6.5 Multilayer Perceptron Classifier (MLP)

A multilayer perceptron (MLP) consists of three levels: input, output, and hidden, and it is a kind of neural network. The number of classes determines the output level's size. The input layer's size is proportional to the dataset space's dimensionality (D), while the output level's size is reliant on the number of classes (C) [114]. The number and the size of the hidden layers are established by applying the backpropagation algorithm used for training the

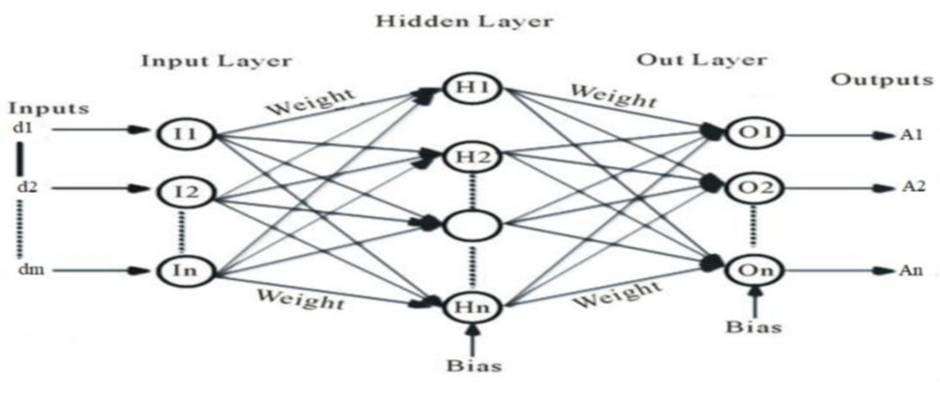


Figure 2-17:Architecture of the used MLP

MLP classifier and optimization technique aimed at lowering the error at the network's output layer. Figure 2-18 illustrates the architecture of the MLP employed in this work. The learning process of an MLP classifier entails two steps. The first is the forward propagation of the input signals through the network and calculating the results to be output. The second step is backward propagation, which is used to update all neurons' weights that have contributed to the error observed. The BP algorithm is an iterative procedure aimed at minimizing the error using a gradient descent technique.

2.7 Evaluation of Registration Performance

The registration algorithm's performance (efficiency and accuracy) is critical in IGS. The registration algorithm's performance is measured concerning robustness, reliability and accuracy. Additionally, registration efficiency is determined by the number of available resources, the complexity of the algorithm, and the clinical application. Proper registration of associated data in numerous pictures lays the groundwork for the treatments and follow-up process. As a result, the registration algorithm's efficiency, precision, and robustness are critical criteria to consider when evaluating it. Additionally, the registration process could be utilized as a clinical apparatus for patient protection and health care by utilizing these parameters. The accuracy, efficiency, reliability, and processing time comprise modality, similarity measurements, conversion, optimization, image content and execution procedures [111].

2.7.1 Accuracy

The registration accuracy is determined directly by the difference between the estimated and estimated values [112]. In the case of picture registration, the correctness of the estimated registration variables can be represented. Accuracy also refers to the means or mean squared space among two images' related points. Accurate registration is crucial in medical practice since it assists the surgeon greatly in perforating in the proper area. The registration approach is more precise since it produces outcomes that are higher in both quantity and quality. The technique's qualitative accuracy is typically determined by optical review by skilled medical personnel.

Moreover, the medical professionals determine whether the associated landmarks are effectively stacked on top of one another. The mathematical or statistical procedures used in medical picture registration determine the technique's quantitative correctness. These methodologies quantify the registration precision. On the other hand, accuracy validation is challenging but critical for the practical use of medical image registration techniques.

2.7.2 Reliability

Perpetually in a trustworthy manner. The term "reliability" refers to the frequency with which an algorithm discovers the correct answer concerning the number of runs done [113]. In other words, the algorithm's dependability implies that it should successfully execute the prescribed task. Robustness refers to the effect of parameter alterations on picture registration. For instance, if image registration is done on n pairs of images and m pairs of images are correctly registered, the algorithm's dependability is m/n [73]. The registration technique's dependability is calculated using the success rate and capture range [174].

2.7.3 Robustness

Robustness quantifies the effect of parameter alterations on image registration. It can be quantified in terms of noise, variance in illumination, occlusion, and non-overlapping region. Robustness quantifies the registration algorithm's stability [74]. In other words, resilience refers to an algorithm's capacity to function effectively in a chaotic environment. A registration process is seen to be robust or stable if it does not give surprising results under slightly varied or abnormal conditions. Due to the inherent inconsistency of medical pictures resulting from the biological activity, registration algorithms must also be robust to efficiently manage slight changes between several images acquired from the same tissue throughout image-guided surgery (IGS).

2.7.4 Efficiency

The data processing sophistication of an algorithm indicates the amount of time necessary to run it. In other words, the registration technique's efficiency is determined by the time required for computation during processing [114]. The registration algorithm's efficiency is critical in IGS and other clinical applications, as a rapid response with precise alignment is always needed. Rigid registration is often quite efficient for the simplicity of transformation and the small number of variables required for registration. Moreover, the distortion registration process is slow because of the high number of variables detected and the asymmetric transformation. Thus, by utilizing symmetric transformation, the performance of the deformation registration process can be increased. Additionally, performance can be achieved by employing a small number of correspondence factors.

2.8 Application of Medical Images Registration

The enhancement of advanced methods in medical image analysis leads to the patient's easy availability of specific information. The clinicians can now quickly diagnose and monitor disease development in the sickness's body [26]. Registration is critical in clinical image treatment since it allows clinicians to monitor the disease's progression and take appropriate measures. Medical image registration (MIR) has many applications both in diagnostics and in therapeutics. Some of the critical applications are in radiation therapy, cancer detection, template atlas application and IGS.

2.8.1 Radiation Therapy:

Radiation therapy aims to treat the tumour and other diseases of the body. Radiation therapy/radiotherapy delivers a therapeutically beneficial dosage to the target tumour while sparing the normal tissues in the surrounding area [78]. Diverse MIR methods have been developed for radiotherapy during the last two decades to use this technology for better health care successfully. In radiation therapy, registration is used in patient position verification, treatment planning and treatment assessment. Both rigid and deformable registration has been used in radiation therapy. Rigid registration, which involves only translation and rotation of the object, has long been used in radiotherapy. For example, rigid registration is amazingly effective in registering CT and MR images obtained from a patient with no anatomic changes in the body.

2.8.2 Cancer Detection:

Medical image registration is critical for cancer detection and treatment monitoring [38]. In early cancer detection, registration techniques detect helpful information about the tissue under examination [18]. In cancer detection, registration translates the segmented areas of interest from the hematoxylin and eosin (H&E) images to the infrared (IR). This process reduces the segmentation of the stained images. Unfortunately, it is often difficult for clinicians to locate the cancerous tissue in early cancer detection properly. The structural information obtained from MR and CT imaging cannot always correctly assist clinicians because of the low contrast between normal and cancerous skin in MR and CT images.

On the other hand, vital information regarding cancer tissue and its proper placement can be gleaned from PET and SPECT scanning images. Image registration is increased further by image fusion, which considerably aids radiologists in detecting cancer early and improving diagnostic accuracy. Testicular cancer, esophageal cancer, breast cancer, and lymphoma all benefit from registration.

2.9 Summary

This chapter has provided background and literature review materials for two categories: medical image registration and algorithm selection. The concept of multimodal medical image registration was discussed, and some of the commonly used medical imaging techniques are highlighted, and typical medical images are explained. Medical image registration types, such as rigid and non-rigid algorithms, are described in detail. Many medical image registration approaches have been produced, and different techniques were utilized to achieve the best performance. Additionally, several criteria have been suggested for their classification, such as the dimension of the dataset (2D, 3D); the registration base intensity and feature-based; the transformation domain (local or global); the nature of the transformation (rigid, non-rigid); the modality (monomodal, multimodal); the subject (intrasubject, intrasubject, atlas subject); and the interaction (interactive, semi-automatic, automatic). Moreover, a list of free, open-source programs that offer several registration techniques is depicted in Tables 2-3.

Throughout the years, numerous strategies for solving the algorithm issue have been offered. Researchers have recognized that algorithm selection approaches can dramatically improve performance in artificial intelligence with relatively little effort. For the most part, these approaches comprise some machine learning that automatically learns the relationship between problem instances and algorithm performance. It is unsurprising since an algorithm frequently has a complicated relationship with its performance that is difficult to describe adequately. In various instances, it is often the case that the algorithm's designer does not have an overall performance model. Although selecting an algorithm is theoretically challenging, multiple systems have shown that it can be achieved successfully in practice. The medical image registration system's effectiveness, durability, and accuracy are based on many variables: modality, impact on picture contents, similarity measures, transformations, optimization, and implementation procedures. Due to the interdependence of the complicated parameters, it is difficult to determine their impact on the registration process. However, preliminary analyses of the effects of these factors are necessary before registration. The final factors included in the discussion are the measures commonly used for evaluating the performance of registration algorithms: accuracy, processing time, reliability, and robustness. The enhancement of advanced techniques in medical image analysis leads to the patient's easy availability of specific information. The clinicians can now quickly diagnose and monitor disease development in the body of the patient. Choosing the most powerful algorithm to resolve a provided problem has focused on numerous researches over the preceding few decades. This work has encompassed novel approaches for resolving the algorithm selection challenge. This review presented a summary of studies on algorithm selection methodologies. This chapter introduced the framework for algorithm choice and discussed various techniques to resolve the algorithm selection problem. Even though the current overview concentrates on the main approaches for algorithm selection problems, several techniques have different parameters for each approach, and the performance may improve if the parameters are tuned.

Chapter 3
Problem Statement and Solution Strategies

3.1 Introduction

Medical image acquisition equipment has advanced rapidly over the past few decades, and doctors of medicine now depend on medical pictures for analysis, therapy planning, follow-up and surgical systems [33]. Medical images have been divided by researchers into two types of structures: functional and anatomical. Anatomical imaging, such as US images, X-Ray, MRI, and other systems, enables medical personnel to examine a body internally with great accuracy, thereby avoiding the risks associated with exploratory surgery [23]. Functional (or physiological) imaging systems, such as positron emission tomography and T1 MRI, are available [[33]. Furthermore, one of these medical imaging models alone cannot usually supply doctors with adequate information. Additionally, data derived from two or more pictures of the same item typically contain supplementary information due to a process known as image processing. Thus, medical image registration could be described as physically mapping the coordinates of two images collected from different devices using separate sensors [29]. Registration is crucial in medical image assessment since it allows a practitioner to monitor the disease's progression and take appropriate measures. MIR has various applications, including radiation therapy, clinical diagnosis and detection, template atlas application, and surgical guidance system [39]. There are two types of registration: manual registration and registration-based computer system. Manual registration is when the radiologist /physician completes all registration tasks interactively with visual feedback provided by the computer system, resulting in serious problems. For instance, investigations conducted by two experts are not the same, and registration correctness is determined by the user's assessment of the relationship between anatomical features. Furthermore, it may take a long time for the user to achieve proper alignment, and the outcomes vary according to the user. As a result, the outcomes of manual alignment are doubtful and unreliable. The second registration approach is computer-based multimodal medical image registration that targets (i) various medical images. (ii) A variety of application types. Without user interaction, automatic registration in medical pictures matches the standard recognized characteristics or voxels in pre and intraoperative images [20]. The multimodal image process is the first stage in combining data from two or more images. Automatic image registration has emerged to mitigate the manual image registration reliability, robustness, accuracy, and processing time. While such registration algorithms offer advantages when applied to some medical images, their use with others is accompanied by disadvantages. Due to the inherent unpredictability of imaging and the varying demands of applications, no one registration technique can outperform all input datasets. However, no algorithm is superior in all potential cases; due to many available solutions, choosing the one that adapts the best to the problem is vital. The critical element is to ascertain which method is most appropriate for the input challenge. The Algorithm Selection Problem has emerged in various research disciplines, including medical diagnosis, machine learning, optimization, and computations [41]. The choice of the most powerful strategy for a particular difficulty example seeks to minimize these issues. The primary purpose of this chapter is to introduce the strategies that will be used in this thesis.

3.2 Problem Definition

Multimodal registration of medical images is used for acquiring information by matching two different medical images of a patient's anatomy, such as the head, liver, or kidney. The results provide complementary information crucial for an appropriate clinical diagnosis, decision-making, or navigation during surgical interventions. Several studies on the registration of medical images have been published in the literature, and various registration algorithms are available. However, no state-of-the-art registration technique outperforms the others across all data, rendering individual registration algorithms unreliable. For example, a registration algorithm is considered unreliable if it produces different results when tested on several medical images [3]. As discussed in Chapter 2, numerous algorithms have been developed for registering medical images of the same objects using different datasets, including CT, PET, SPET and MRI. Registration algorithms are developed for various reasons, such as the diversity of medical images for distinct organs and the variety of medical applications they can use. The diversity of medical images and differences in the degradation of the same object (affection of image contents) creates problems concerning registering the performance of an algorithm, such as increased processing time and decreased accuracy. However, as stated in the thesis's encouragement section, important concerns in this sector remain unanswered. A further consideration is that evaluating the registration of medical images by visual inspection is also intrinsically unreliable. In [15], analysis of 656 imaging examinations collected over eight years, 1279 errors were found, 42% were under-reading. More seriously, 28% of 583 diagnostic mistakes were life-threatening and had resulted in permanent disability or death [5]. Among the 6400 physicians surveyed, 10% of misdiagnoses led to patient harm [6]. Medical image registration accuracy and processing time are crucial in surgical operations' accuracy and quality in surgical guiding systems. If the selection of a registration algorithm is imprecise, a guidance system might be ineffective and life-threatening. Also, one of the many issues in the current MIR is the unavailability of highly precise, computationally efficient, clinically acceptable, and robust registration techniques [17]. Although the available registration methods provide useful information from separate images, the accuracy and efficiency are often compromised. An important aspect of MIR in clinical practice is its computational efficiency, registration accuracy, and robustness to several other biases affecting medical images. Other unresolved difficulties involve intelligent image registration, effective landmark detection, multimodal image registration, and outlier rejection in medical images. Due to the inherent variability in imaging and the wide range of applications. Many registration algorithms were suggested in the literature, all of which demonstrated superior registration problems. However, no algorithm outperforms all conceivable cases, and because there are several techniques available, selecting the registration algorithm best fits the problem is necessary. The essential aspect is to comprehend which approach is most appropriate for the situation and why. The Algorithm Selection Problem has emerged in several research fields in various guises and titles in recent decades. There is growing interest in algorithm selection among researchers and practitioners in various disciplines, including medical diagnosis, machine learning, and optimization. Choosing the best algorithm for a particular difficulty example minimizes these issues and significantly improves the results. Furthermore, any registration algorithm has several stages of the registration process; first, similarity measure is statistical concepts used to correct source and target images during registration. These measures determine the registration level of images through a given location. Based on image intensities or characteristics, similarity measurements among source and target images are calculated. The second stage is the optimization algorithm to search the parameter space to collect transformation parameters that ideally align the two images using the stated similarity measure. Because the similarity metric's hypersurface is frequently high-dimensional but not always a convex function, optimization approaches converge on local extrema [10]. Therefore, no registration algorithm can yield optimal results when used with CT-PET or MRI-SPET datasets. However, selecting the best-performing registration algorithm can optimize the results and enhance the reliability of the system. This thesis aims to investigate algorithm selection methods in the context of automatic registration algorithms. The objective is to develop an algorithm selection system (Framework) structured as a machine-learning task and select the optimal registration algorithm.

Given a set of different registration algorithms and a set of images from different modalities, these images must be registered to derive a comprehensive insight into the target area of the body.

- Manual registration is time-consuming, inaccurate, tedious and entirely subjective.
- Automatic registration is more practical; however, there is no single registration algorithm that is guaranteed to achieve high performance for all input modalities at all times.

The question is: What is the best registration algorithm for a given dataset of multi-modal images?

The concerns here are:

• Investigate whether an assembly of well-chosen algorithms can construct a group that offers the best registration performance possible as a function of the image set on hand?

• Is it possible to design a strategy to select the one candidate that delivered the best performance based on the images to be registered?

Further:

• How reliable is this selection strategy?

• How robust is this strategy?

• How accurate is the registration performance of the selection compared to the average performance of the group?

The problem statement is described in this chapter based on the literature review, emphasizing the importance of developing a universal medical image registration framework capable of producing the optimal solution for all input datasets.

3.2.1 Problem Formulation:

Ideally, the collection of algorithms should be sufficiently diverse so that for each possible problem instance, at least one algorithm in the portfolio does well on that problem instance. However, more extensive gatherings may slow down the learning process and lower performance due to selection errors. Therefore, in this chapter, we consider a relatively small but diverse set of algorithms. As shown in figure 1, the algorithm selection system can briefly be explained: The (d_m) is a subsection case of the problem space P. The feature domain F is the features of all instances found in the problem space, which is premeditated based on a feature removal process. {a} is a division of the algorithms space $\{A\}$. Along with the performance measure space P(Rn), which denotes the mapping of all algorithms in (A) to several performance metrics, machine-learning is used to evaluate (i.e., problem-algorithm mapping) to generate a more performant algorithm that represents a selection mapping S: F→Rn, A. Figure 3-1 shows the model comprises three main modules: problem space, algorithm space, and performance space.

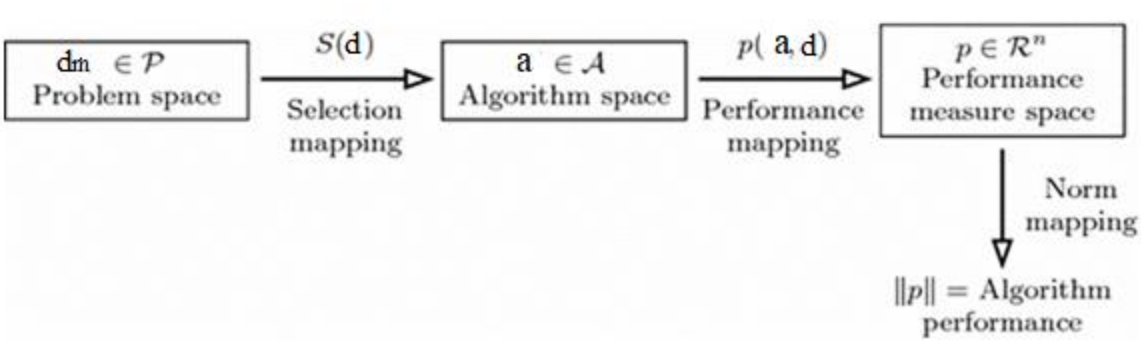


Figure 3-1:Algorithm Selection Model

The algorithm space is defined as the number of algorithms that facilitate selecting a solution to the provided problem. The makers of the specific algorithm created it in order to adjust the performance of the machine-learning algorithm. According to our settings, the algorithm space also incorporates potential restriction sets that the machine learning process assumes.

Choose the best appropriate registration algorithm for each pair of medical images (dataset) from a set of available registration methods to maximize the overall registration accuracy, as shown in figure 3-2.

Given:

- Image dataset D = $\{d_1, d_{2,} \ldots. d_j\}$.
- A set of registration algorithms A = $\{A_1, A_{2,} \ldots A_{n.}\}$
- Each algorithm A_i achieves performance, $P_{i,k}$ when applied to the dataset $d_{k,} \in$ D.

Now:

- Given x, a new set of images that we wish to register. X
- Let P(x, i) be the registration performance of the algorithm A_i on the new set x
- The objective is to design a selection strategy S such that
- $S(x \mid D, P_{i,k} : \forall d_i \in D, A_{k.} \in A), = A_s \in A$,such that
- $P(x, s) \geq P(x,i)\ \forall i \in (1 \ldots\ldots. n)$ (3-1)

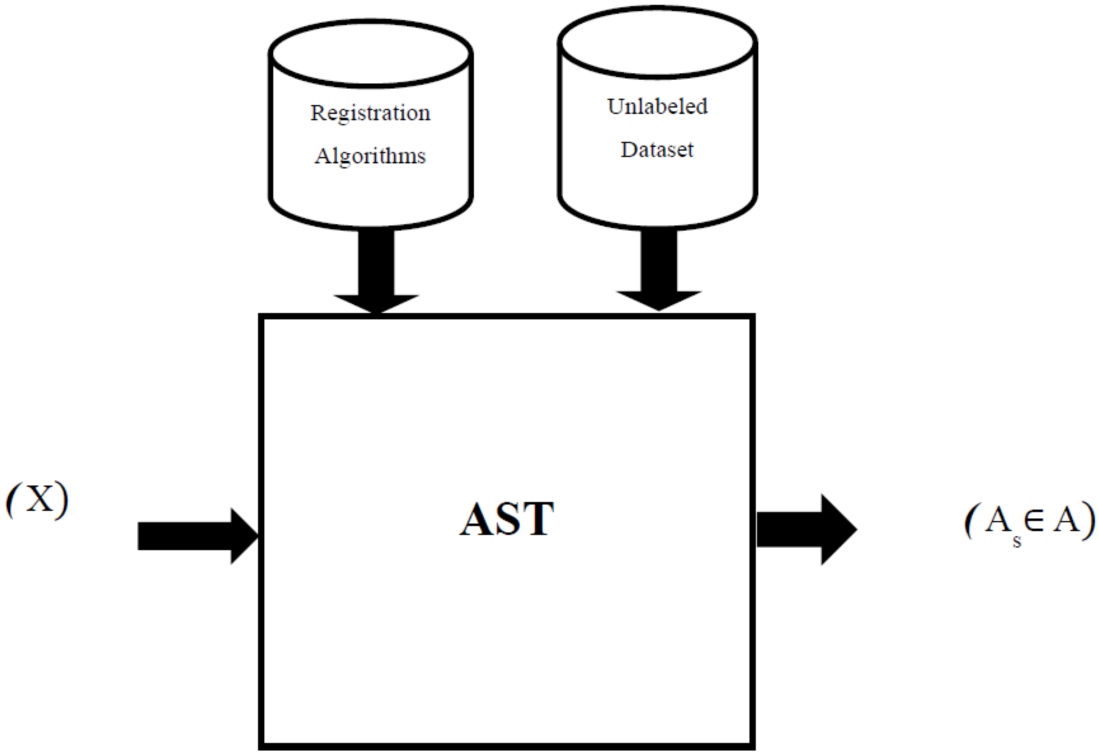
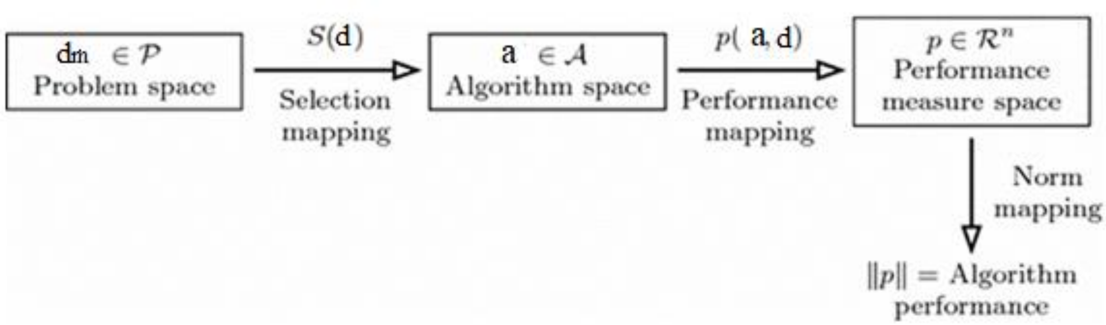


Figure 3-2: Problem Formulation Schimatic Diagram

Where P is an accuracy measure and S is the selection function. Selecting a registration algorithm can be viewed as a three-dimensional space problem., as depicted in Figure 3-3, where the x-axis represents 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.



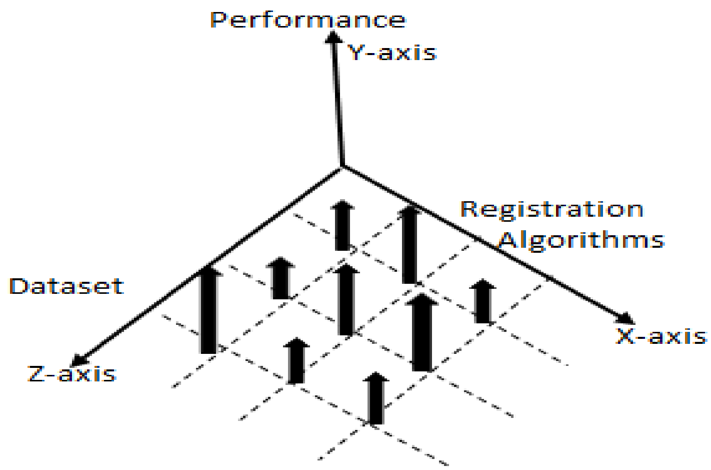


Figure 3-3:Algorithm Selection based Three-dimension Space

For example, as shown in Figure 3-4, the registration algorithm A_1 gives the best performance with dataset d_3, and the registration algorithm A_2 produces the most excellent accuracy with d_1. Therefore, the results will be dissimilar if dataset d1 is selected and mapped to several registration algorithms, A1, A2, and A3. Moreover, if the same procedure is repeated with the d_2 dataset, the results will be different. On the other hand, if a registration algorithm such as A_1 is used with different datasets (d_l, d_2, d_3, d_m), the outcome performance is different, as shown in Figures 3-4, 3-5, and 3-6. 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. As a result, the dilemma of choosing a registration technique that will produce high-performance outcomes across all datasets arises.

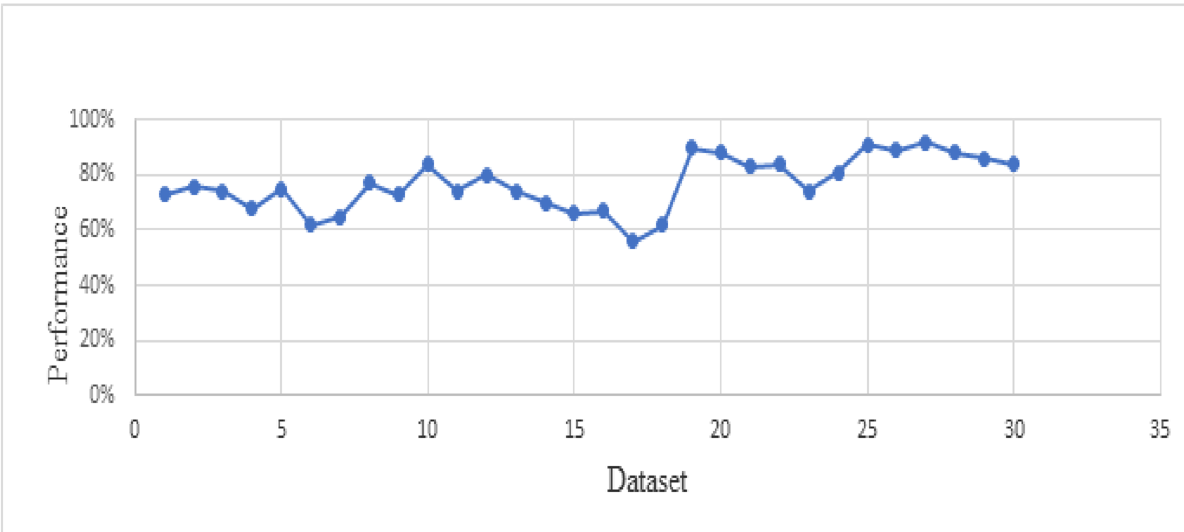


Figure 3-4:Registration Algorithm A1 Versus Dataset

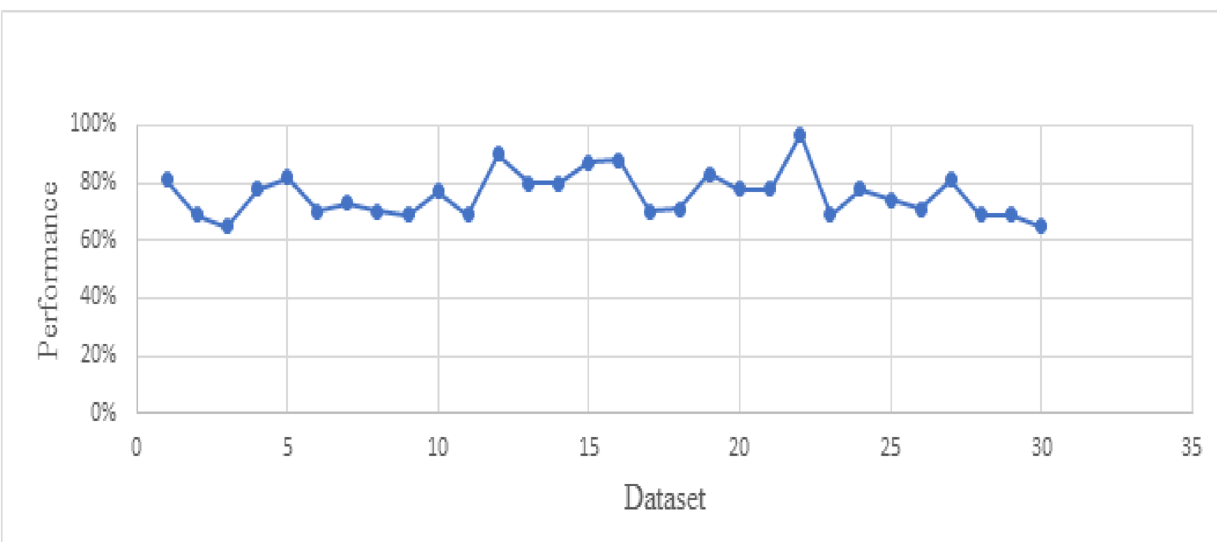


Figure 3-5:Registration Algorithm A2 Versus Dataset

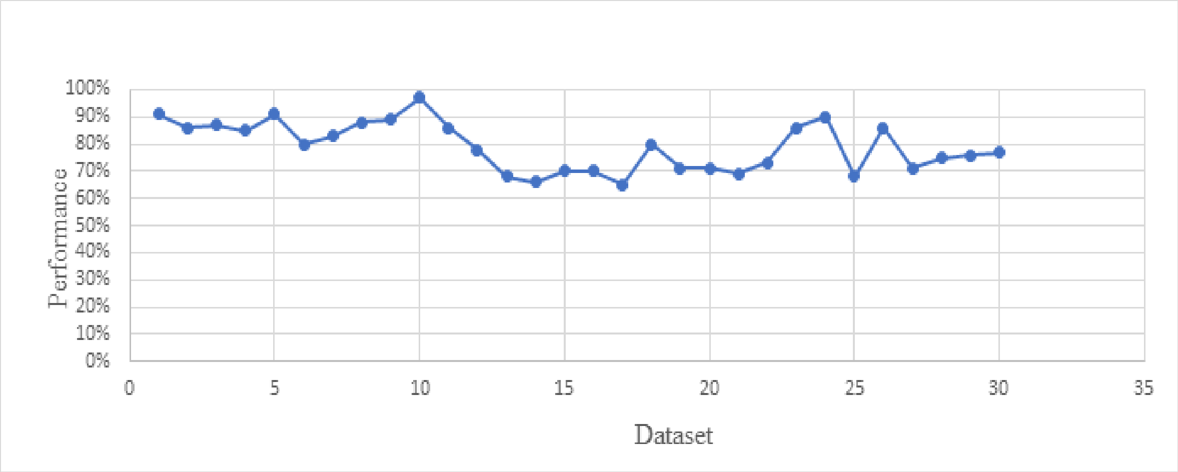


Figure 3-6:Registration Algorithm A3 Versus Dataset

In the three-dimensional dataset space, the information given is in the form of datasets (D), and different rigid registration algorithms are expressed as a registration algorithm space (A), where the output is the performance (P) of each input dataset with all registration algorithms or vice versa. P is a function of D and A, and S(.) is the selected function, as represented in equation 3-1. The registration algorithm A_n is selected to be the one that presents the best value of P with dataset d_j.

3.3 Solution Strategies Overview

This study presents generic and efficient solution strategies for multimodal registration algorithm selection. The primary goal of this study is to offer a novel framework for creating a multimodal medical image registration system capable of picking the most recognized (best) registration technique for a variety of input datasets from a group of registration algorithms. Additionally, to achieve that, three solutions strategies were constructed to examine the proposed framework.

3.3.1 Greedy selection strategy

The first strategy is adapted from the greedy algorithm strategy, where it transforms the problem of algorithm selection into a classification problem. Therefore, to accomplish that, a supervised machine learning technique was used. Moreover, a supervised dataset was created to establish a learning model, where candidates' algorithms represent the dataset labels, as shown in table 3-1 and equation 3-2. Finally, more details will be found in the next chapter.

Table 3-1: Dataset Labelling: Registration Algorithm

	Registration Algorithms			
Dataset	A1	A2	A3	Label
1	**91%**	81%	73%	A1
2	78%	**90%**	80%	A2
.	.	.	.	.
.	.	.	.	.
120	61%	70%	**80%**	An
Average	93%	79%	85%	

3.3.2 Optimal registration parameters guided Selection Strategy

The second strategy investigates the effect of various characteristics, such as optimization control points, on the optimal selection. Despite the first strategy's success in selecting the suitable registration algorithm but it has some disadvantages. (i) the first strategy is the best if that tested image is the same data point in the learned model. (ii) The system's performance is determined by the learned dataset. (iii) due to the extraction of erroneous landmarks, the local maxima of the similarity measure also impair registration accuracy in the elastic transformation. Therefore, optimization measures are critical for improving MIR performance. The second strategy was created to overcome the problems in the first strategy. Therefore, the roulette wheel selection approach enhances the selected registration strategy's accuracy, reliability, and robustness. Moreover, a supervised dataset was created to establish a learning model, where candidates' algorithms and optimization strategies represent the dataset labels, as shown in table 3-2 and equation 3-3. Finally, the output of the learned model is regarded as the labelled dataset, and that label represents the registration algorithm and optimization algorithm (An, Ok), which are one of the twelve candidates.

Table 3-2:Dataset Labelling: Optimal registration parameters and Registration Algorithm

Dataset	**A1**				**A2**				**A3**				**Labels**
	O_1	O_2	O_3	O_4	O_1	O_2	O_3	O_4	O_1	O_2	O_3	O_4	Znk=(An, Ok)
1	80	92	88	85	87	82	89	93	84	89	85	**95**	Z (3,4)
2	88	85	**95**	90	87	76	86	93	85	93	87	89	Z (1,3)
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
179	**93**	87	85	86	84	90	88	91	89	85	87	88	Z (1,1)
180	85	88	83	92	89	85	**94**	88	89	76	84	90	Z (2,3)

Therefore, the best registration algorithm and optimization strategy for the unknown dataset can be selected. The roulette wheel approach selects the best registration strategy (Znk) from a set of candidates to make the proposed method more reliable, accurate, and robust. Finally, more detailed explanations will be found in chapter 5.

Given:

- Image dataset D = $\{d_1, d_{2,} .... d_j\}$.
- A set of registration algorithms A = $\{ A_1, A_{2,} \dots .. A_{n.} \}$
- Each algorithm A_i achieves performance $P(A_i, d_k, O^i)$ when applied to the dataset $d_{k,} \in D$, under the set of parameters $O^i \in R^i$
  - R^i : *parameters space of algorithm* A_i
  - O^i_{opt} *is said to be optimal on dataset* d_k *if*

    $P(i, k, O^i opt) \geq p(i ,k , \forall O^i \in R^i)$ (3-2)
  - Now:
  - Given x, a new set of images that we wish to register.

- The objective is to design a selection strategy S such that
- *S(x | D, p(i, k, O^i): ∀ d_k ∈D, $A_{i.}$ ∈A, O^i ∈R^i) = {A_s , O^sopt}, A_s ∈A, O^sopt ∈R^s such that P(x, s, O^sopt) ≥ P(x,i) ∀ Ai ∈(A)& O^i ∈R^i*

The registration algorithm performance space is then utilized to assess the accuracy of every registration procedure based on the input dataset and optimization control point.

3.3.3 Task-driven algorithm selection strategy

The third strategy contended that the concept of "best registration" is meaningful only in the context of application and performance measures. Additionally, we expressed that we could increase the application's efficiency by taking the application and performance type into account when registering. This strategy presents a framework for determining the ideal registration procedure for a particular registration dataset using two significant criteria: registration algorithm applicability and performance measures. The strategy discussed here is based on weighting two parameters: the MIR application and performance measures. Numerous trials and situations have been done, and the findings indicate that the novel framework results are robust, reliable, and accurate. The influence of performance and application weighting on selecting the best algorithm for registration, as shown in equation 3-4, is discussed in this research:

Given:

- Image dataset D = $\{d_1, d_{2,} .... d_j\}$.
- A set of registration algorithms A = { $A_1, A_{2,} ... .. A_{n.}$ }
- W_m Is the application weight.
- Each algorithm A_i achieves performance P(A_i, d_k, O^i) when applied to the dataset $d_{k,}$ ∈ D, under the set of parameters O^i ∈ R^i and application weight W_m.
  - R^i : *parameters space of algorithm* A_i
  - O^i_{opt} *is said to be optimal on dataset* d_k *if*

P(i, k, O^iopt, W_m) ≥ p(i ,k , ∀ O^i ∈ R^i) (3-3)

- Now:
- Given x, a new set of images that we wish to register.
- The objective is to design a selection strategy S such that
- $S(x \mid D, p(i, k, O^i): \forall d_k \in D, A_{i.} \in A, O^i \in R^i) = \{A_s , O^s opt\}, A_s \in A,$ $O^s opt \in R^s$ *such that* $P(x, s, O^s opt, W_m) \geq P(x,i) \; \forall Ai \in (A) \& \; O^i \in R^i$

Furthermore, the performance consists of three dimensions: accuracy, processing time, and memory consumption, as shown in Figures 3-7.

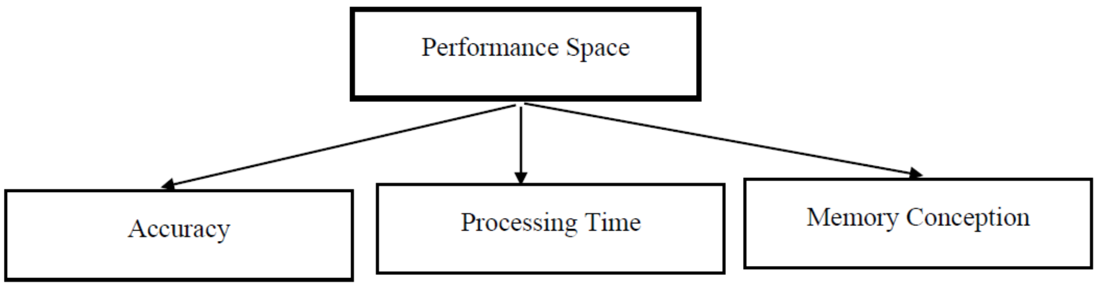


Figure 3-7:The Performance Space

Also, the registration algorithms can include three types of registration algorithms, such as registration algorithms for diagnosis, treatment, and surgery guide system, as presented in figure 3-8.

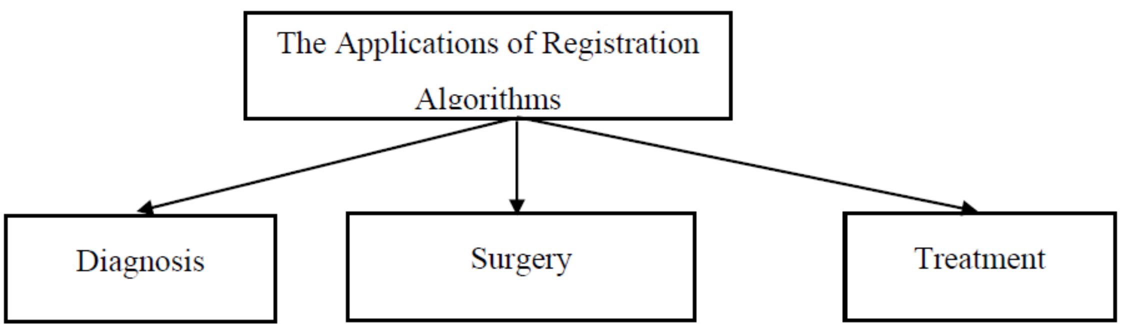


Figure 3-8:Registration Algorithms Applications

3.4 Noise's Effect on The Algorithm's Performance (Robustness)

The robustness is one of the crucial performances in the medical image algorithm selection and registration. The definition of robustness in the medical image process and algorithm selection is the ability of the system or framework to deliver its emission in the presence of noises. Medical data are susceptible to being degraded by noise due to various circumstances during the acquisition phase. This thesis aims to discuss and show the impacts of noises on the proposed system's robustness. The experiments are conducted using CT/PET picture pairs from the data set and increased varying degrees of Gaussian white noise to one of the images with a mean (m = 0) and variation (d = 0.0001, 0.0004, 0.003, 0.008, and 0.01). Gaussian white noise with varying variances produces noise levels of roughly 1%, 2%, 5%, 8%, and 10% for these photos. It is futile to increase the noise level above 10%, as Gaussian white noise degrades the information richness of medical pictures dramatically. The effect of noise on the robustness of the proposed framework was investigated under these conditions, which are various noise levels. The "Accuracy" values represent the difference in accuracy between the candidate's registration algorithms, including the suggested approach, when the input moving medical images are noise-free and without noises. The proposed framework’s performance remained essentially consistent when noise levels grew.

Moreover, that is not the case for other candidates, whose performance is influenced by noise artifacts and whose accuracy decreases as noise levels grow, with a substantial increase in performance error. The demonstrates that the suggested framework is significantly less sensitive to noise rise than the other candidates.

3.5 Overview of The Framework

An essential aspect of MIR in clinical practice is its computational efficiency, registration accuracy, and robustness to several other biases affecting medical images. Numerous studies on the registration process for medical images have been published in the literature, and various registration algorithms are available. However, none of the registration processes outperform others for all datasets, making individual registration algorithms unreliable. One of the many issues in the current MIR is the unavailability of highly precise, computationally efficient, clinically acceptable, and robust registration techniques. Although the available registration methods provide helpful information from separate images, the accuracy and computational efficiency are often compromised. Other unresolved difficulties include effective landmark detection, multimodal image registration, and outlier rejection in medical pictures. Due to the inherent variability of imaging and the varying requirements of applications, no single registration algorithm outperforms all input datasets. The critical point is to understand which solution is the best fit for the issue and why. This study establishes a standardized and efficient structure (as shown in Figure 3-9) for algorithm selection for multimodal registration using Machine-Learning and Neural Networks. The novel method created allows for selecting the most widely accepted registration algorithm from various registration processes for various datasets.

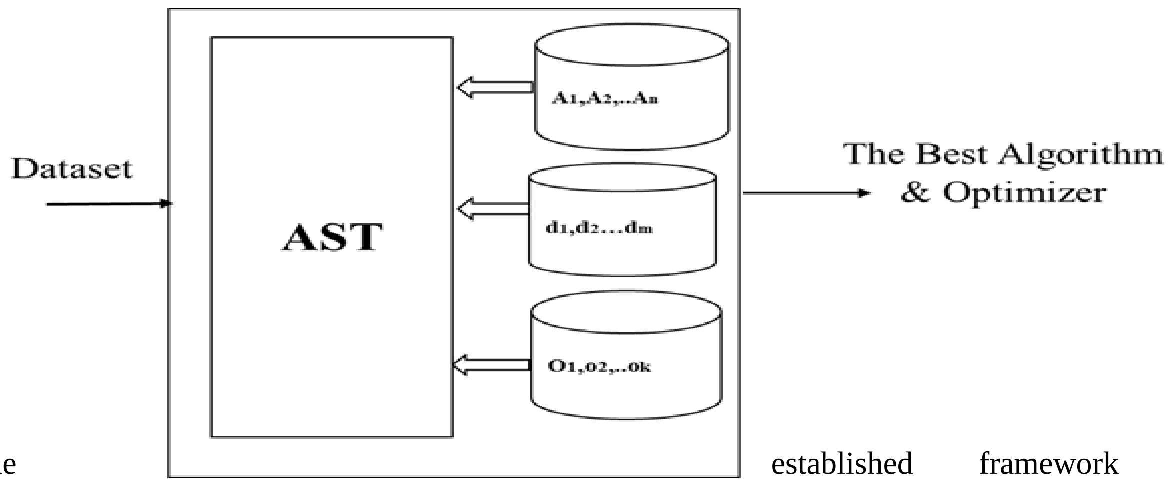
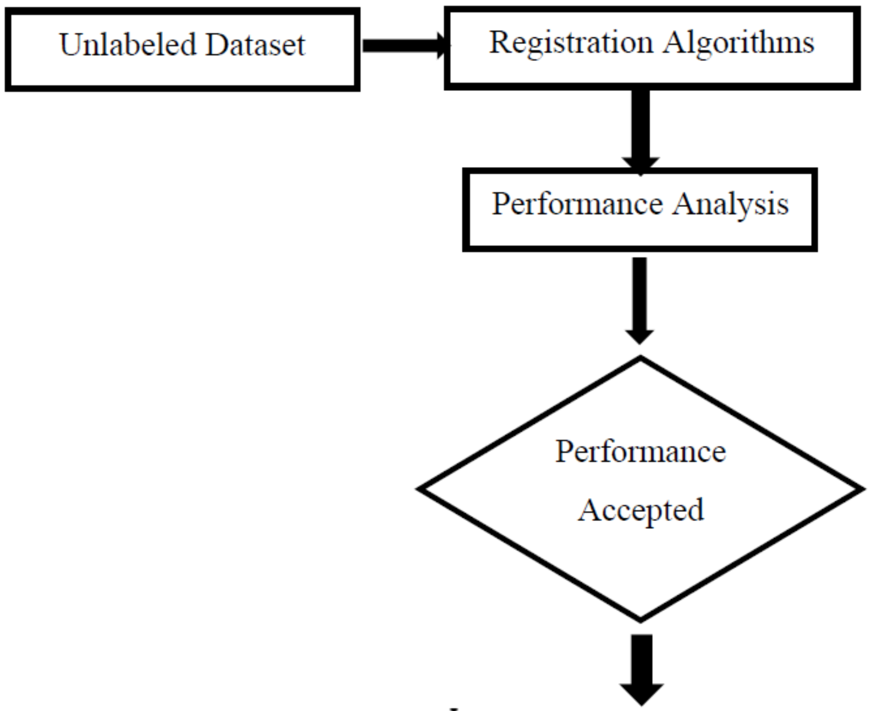


Figure 3-9:Overview of The Proposed Framework

The established framework solution was evaluated in various strategies using various registration algorithms and performance metrics. The method maximizes registration accuracy for an unseen instance by learning with a neural network and evaluating N-fold cross-validation.

3.6 The Proposed Framework

The suggested framework is separated into two operational phases: training (as depicted in Figure 3-10) and testing (Figure 3-12). The following subsections provide a complete description of the framework.



Dataset	A1		A2		A3		Labels
	Accuracy	P-Time	Accuracy	P-Time	Accuracy	P-Time	
1	89	82	87	82	84	89	(A1)
2	88	85	87	76	85	93	(A2)
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
121	**93**	87	84	90	89	85	(A3)

Figure 3-10:Registration Algorithm and Dataset Mapping

3.6.1 Training Phase

This phase aims to train a learning model that will be utilized to make algorithm selection automatically. The training framework stage consists of three major components: (i) the input dataset, (ii) the algorithm scoring module, and (iii) the machine-learning system. Following that, each of these phases and their complex operations flow will be described. First, a database is created, and a collection of medical pictures is recorded. Figure 3-11 illustrates that the labelled dataset is constructed by applying all accessible medical

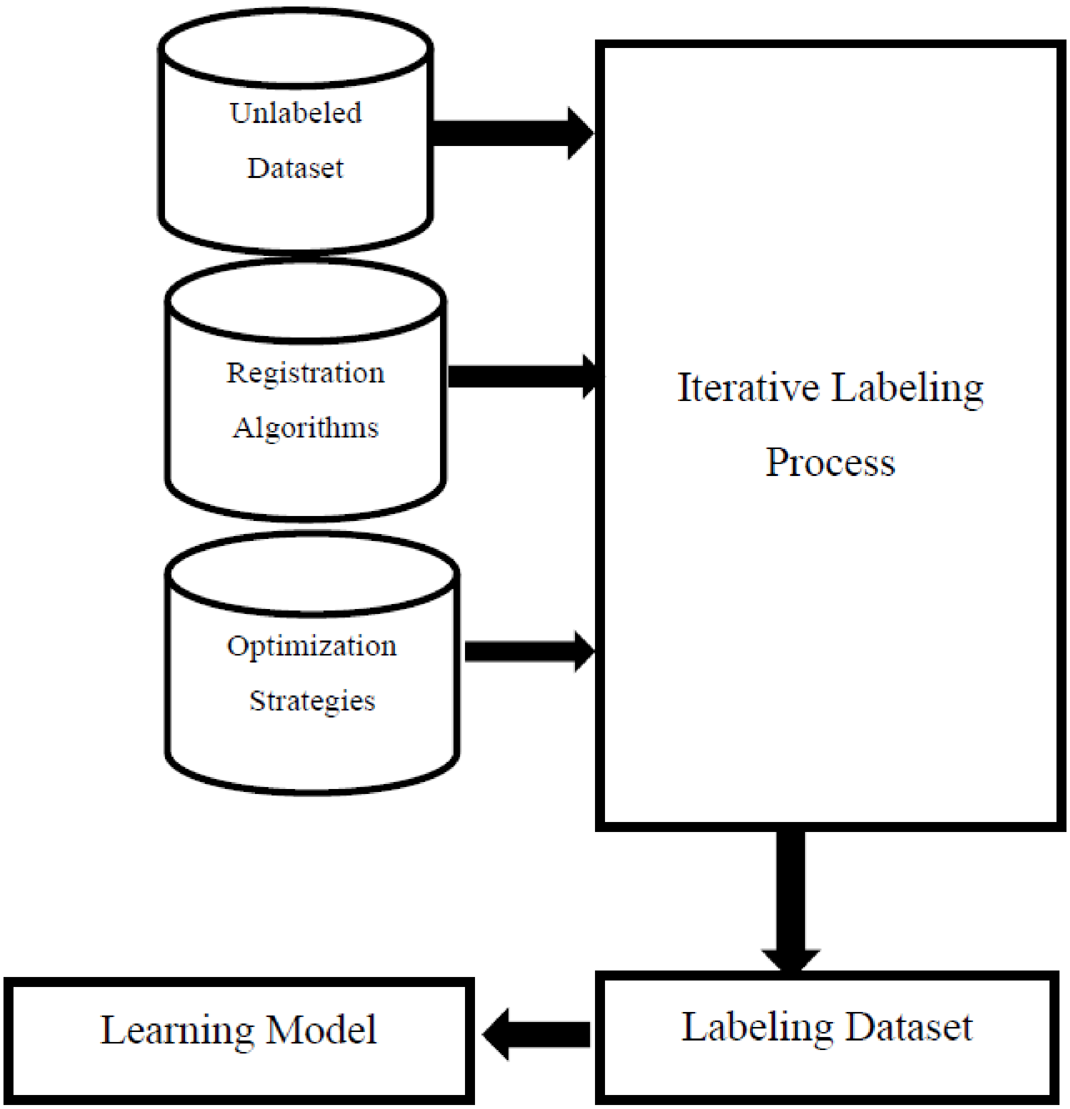


Figure 3-11:Creating Learning Model

The framework is adaptable and can be used with any machine-learning categorization technique (e.g., Naïve Bayes, K-Nearest Neighbor (KNN). image algorithms to all relevant datasets, providing the performance measurements (Labels) necessary to train the learning technique. As illustrated in Figures 3-8, the training data for the learning model includes both the data and the performance of the candidate processes (labelled dataset). The training process is depicted graphically in Figure 3-12.

3.6.2 Testing Phase

Changing the learning model entails modifying the training and testing processes. When a novel dataset is examined, the trained MLP uses the attributes as inputs to choose (predict) the most appropriate method. This procedure does not require a track set or any of the previous procedure's training ingredients. The testing phase comes after the training phase, and the last weights of the learning model are utilized as a testing model for the online estimate that follows.

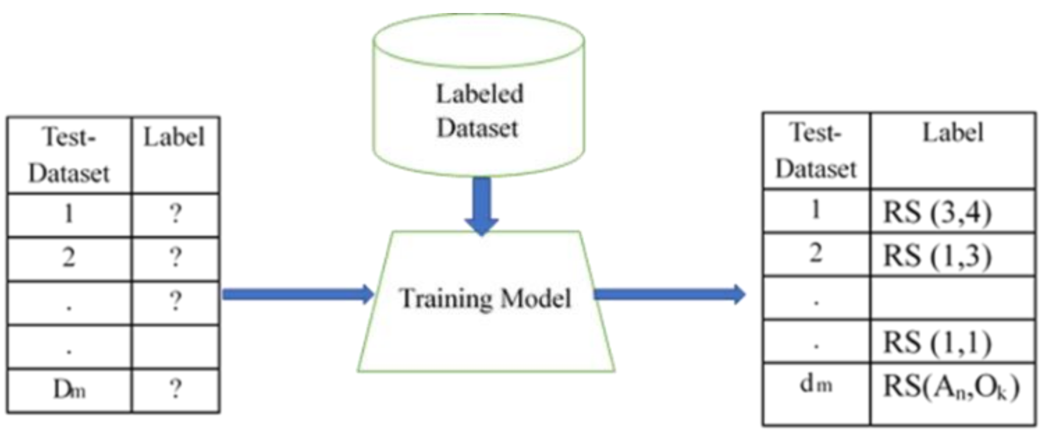


Figure 3-12:Testing Phase

3.7 summary

As previously mentioned, it is essential to locate a universal medical image registration framework that can present the best outcome for every input dataset. The proposed system uses a supervised machine learning approach to select the best registration strategy (Zn,k). The special registration algorithm does not supply the best performance for every dataset forms the footstone of the problem statement. Consequently, it is essential to find the most active registration algorithm appropriate for resolving this problem instead of developing new registration algorithms. The dataset was mapped to three registration algorithms to generate a labelling dataset. The MLP classifier was trained with a labelled dataset to create a learning model. The second stage in the proposed framework is the testing stage. After the training phase, the learning model's final weights test the subsequent online estimate. Changing the learning model would necessitate a change in the training and testing processes. When examining an unknown dataset, the trained MLP uses the images as inputs to select (predict) the most proper technique. Finally, to examine the robustness of the proposed framework, The study utilized CT/PET picture pairs from the data set and added varying degrees of Gaussian white noise to one of the images with a mean (m = 0) and variation (d = 0.0001, 0.0004, 0.003, 0.008, and 0.01). Gaussian white noise with varying variances produces noise levels of roughly 1%, 2%, 5%, 8%, and 10% for these photos. It is futile to increase the noise level above 10%, as Gaussian white noise degrades the information richness of medical pictures dramatically.

Chapter 4
Greedy selection strategy

4.1 Introduction

A medical analysis might be augmented by registering medical pictures from sensors for the same subject or scanning for various patients. The registration method attempts to match the coordinate systems of the pictures [25]. Numerous medical imaging modalities exist, including magnetic resonance imaging, X-Ray, and positron emission tomography (PET) (PET). Soft matters are visible in ultrasound images, whereas bones are visible in CT images, which allows for collecting valuable information if CT and MRI images of the same patient's subjects are registered [1-2]. However, no state-of-the-art registration technique outperforms the others throughout all datasets, rendering individual registration algorithms untrustworthy. The absence of highly precise, computationally efficient, clinically acceptable, and robust registration techniques is one of the difficulties in the existing MIR. Although the available registration methods provide helpful information from separate images, the accuracy and computation efficiency are often compromised. Therefore, an essential aspect of MIR in clinical practice is its computational efficiency, registration accuracy, and robustness to several other biases affecting medical images.

The primary purpose of this solution strategy is to transform algorithm selection into a classification problem. Therefore, to accomplish that, a supervised machine learning technique was used. Moreover, a supervised dataset was created by mapping a dataset to a set of selected registration algorithms, and finally, the performance (Accuracy) was measured. Consequently, the registration algorithm that produces the best accuracy is selected as a label to their input dataset. As a result, the labels denote the "most appropriate" algorithm for each input dataset. Therefore, the solution strategy dependent on transforming the algorithm selection problem into a classification problem.

4.2 Problem Statement

As seen in Figure 4-1, selecting a registration algorithm could be seen as a three-dimensional space problem. Wherever 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

.

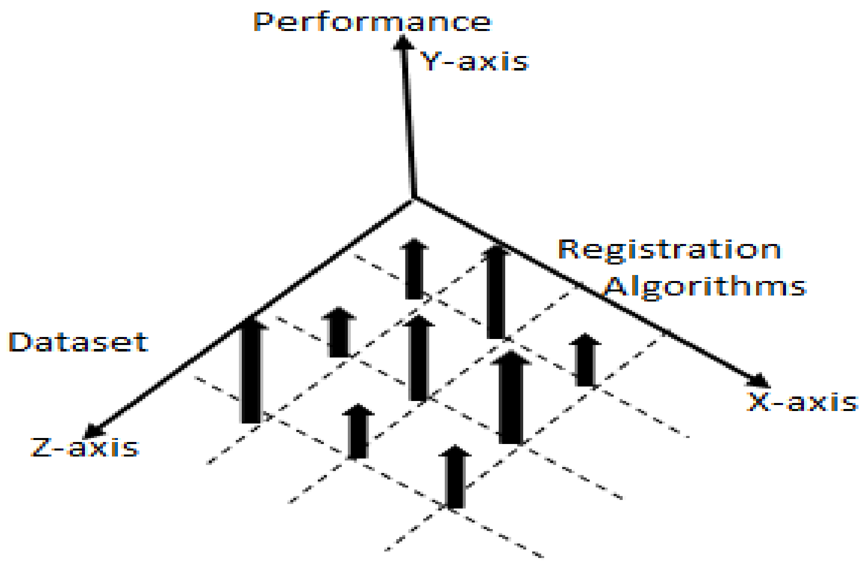


Figure 4-1:Algorithm Selection Problem: Three Dimension Space

For example, as shown in Figure 4-1, the registration algorithm A_1 gives the best performance with dataset d_3, and the registration algorithm A_2 produces the most excellent accuracy with d_1. Therefore, the results will be dissimilar if dataset d1 is selected and mapped to several registration algorithms, A1, A2, an

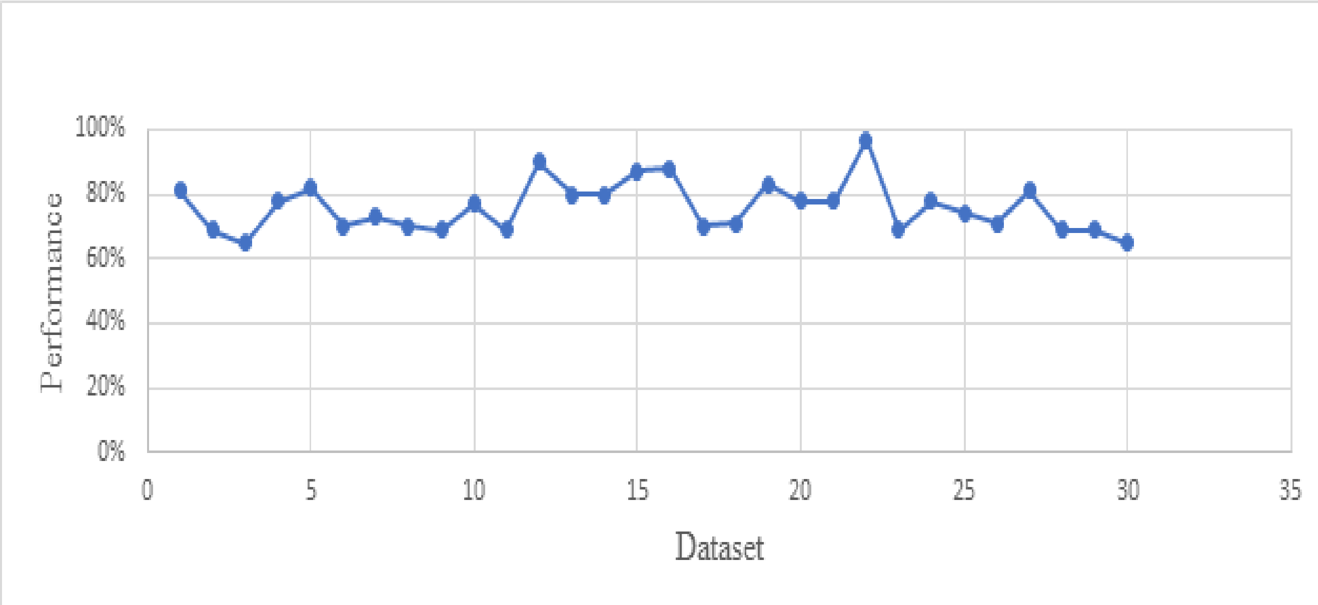


Figure 4-2:Registration Algorithm A1 Versus Dataset

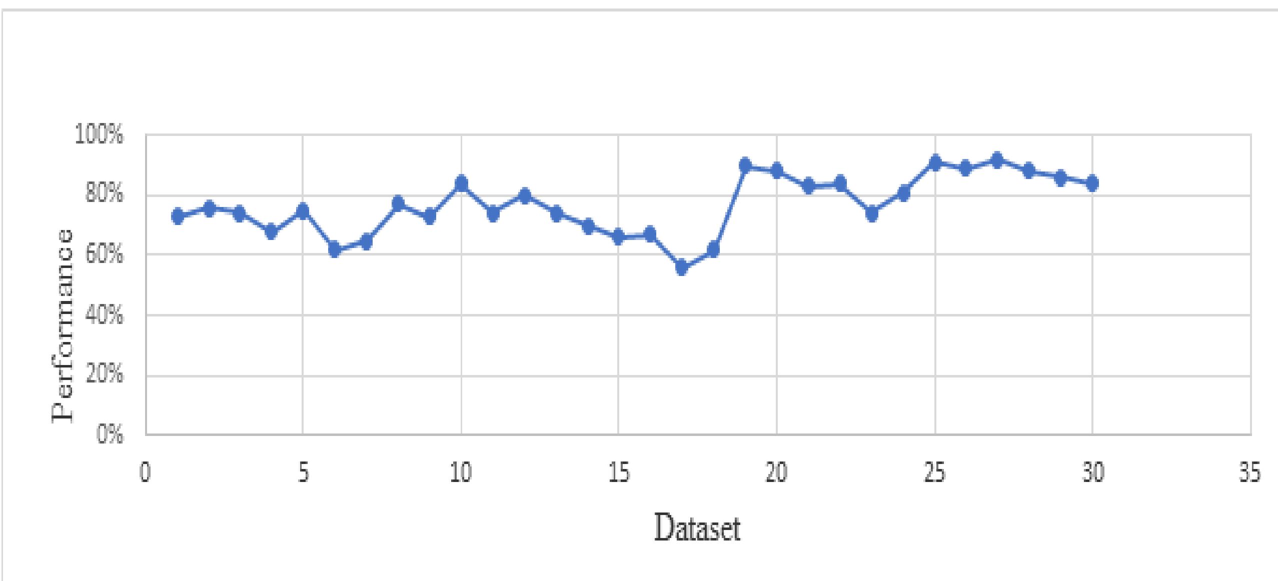


Figure 4-3:Registration Algorithm A2 and Dataset

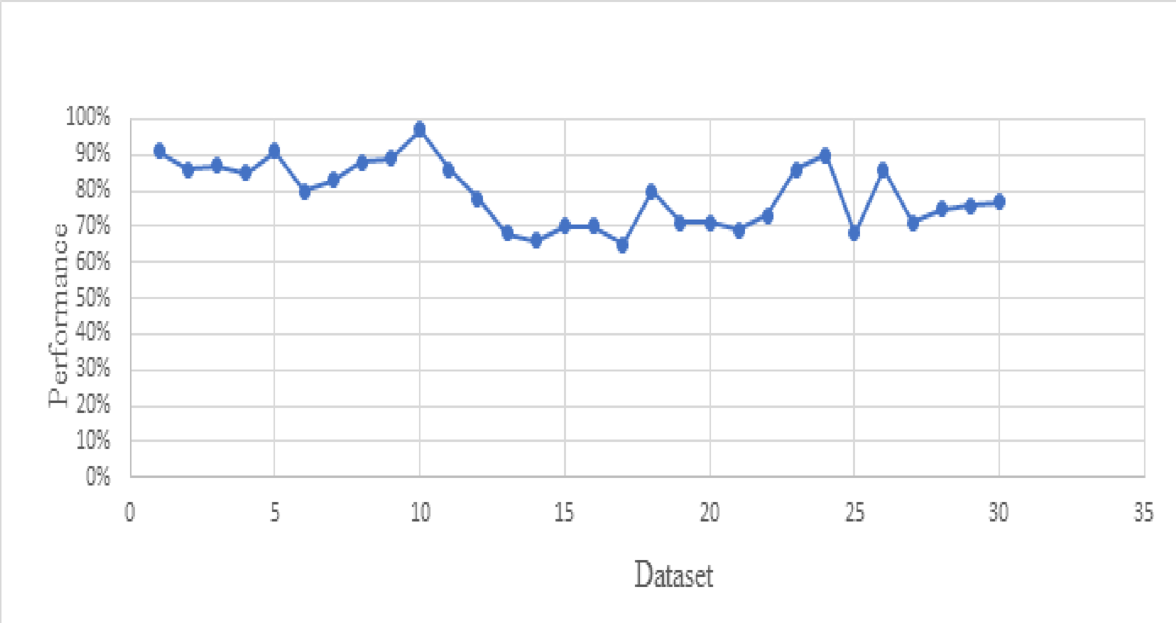


Figure 4-4:Registration Algorithm and Dataset

Moreover, if the same procedure is repeated with the d2 dataset, the results will be different. On the other hand, if a registration algorithm such as A1 is used with different datasets (d_l, d2, d3,…, dm), the outcome performance is different, as shown in Figures 4-2, 4-3, and 4-4. 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. As a result, the issue of how to choose a registration algorithm that will produce high-performance outcomes across all datasets arises. Choose the best appropriate registration algorithm for each pair of medical images (dataset) from a set of available registration methods to maximize the overall registration accuracy.

Given:

- Image dataset D = $\{d_1, d_2, \ldots d_j\}$.
- A set of registration algorithms A = $\{A_1, A_2, \ldots A_n\}$

- Each algorithm A_i achieves performance, $P_{i,k}$ when applied to the dataset $d_{k,} \in$ D.

Now:

- Given x, a new set of images that we wish to register. X
- Let P(x, i) be the registration performance of the algorithm A_i on the new set x
- The objective is to design a selection strategy S such that
- $S(x \mid D, P_{i,k} : \forall d_i \in D, A_{k.} \in A), = A_s \in A$,such that
- $P(x, s) \geq P(x,i) \; \forall i \in (1.......n)$ (4-1)

4.3 The Proposed Solution

Due to the inherent variability of imaging and the varying requirements of applications, no single registration algorithm outperforms all input datasets. The critical point is to understand which solution is the best fit for the issue and why. As illustrated in Figures 4-6, the novel method enables selecting the most frequently recognized registration algorithm for collecting datasets from a group of registration algorithms. The established solution strategy's essential notion is to convert the selection problem to a classification problem. The ANN is used as a learning model to guess the best algorithm for unseen datasets, and the N-fold cross-validation is used as assessment criteria. The proposed solution has three phases, the first one is creating a supervised dataset, the second phase is training the selected system with a labelled dataset to create the learning model, and the last phase is the testing phase; this is used to estimate the optimal registration strategy for a previously unknown dataset.

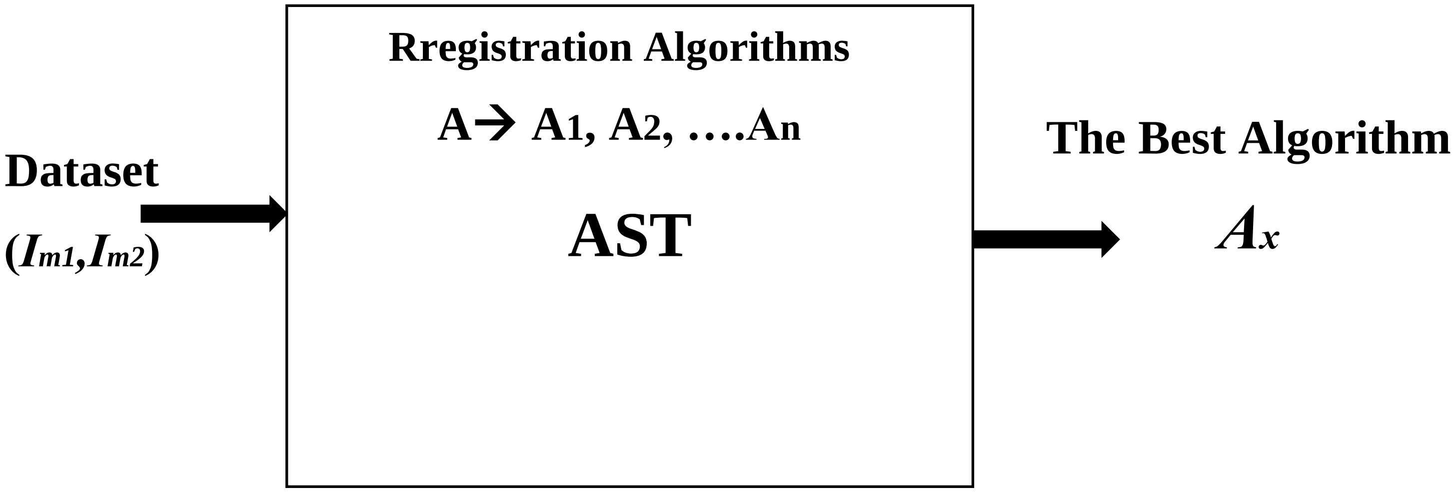


Figure 4-5:The Proposed Selection System

4.3.1 Dataset Labeling

The proposed solution is broken into three stages and is based on supervised machine learning:

1-The first stage encompasses labelling dataset generator based on registration algorithms as shown in Figure 4-6. The labelling system contains three stages:

1- Dataset Space: A set of benchmarked datasets (a pair of medical images)
2- Problem Space: A set of registration algorithms
3- Performance Measure: The accuracy is used as a criterion for measuring the highest degree of accuracy obtained by an algorithm for a specified dataset.

The primary goal is to identify the registration process with high accuracy and chosen as the label for the input dataset (dm).

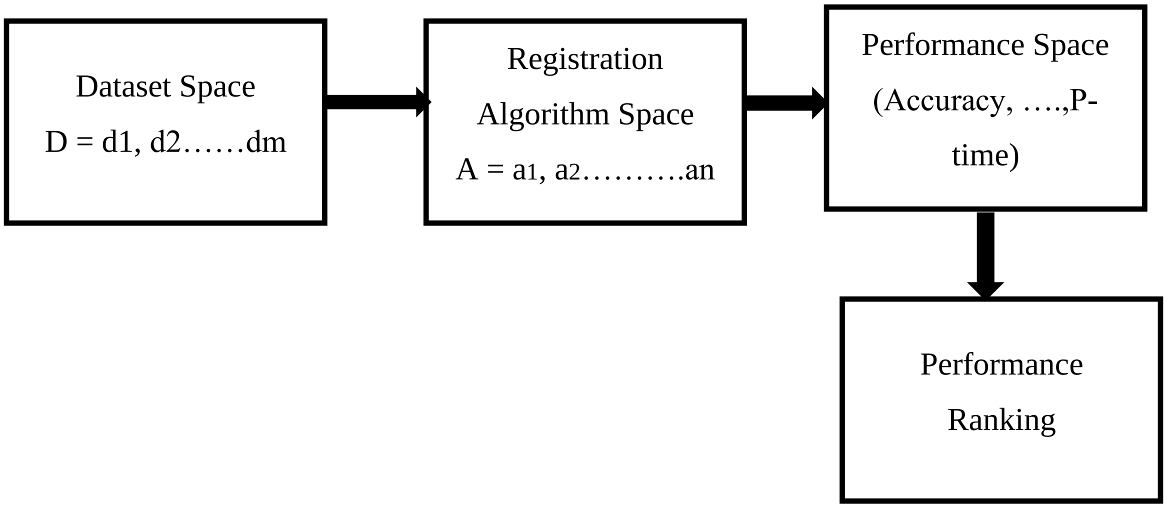


Figure 4-6:Dataset Labeling

The system provides the learning model with final training samples (i.e., labels). The tags indicate the algorithm that is "best appropriate" for each dataset. The process began with mapping every dataset in the dataset space to every registration algorithm in the registration algorithm space. For this purpose, three registration algorithms were selected: a points-based registration algorithm, an external 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. The registration algorithm performance space is then utilized to assess the accuracy of every registration algorithm based on the input dataset. The registration algorithm that provided the highest accuracy concerning the input dataset was selected as a label for that dataset, as indicated in Table 4-1.

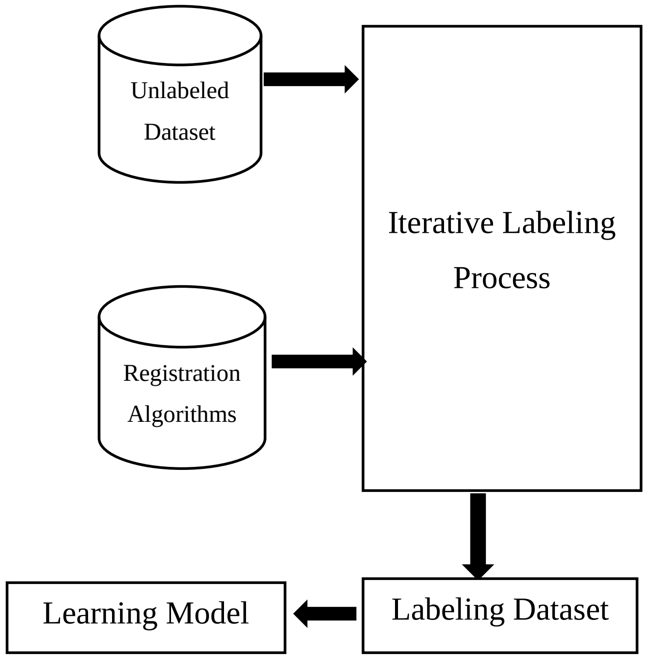


Figure 4-7:Schematic Diagram of the Proposed Framework

The same procedure is then applied to all unlabeled datasets, and the registration algorithm based on the labelled dataset was then produced. Three classes of registration algorithms are then created: A_1, A_2, and A_3. The last step calculates a mean accuracy level for each of the three classes, as shown in Table 4-1. The final output of the first substage is that of the labelled-dataset-based registration algorithms (training dataset). After that, the training data is prepared for the subsequent stage.

Table 4-1:Dataset Labelling: Registration Algorithm

Dataset	A1	A2	A3	Label
1	**91%**	81%	73%	A1
2	78%	**90%**	80%	A2
.	.	.	.	.
.	.	.	.	.
120	61%	70%	**80%**	An
Average	93%	79%	85%	

Table 4-1 compares algorithms solely based on their accuracy. The ranking is then denoted by the candidates' initials (A1, A2, A3), with "A1" denoting the candidate with the best score (first rank case). It converts the challenge into a classification problem that can be resolved with machine learning techniques such as a Neural Network.

4.3.2 Training Phase

This phase will train a model that will be used to select algorithms automatically. The training system stage comprises three major components: (i) a dataset generator for labelling, (ii) a module for ranking algorithms, and (iii) a model based on machine learning. Following that, each of these components and their general flow will be discussed. First, a database is created and populated with a collection of medical photographs. Following that, the training phase employs all accessible registration techniques on each given dataset, resulting in developing performance indicators for training the learning model, as seen in figures 4-3. The training dataset for the learning model comprises both the data and the performance of the potential processes. The system is versatile and may be used with any machine-learning classification technique (for example, decision tree DT and K-Nearest Neighbor). Choosing the optimum registration algorithm is thus interpreted as a classification problem encouraged by the observation that, in many practical problems, algorithms exhibit different performances with varied datasets. While one algorithm performs well on some datasets, it performs poorly on others and vice versa for another algorithm. If the best registration algorithm can be identified for a given dataset, It becomes feasible to combine the perfect combination and significantly boost overall performance

4.3.3 The Learning Model

The learning model component of our architecture provides an overview of the system that would train from 's mission and algorithm ranks. When a system user implements it to algorithms choosing assignment, they must choose which model to utilize. We chose an Artificial Neural Network as the learning model. This model optimization does not exclude the use of possible alternatives such as Naïve Byes or Decision Trees (DT). Nevertheless, in various circumstances, Convolution neural networks are commonly utilized in various areas and are often regarded as "state of the art." ANNs can be extended in various approaches, as shown in our observations, where they model various tasks (as shown in Figures 4-8). The data is supplied to the network via the input neurons on an instance – basis during each iteration. Following that, the data is transmitted forward through the

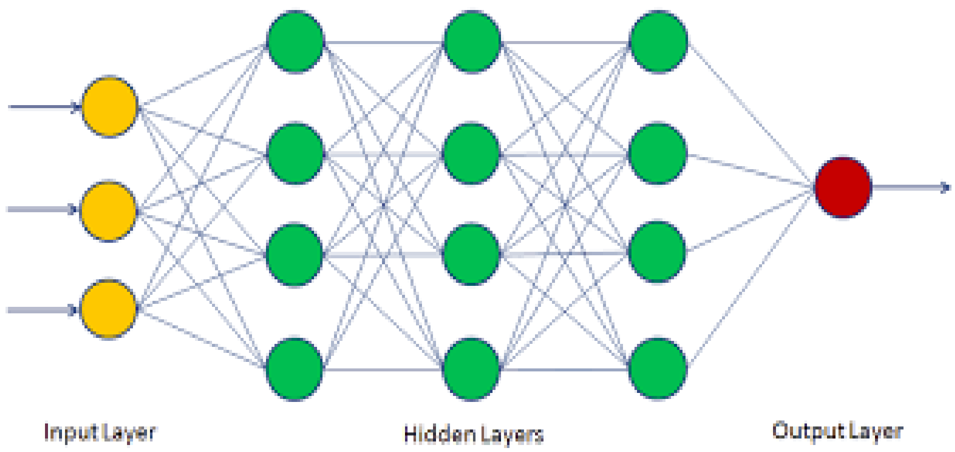


Figure 4-8:Multilayer Perceptron Classifier (MLP)

Network levels till it achieves the output level. The error is computed at the network's output level, representing the output and real values variation. The measured error is then spread through the network in a backward run using backpropagation [4] (chain rule differentiation), adjusting the network's weights to generate an output nearer to the definite value. Training is the term used to describe this iterative offline method.

4.3.4 Mathematical Description of Learning Model

Mapping inputs to corresponding desired outputs by optimizing the network weights are identified as a learning MLP. Moreover, finding the disparity between the concrete and required outputs is known as the inaccuracy function. Therefore, finding the best learning model is equivalent to minimizing the error function of the network.

Given vector:$D = d1, d2, d3, \dots . dm$ as an input.

Given vector:$A = a1, a2, a3, \dots . an$ as the desired output.

Given vector: $W = w0, w1, w2, \ldots\ldots wi$ as network weights.

These are called *inputs*, *outputs*, and *weights*, respectively.

In Figure 3-11, the output equation at the hidden layer is

$O_j = f\left(\sum w_{ij} \cdot d_i\right)$ where:

$W_{ij} \rightarrow$ The input and hidden layers weight difference.

An equation represents the network's actual output.

$\grave{A}_n = f\left(\sum w_{ij} \cdot O_j\right)$, which, given a weight (w), maps an input d_m to an output Àn.

As illustrated in, the error function is the disparity between the expected and actual outputs.

$$E = \frac{1}{E} = \sum_n \left(An - \grave{A}n\right)^2 \qquad (4\text{-}2)$$

The network's output signal (n) is compared to the training data set's required output value (the target). The discrepancy is referred to as the output layer neuron's error signal (E). Therefore, the main goal is minimizing the error by changing the weights using a gradient descent optimizer.

The objective function is: Minimize Error (E)

Variables: network weights w_{ij},

Algorithm: local search via gradient descent.

Randomly initialize weights.

4.3.5 Testing Phase

As depicted in Figures 4-9, the next stage is to select the best possible registration algorithm built on the learnt model. Following training, the ultimate weights of the ANN are employed as a testing model for further online prediction. Changing the learning model would necessitate a change in the training and testing processes. Following that, the qualified MLP uses the characteristics as inputs to determine the appropriate algorithm. This method does not require a trace collection or any of the previous training process's other components. The research process is conducted entirely online.

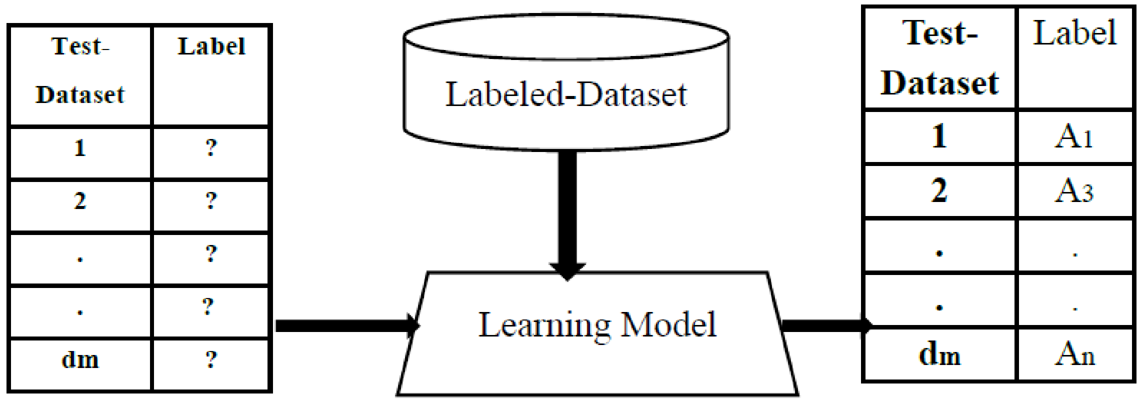


Figure 4-9:Framework Selection for Unseen Dataset

The learned model created during the former stage is applied for labelling the test dataset, which is unlabeled. The primary function of the learned model is to designate a tag to the input. When the test datasets, which are 100 unlabeled datasets, 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. Therefore, the output of the learned model is the labelled dataset, whose label represents the registration algorithm, which is one of the three candidates: A_1, A_2, or A_3. Thus, the chosen algorithm will be the best registration algorithm for the unknown input dataset, as shown in Figures 4-10,4-11.

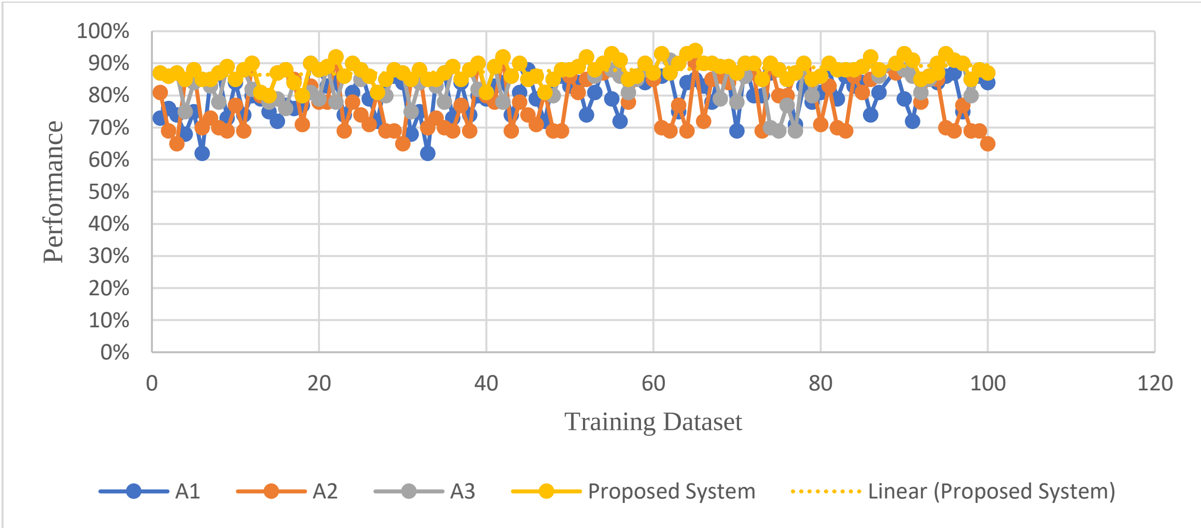


Figure 4-10:Proposed System performance: Learning Dataset

On the other hand, when the proposed system examines under an unlearned dataset, some issues appear in Figures 4-11. For example, at dataset number 10, the proposed system unsuccessfully selected the

best registration algorithm, where the registration algorithm A3 gave us the best performance. The main reasons for this problem will be discussed in the next section.

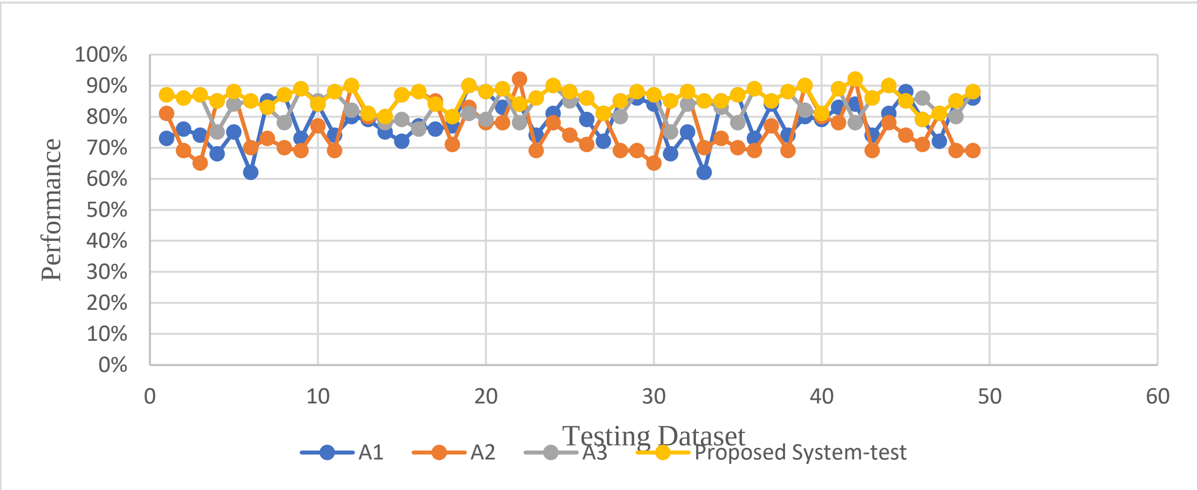


Figure 4-11:Proposed System Performance: Unlearned Dataset

4.4 The Solution Strategy Drawbacks:

Generally, the goal is accomplished utilizing the planned approach. As presented in Figures 4-10 and 4-11, the proposed solution achieves the desired goal, choosing the best registration process for unseen input instances. The proposed approach is the best if that tested image is the same data point in the learned model. The performance of the system is a function of the learned dataset. A multimodal medical registration algorithm's robustness and accuracy depend on numerous factors, including modality, image content impacts, similarity functions, conversion, optimization, and implementation mechanisms [20]. Due to the interdependence of these complicated characteristics, it is difficult to ascertain how each one influences the registration process. However, preliminary evaluations of the effects of these criteria are critical before registration.

The local minima of similarity measure also affect registration accuracy in the elastic transformation due to the extraction of inaccurate landmarks. c) When local peaks of the similarity measure exist in multimodal medical picture registration, the optimization strategy compromises registration accuracy. As a result, optimization tactics are critical for enhancing the performance of MIR.

4.5 Summary

The registration process is the essential method in image processing applications such as medical applications. Also, from the literature review, no single registration algorithm can outperform for all input datasets. The proposed solution strategy aims to obtain the best registration process for any input dataset to overcome the drawbacks in medical image registration (Manual and computer-based). The suggested solution is dependent on transforming the algorithm selection problem into a classification problem. Moreover, the solution strategy has three stages, and the first one is creating a labelled dataset where the registration algorithm is used as a label. The second stage is the training phase, where an MLP classifier establishes a learning model. The third phase is the testing stage, where the unseen dataset is examined to predict the best registration algorithm. Although the proposed solution provides the accepted solution, it still has some drawbacks, as declared in the previous section. Therefore, the need to improve the first strategy is necessary to overcome the problems in it. The second solution strategy is established to overcome the problems in the first solution strategy, and from the literature review conducted on the MIR, the optimization strategies have a crucial effect on the performance.

Chapter 5

Optimal Registration Parameters Guided Selection Strategy

5.1 Introduction:

Algorithm Selection is vital in situations where the choice of an algorithm is not trivial, and the cost of applying each algorithm is prohibitively expensive. As mentioned in the previous chapter, the developed solution was adapted from the greedy algorithm strategy. The main objective was to find the best registration algorithm for the input dataset without considering global performance parameters. In this chapter, the developed solution was also adapted from the greedy algorithm strategy and aimed to find the optimal registration algorithm with optimal registration parameters. The argument is that the concept of "best registration algorithm selection " means selecting the optimal registration algorithm and optimal registration parameters. It is widely acknowledged that no registration algorithm can deliver the required accuracy under all possible conditions. This research establishes a novel selection system that can choose the most suitable registration algorithm with the optimal registration parameters for various input datasets from a group of registration algorithms. Each registration algorithm comprises several stages, such as geometric transformation, similarity measure, and optimization technique. Each of these stages affects the final registration performance. Due to the interdependence of these complicated characteristics, it is difficult to understand how each characteristic influences the accuracy of the registration process . However, preliminary evaluations of the effects of these criteria are critical before registration. Moreover, the literature review that has been conducted in this study shows that similarity measures have a crucial impact on registration algorithm performance. Therefore, the registration process starts by determining the transformation function that minimizes or maximizes the cost function that defines the dis/similarity between the fixed image and the transformed moving image, as shown in figure 5-1.

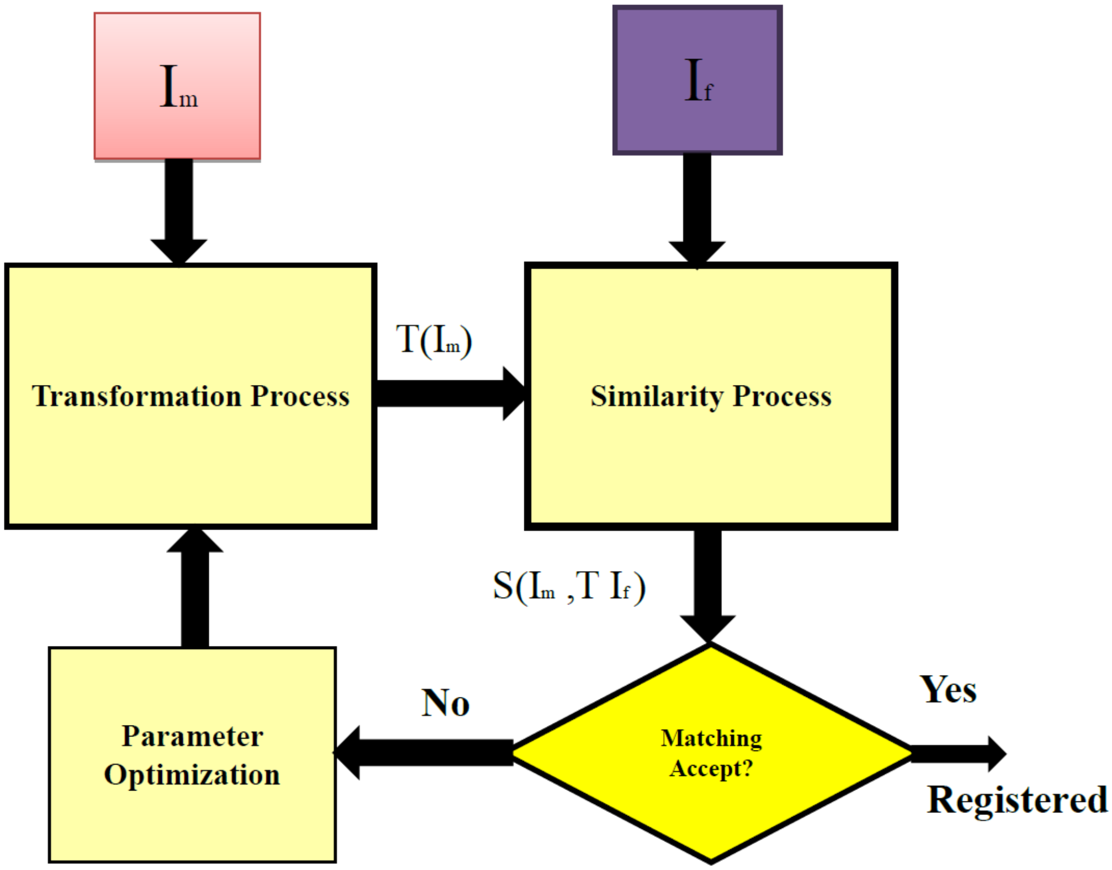


Figure 5-1:Automatic Image Registration Process

There are two approaches for medical image registration, either feature-based or intensity-based, and each method has different similarity measures. The method used in this research is feature-based, and the primary measure for similarity is the distance measure such as Ecludian (spelling?) and Manhattan distance. Therefore, this solution will examine the impact of registration parameters such as similarity measures on the performance of the global selection system.

5.2 Problem formulation

Due to the medical modalities represented by features (points), distance measures are the primary measure for similarity. Examples of these types of geometric distance measures are Euclidean (spelling?) distance and Manhattan distance. Therefore, the optimal registration parameters are Euclidean (spelling?) distance and Manhattan distance and represented by O^{i}_{opt}

Given:

- Image dataset D = $\{d_1, d_{2,} \ldots. d_j\}$.
- A set of registration algorithms A = $\{A_1, A_{2,} \ldots \ldots A_{n.}\}$
- *Each algorithm A_i achieve performance $P(A_i, d_k, O^i)$ when applied to the dataset $d_{k,} \in D$, under the set of parameters $O^i \in R^i$*
- R^i : *parameters space of algorithm* A_i
- O^{i}_{opt} *is said to be optimal on dataset* d_k *if*

$$\boxed{P(i, k, O^{i}_{opt}) \geq p(i, k, \forall O^i \in R^i)}$$

- *Now:*
- *Given x, a new set of images that we wish to register.*
- *The objective is to design a selection strategy S such that*

$S(x \mid D, p(i, k, O^i): \forall d_k \in D, A_{i.} \in A, O^i \in R^i) = \{A_s, O^s opt\}, A_s \in A, O^s opt \in R^s$ *such that* $P(x, s, O^s opt,) \geq P(x,i)\ \forall Ai \in (A) \& O^i \in R^i$

5.3 Solution Strategy

The block diagram represents the main components needed to solve the problem of registration algorithm selection based on optimal registration parameters., The main idea of this solution is adapted from the greedy algorithm strategy, where optimal local selection directly impacts the optimal global selection concerning the registration parameters. Therefore, the main objective of forgiven inputs, dataset, registration algorithms and registration parameters is to find the best selection strategy that selects the best registration algorithm and the best registration parameters for the unseen input dataset.

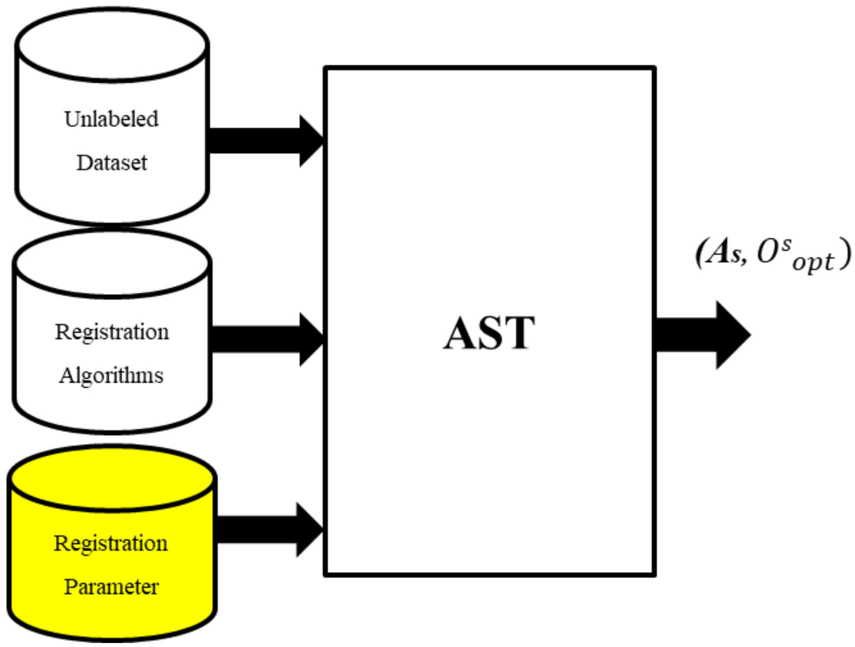


Figure 5-2:Optimal Registration Parameters Guided Selection Strategy

The proposed solution has three phases. The first phase is creating a supervised dataset, the second phase is training the selected classifier with a labelled dataset to create the learning model, and the last phase is the testing phase, which is undertaken to guess the best registration process for the unseen dataset.

5.3.1 Labelling Dataset

The dataset is applied to the registration algorithms and registration parameters, and the output is the performance (Accuracy) of each registration algorithm and each registration parameter, as shown in the table below. The next step is to apply the ranking process to select the best registration algorithm and registration parameters (A_n, $O^i opt$) regarding the best performance as a label for the input dataset. The process is repeated iteratively for all input datasets. As a result, the supervised dataset is created. Figure 5-3 explains and represents the iterative labelling process.

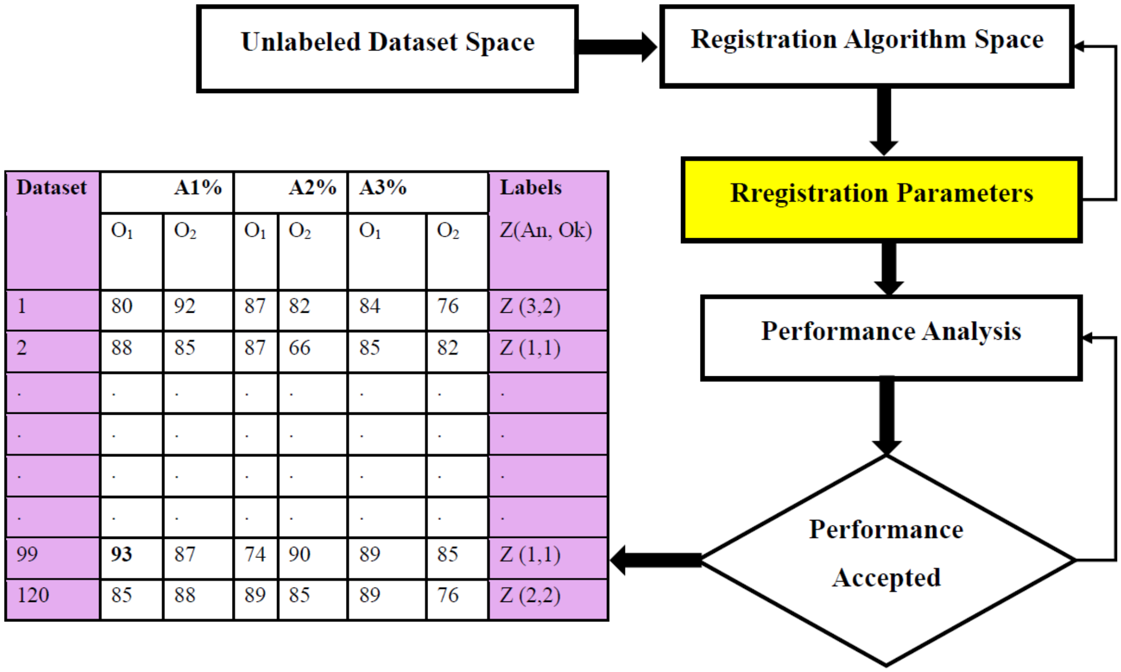


Figure 5-3:Datset Labelling Process

Table 5-1:Dataset Labelling: Registration Algorithm and Registration Parameters

Dataset	**A1**				**A2**				**A3**				**Labels**
	O_1	O_2	O_3	O_4	O_1	O_2	O_3	O_4	O_1	O_2	O_3	O_4	**(An, Ok)**
1	80	92	88	85	87	82	89	93	84	89	85	**95**	RS (3,4)
2	88	85	**95**	90	87	76	86	93	85	93	87	89	RS (1,3)
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.
179	**93**	87	85	86	84	90	88	91	89	85	87	88	RS (1,1)
180	85	88	83	92	89	85	**94**	88	89	76	84	90	RS (2,3)

5.3.2 The Learning Model

Our approach's learning model offers a high-level outline of the system that will be informed by task datasets and algorithm scores. When a system user utilizes it for an algorithm choice assignment, they must choose which candidate to use. An Artificial Neural Network was employed as the learning model. Neural networks are widely utilized in various industries and are regularly described as "state of the art" in various contexts. As proved in the studies, a Neural Network may be extended in various ways to mimic various tasks. As demonstrated in the performed experiment, ANNs can be generalized in several ways to model various tasks. Training is the term used to describe this iterative offline method. Figure 5-5 shows that this stage results in a learned model trained on a labelled dataset which is now ready to identify an unknown (unlabeled) dataset. As presented in Figure 5-4, the outcome of this stage is a learned model, whose learning was achieved based on a labelled dataset and is ready to classify an unknown (unlabeled) dataset.

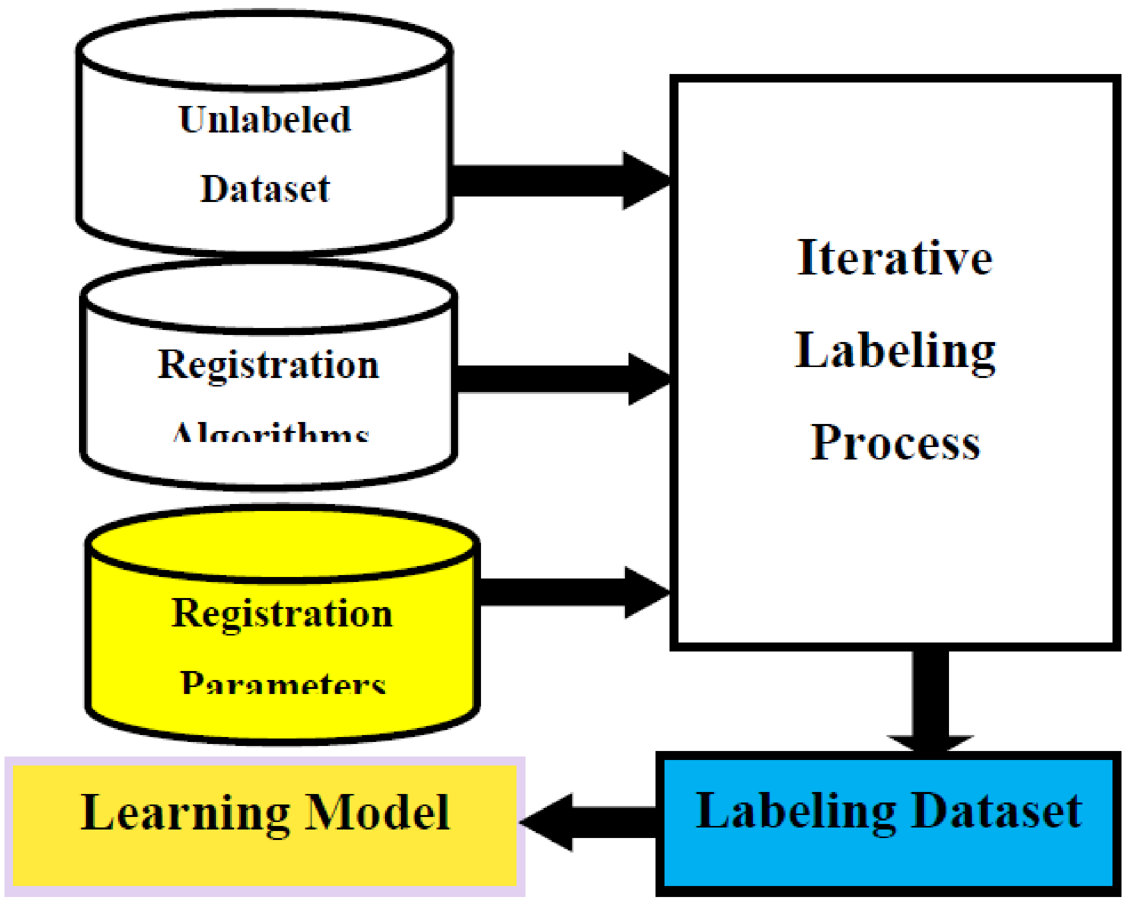


Figure 5-4:Creating Learning Model

5.3.3 Testing phase

The final stage represents the generalization of the unseen dataset. The learned model was created during the previous stage, and it is used for labelling the test dataset. The primary function of the learned model is to designate a tag to the unseen input dataset. When the test datasets are mapped to the learned model, the output is the label for the unseen input dataset, and the label represents the best registration algorithm and the best registration parameters, as shown in Figures 5-5.

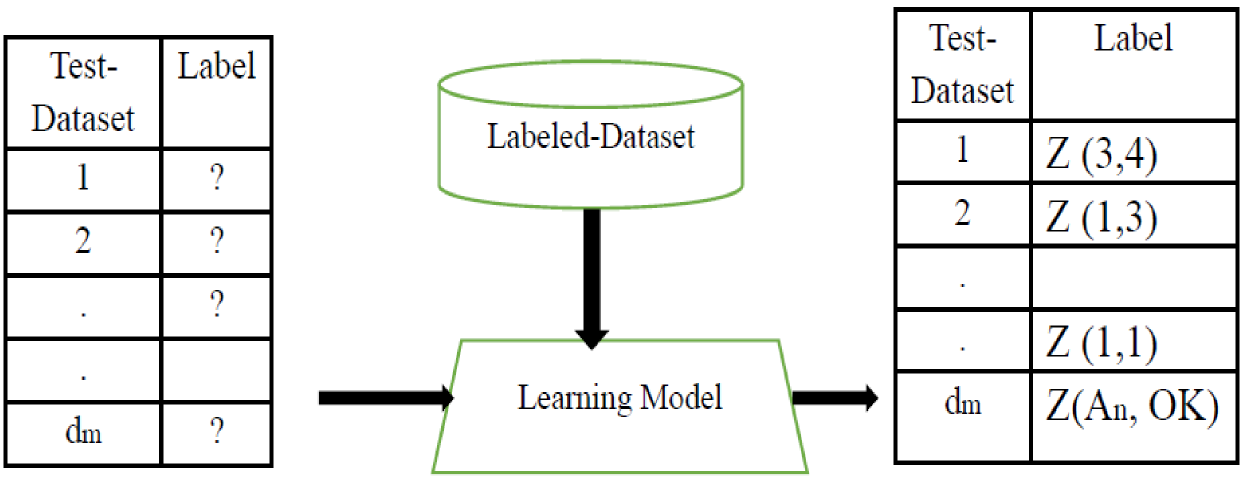


Figure 5-5:Unseen Dataset Generalization

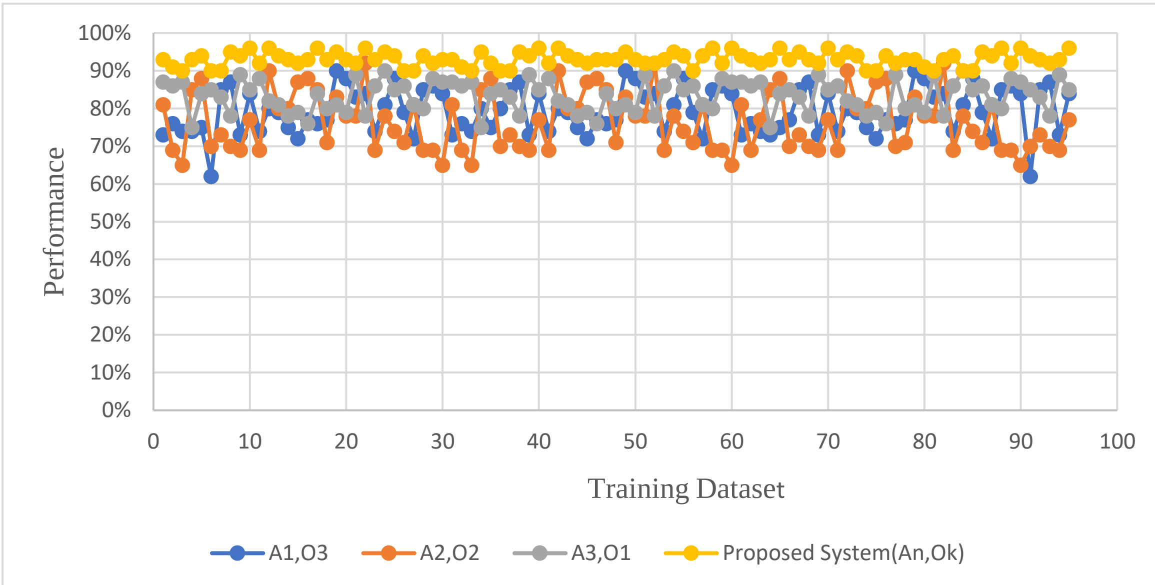


Figure 5-6:Proposed System Performance based Learned Dataset

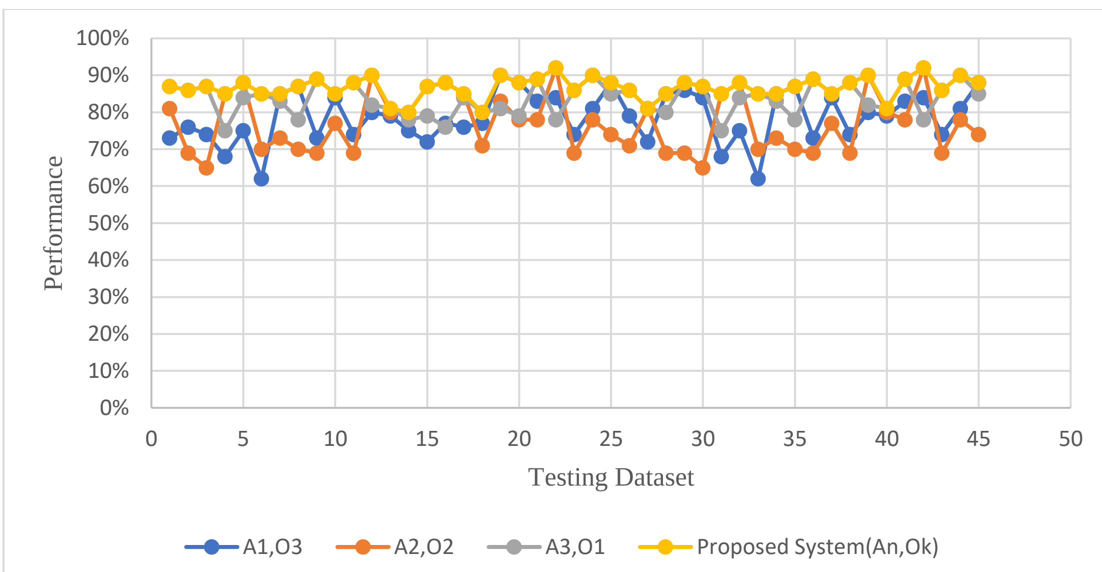


Figure 5-7:Proposed System Performance based Unseen Dataset

5.4 Roulette Wheel Selection Method (Reliability)

The roulette wheel selection method is used to examine the reliability of the proposed system. This approach is also used to select the best registration strategy (Zn,k). The output of the learned model is regarded as the labelled dataset, and that label represents the registration algorithm and optimal registration parameters ($\boldsymbol{As},\ O^{S}{}_{opt}$), which are one of the candidates. As a result, the best registration algorithm and an optimal registration parameter for the unknown dataset can be selected, as described in Figures 5-7,5-8. Numerous approaches for picking the best chromosomes have been discussed in roulette wheel selections, including a roulette wheel, rank, and steady-state selection [115]. The most straightforward selection approach, the roulette wheel system, involves placing all chromosomes (candidates) on the roulette wheel in order of fitness or performance value. In proportion to that individual's fitness value, a segment of the roulette wheel is allocated to each individual. A greater-sized segment is assigned to those with a higher fitness or performance value, as shown in Figures 5-9. Subsequently, the virtual roulette wheel is spun and whoever corresponds to the algorithm occupying the segment where the wheel stops is chosen. The procedure is repeated until the selection of the required number of individuals is complete [24]. In this method, the fitness of the candidates must be measured. A few individuals from a dataset are used to assess all candidates' correctness (fitness), including the optimal registration method (Zn,k) generated from a learned model. Consider that N is the number of candidates, each described by their fitness $wi > 0$, (i = 1, 2, N). Thus, the ith individual's selection likelihood is given in equation 5-2.

$$Pi = \frac{Wi}{\sum_{1}^{N} Wi}\ , i = 1, \dots, N,\ \ Wi = 1, \dots., N \qquad \textbf{(5-2}$$

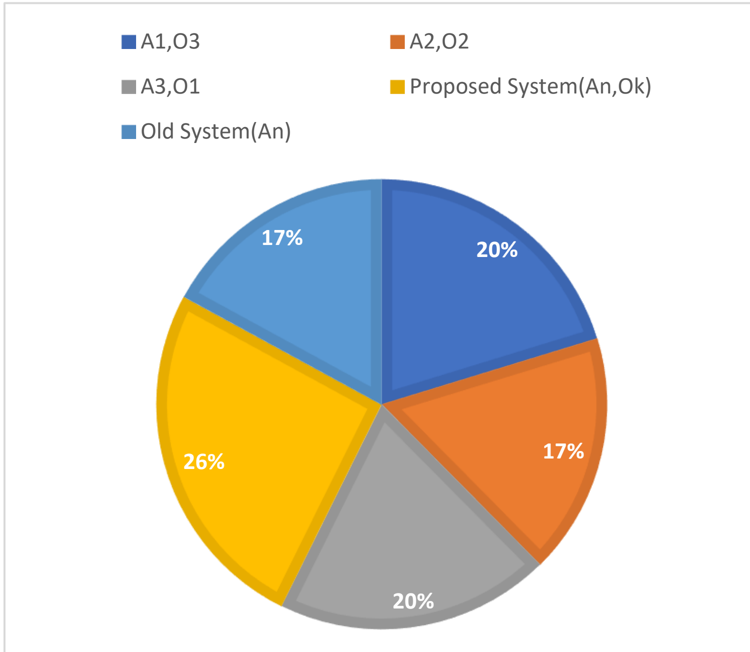


Figure 5-8:Roullet Wheel Selection

Then, the number of candidates must be determined. From Table 5-2, this number can be seen to be twelve candidates. The performances of all twelve candidates were determined through a series of experiments. Consequently, each dataset was examined with all candidates, and the respective output was the accuracy. Finally, the fitness values were shown as the performance (accuracy), as revealed in Table 5-2. The number of spins of the roulette wheel was proportional to the population size. As can be observed from the new division of the wheel, each time the wheel came to a halt, the fitter individuals had a greater chance of being selected. MATLAB software was used to run the roulette wheel selection algorithm, and the results supported the learned model selection for all datasets as listed in Table 5-2. Therefore, the novel method makes the proposed system more reliable, robust, and accurate than the first strategy

Table 5-2:The Best Performance of Candidates

Dataset	Registration Algorithms			Solution Strategy	Solution Strategy
D	A_1	A_2	A_3	(An, Ok)	(An)
1	73%	81%	87%	93%	88%
2	76%	69%	86%	91%	86%
3	74%	65%	87%	90%	87%
4	74%	85%	75%	93%	85%
5	75%	88%	84%	94%	88%
6	62%	70%	85%	90%	85%
7	85%	73%	83%	90%	85%
8	87%	70%	78%	95%	88%
9	73%	69%	89%	94%	89%
10	84%	77%	85%	96%	85%
11	74%	69%	88%	92%	86%
12	80%	90%	82%	96%	90%

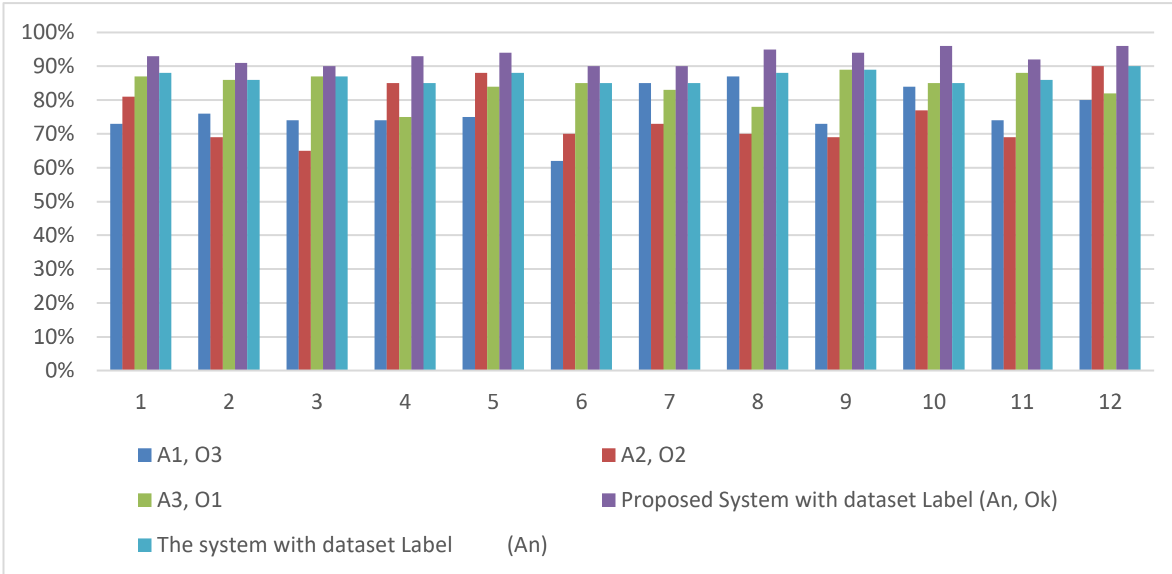


Figure 5-10:Proposed System with Roullet Wheel Selection

The roulette wheel selection strategy is used to enhance the reliability of the proposed framework. As shown in the paragraph, there are five registration algorithms with different performances for each input dataset. According to the roulette wheel selection method, the best registration algorithm was selected using the proposed framework.

5.5 The Effect of Noise on The Registration Algorithm's Performance (Robustness)

The robustness is one of the crucial performances in algorithm selection and registration. The definition of robustness in algorithm registration and algorithm selection is the ability of the system or framework to deliver its emission in the presence of noises.

The MRI/CT image used in the experiment is described in Figure 1. MATLAB diminishes the size of the image to 256*256 pixels. Figure 1 indicates that a gaussian white noise with a deviation of 10, 20, 30, 40, and 50 is used to noisfy the input MRI image. Gaussian noise with a mean of 10 and a variance of 20 is modest noise levels. Gaussian noise at a level of 30 is regarded as moderate, whereas noise at 40 or 50 is deemed deafening.

Due to various situations during the acquisition phase, medical models are susceptible to being damaged by noise. This experiment aims to discuss and show the effects of noises on the framework's robustness. The experiment used CT/MRI images from the dataset and increased numerous degrees of Gaussian white noise to the floating images with a mean (m = 0) and variance (v = 0.0001, 0.0003, 0.002, 0.007, and 0.01). Gaussian white noise with varying variances produces noise levels of roughly 1%, 2%, 5%, 8%, and 10% for these photos. It is pointless to increase the noise level above 10% since Gaussian white noise significantly pollutes the data content of medical photographs. The effect of noise on the robustness of the proposed framework was investigated under these conditions, which are various noise levels. The "Accuracy" values represent the difference in accuracy between the candidate's registration algorithms, including the suggested approach, when the input moving medical image is noise-free and with noises. The proposed framework's performance remained essentially consistent when noise levels grew.

Moreover, that is not the case for other candidates, whose performance is influenced by noise artifacts and whose accuracy decreases as noise levels grow, with a substantial increase in performance error at v = 0.01. The demonstrates that the suggested framework is significantly less susceptible to noise rise than the other choices.

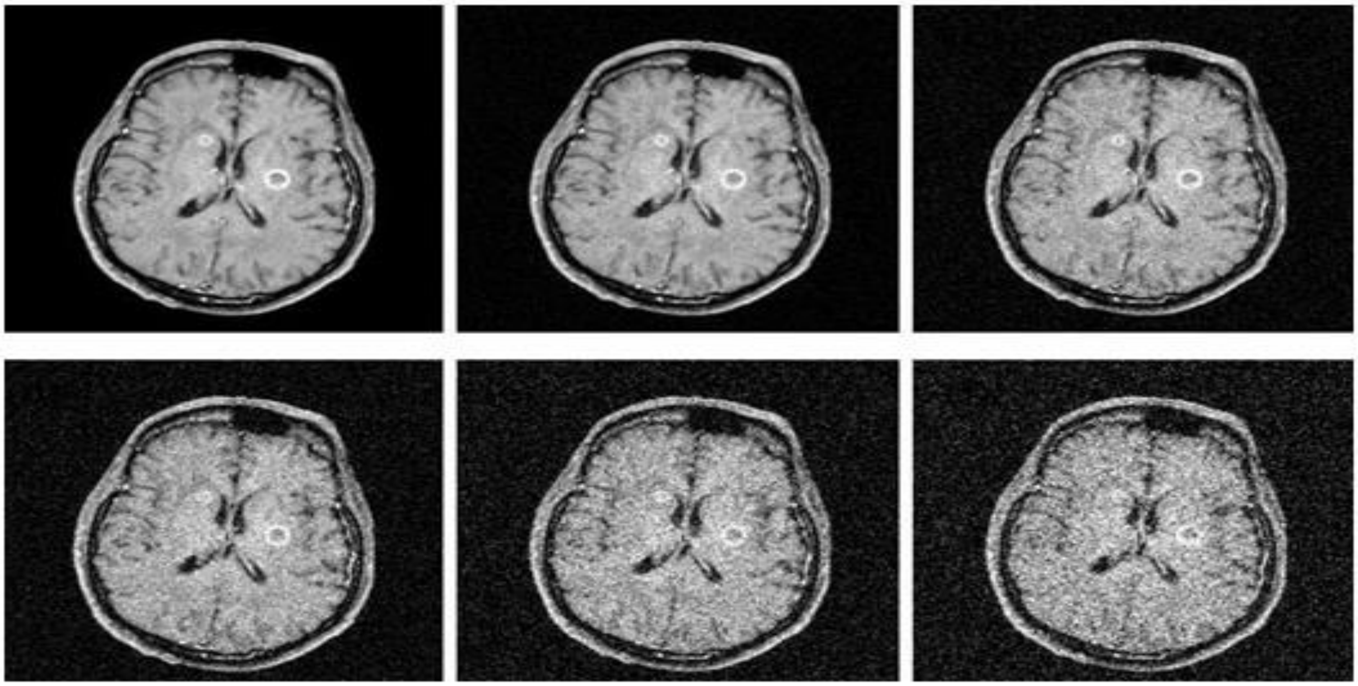


Figure 5-11:MRI Images with and Without White Gaussian Noise

Robustness quantifies the effect of parameter alterations on image registration and quantifies the registration algorithm's stability [74]. It can be quantified in terms of noise, variance in illumination, occlusion, and non-overlapping region. Furthermore, a registration algorithm's robustness describes its ability to operate efficiently in a noisy environment. Additionally, the registration algorithm is robust or stable if it does not produce variable results under slightly different or abnormal circumstances. Due to the inherent inconsistency of medical images resulting from biological activity, registration algorithms must also be robust to efficiently manage slight changes between several images acquired from the same subject through image-guided surgery (IGS).

5.6 Discussion

As previously mentioned, it is necessary to locate a universal selection strategy that can perform the best outcome for every input dataset. A novel system is provided for the multimodal medical image registration algorithms. The created system selects the best registration algorithm based on several parameters such as dataset and the optimization strategy used. The proposed system uses a supervised machine learning strategy and a roulette wheel to select the best registration strategy ($Z_{n,k}$). The special registration algorithm does not supply the best performance for every dataset forms the footstone of the problem statement.

Consequently, it is essential to find the most active registration algorithm appropriate for resolving this problem instead of developing new registration algorithms. As such, the machine learning and roulette wheel technique formed the foundation of the recommended strategy. Two factors govern the new technique submitted in this research: an optimization algorithm and a registration algorithm utilized as labels for unlabeled datasets. The dataset was mapped to three registration algorithms to generate a labelling dataset and an MLP classifier as a learning paradigm to test the datasets to assess the learned model. The comparison procedure demonstrated that the new technique surpassed all of the other registration algorithms in every dataset. Combining the optimization algorithm and the registration algorithm having a critical impact on the ultimate performance of the chosen registration process strategy forms the cornerstone of this argument. Two techniques formed the second comparison between the former system that is uniquely dependent on labels and the basis of randomly chosen registration algorithms—the novel technique in which the labels were based on the optimization process and the registration algorithm. Furthermore, the findings confirm the excellent performance of the novel technique with every input dataset compared to the other systems. Consequently, a vital function is occupied by the optimization strategy in enhancing the performance of the registration algorithm.

5.7 Summary

The primary goal of this solution strategy was to establish a scheme for choosing the optimal registration process for a given dataset using machine learning and a roulette wheel selection mechanism. As image diversity and application diversity present a significant challenge for any single registration algorithm-based solution concerning reliability and accuracy, selecting the best-performing registration algorithm can optimize the results and enhance the performance of the registration system. A new registration strategy (machine learning and roulette wheel selection method) produces the best registration strategy, consisting of the registration and optimization strategies (An, OK). Thus, the decisions produced will be more reliable, robust, and accurate than those obtained using the previous system and employ current registration algorithms from the proposed system results. Although the current solution strategy achieves the primary goal of selecting the best registration algorithm, various parameters still need to examine their effects on selecting the best registration algorithm.

Chapter 6
Task-driven algorithm selection strategy

6.1 Introduction:

Multimodal medical images registration is used for acquiring information by matching two different modalities of a patient's anatomy, such as the head, liver, or kidney. The results provide complementary information crucial for an appropriate clinical diagnosis, decision-making, or navigation during surgical interventions. As found in the literature review, numerous registration algorithms have been developed to register medical images of the same objects using different datasets, including CT, PET, SPET, and MRI. Registration algorithms are developed for two main reasons: first, 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. The diversity of medical images and differences in the degradation of the same object create problems for registering an algorithm's performance, such as decreased speed and accuracy. However, none of the state-of-the-art registration algorithms outperform others for all datasets, making individual registration algorithms unreliable. Therefore, image diversity and application diversity present significant challenges for any single registration algorithm-based solution: reliability, diversity, robustness, and accuracy.

In addition to the previous challenges, prior knowledge and expert knowledge play an essential role in enhancing the proposed system performance. The prior knowledge, such as the type of images (structural, functional) for rigid or non-rigid organs and the age of patents (do you mean "patients"?), is used to improve the system performance. Moreover, the expert's knowledge has a direct effect on the outperformance of the created system. For example, determining the region of interest in medical images is helpful in diagnosis and treatment, and often requires medical (or anatomical) background knowledge and prior expertise to understand where to look. This involves reducing the image size by discarding pixels that are of low relevance to the segmentation process as shown in figure 6-1. There are also situations where one modality may support a diagnosis but requires definitive confirmation by using another modality determined by the expert. For example, a head CT might have findings supporting a stroke diagnosis, but an MRI could definitively confirm this diagnosis. Finally, expertise can provide information regarding the required performance for each application. For example, , a diagnosis requires high accuracy, and surgical guide systems need high accuracy and speed, as shown in table 1. Therefore, all the provided information may contribute to enhancing the performance of the created selection system.

The essential work is to develop a framework that can select the best registration algorithm and parameters for the offered registration dataset based on several criteria: prior knowledge, expert knowledge, registration algorithm applications, and their performance.

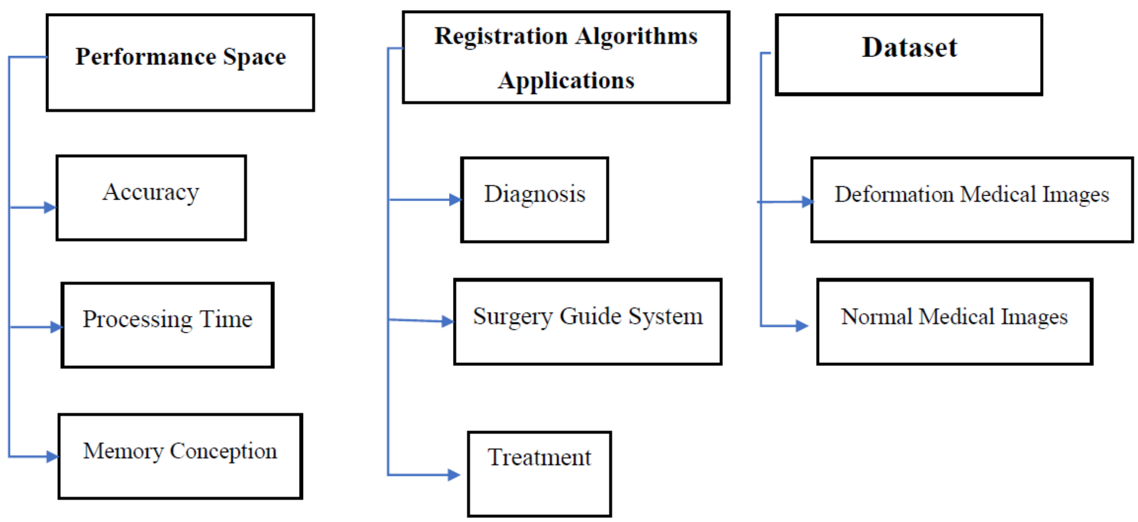


Figure 6-1:Prior and Expert's Knowledge

Table 1. The performance weighting for Medical images applications

The performance weighting		Required Application
Accuracy	Processing-time	
1	0	Medical Diagnosis
1	1	Surgery Guide System

6.2 Problem Formulations

The resulting performance is measured in accuracy and processing time, given a compilation of distinct medical images, and applied with a set of registration algorithms. The applications of medical image registration algorithms are dependent on their performance. For instance, , the surgery guide system application needs high accuracy and low processing time. Additionally, , the diagnosis application requires high accuracy. Therefore, the registration algorithm application has its performance requirements. The following graphs illustrate the link between accuracy and speed for all candidates considered.

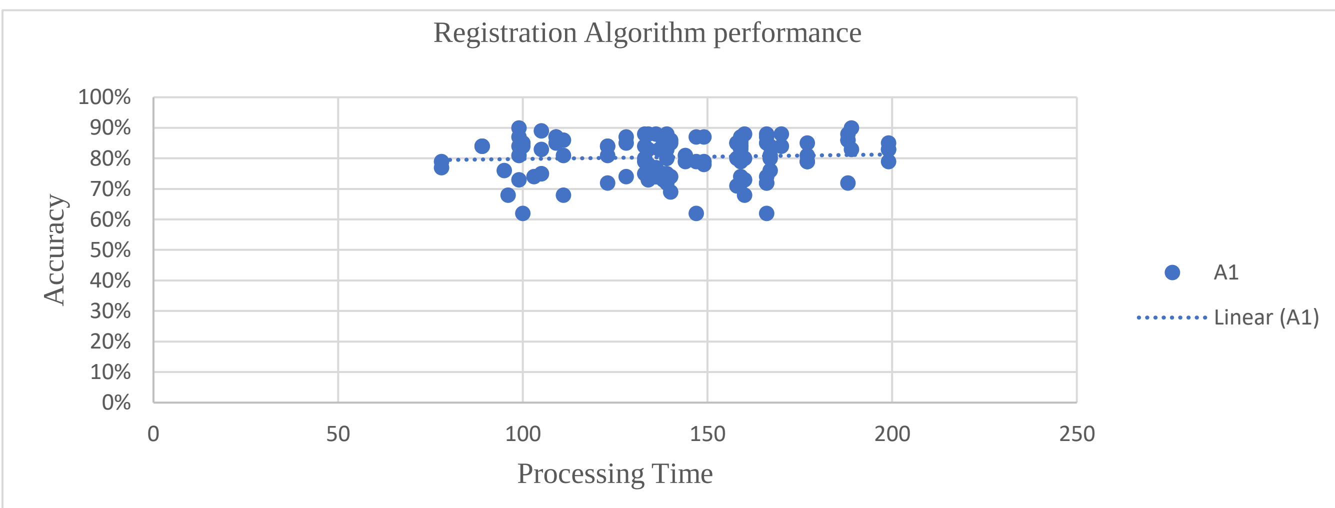


Figure 6-2:Accuracy Versus Processing Time (AlgorithmA1)

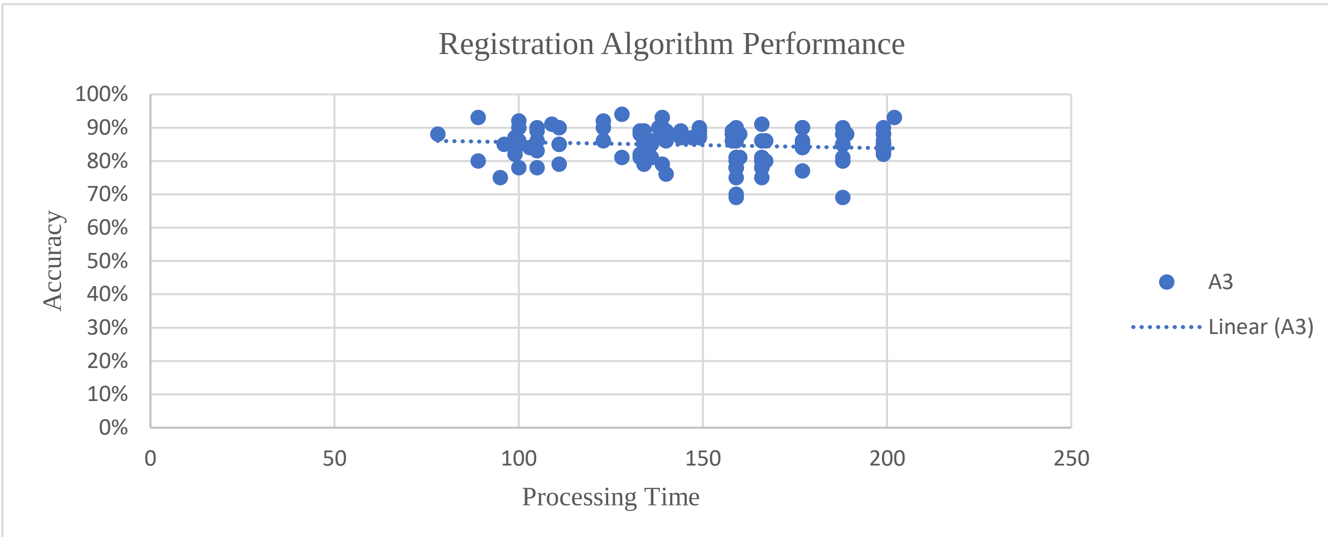


Figure 6-3:Accuracy Versus Processing Time (Algorithm A3)

Figures (6.2, 6.3, 6.4) represent the registration algorithm A1, A2 and A3 performance,

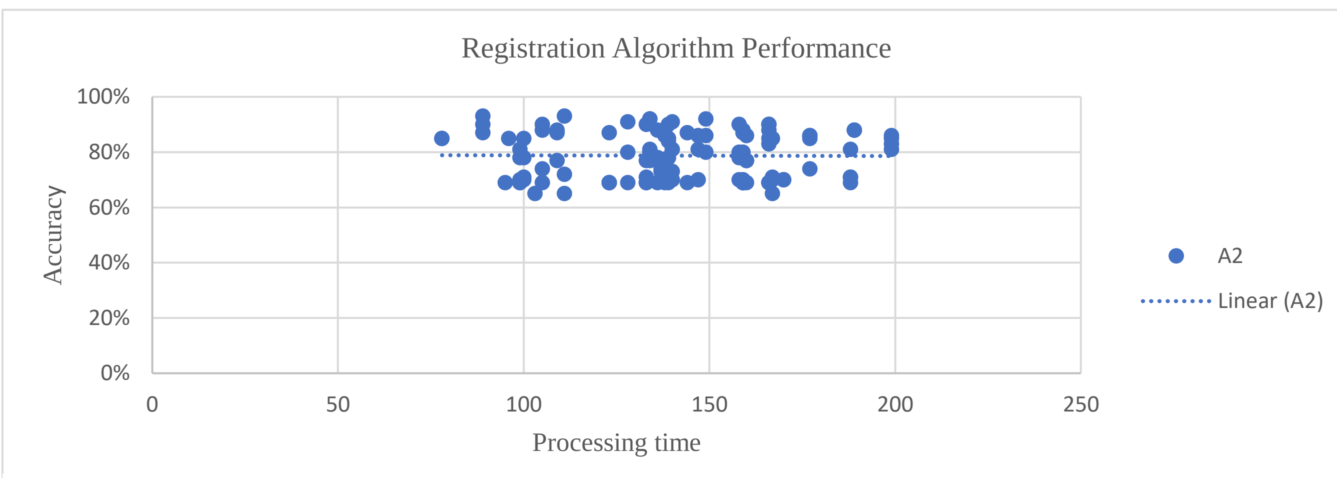


Figure 6-4:Accuracy Versus Processing Time (Algorithm A2)

where the accuracy is represented by the y-axis and the processing time represented by the x-axis. Overall, there are four categories which are (Low Accuracy, High p-time), (Low accuracy, Low P-time) and (High accuracy, Low P-time), (High Accuracy, High P-time). Therefore, there are four regions of processing time and two regions of accuracy from the three figures. This criterion of segmentation was followed for different applications, because each application has its own requirement. For example, the registration algorithm used for diagnosis needs high accuracy and low P-time, and the indifferent way the registration algorithm is used in the surgery guide system needs high accuracy and high P-time. The problem statement recognizes that a single algorithm can solve a part of the problem, but it cannot solve all problems. Therefore, instead of creating new registration algorithms with the same disadvantages, the best resolution is to find a universal selection system that will boost overall efficiency by choosing the best process. It is crucial to obtain the best existing algorithm for registration to solve a problem and not build new algorithms. The problematic statement is that one algorithm does not deliver the best execution through the applications and the datasets. Thus, selecting the best standing algorithm for registration is vital for solving a problem, not building new algorithms. The influence of performance weighing on selecting the best registration algorithm, as shown in equation (6-2), is discussed in this solution strategy.

Given:

- Preprocessing Image dataset D $= \{d_1, d_{2,} \ldots. d_j\}$. (Prior knowledge & expert knowledge)
- W_m Is the application weight. (expert knowledge)
- A set of registration algorithms A = $\{A_1, A_{2,} \ldots .. A_{n.}\}$
- *Each algorithm A_i achieve performance $P(A_i, d_k, O^i, W_m)$ when applied to a dataset $d_{k,} \in D$, under the set of parameters $O^i \in R^i$ and application weight W_m*
- $R^i: parameters\ space\ of\ algorithm\ A_i$
- *O^i_{opt} is said to be optimal on dataset d_k if*

  $P(i, k, O^i opt, W_m) \geq p(i, k, \forall O^i \in R^i)$ (6-1)
- *Now:*
- *Given x, a new set of images that we wish to register.*
- *The objective is to design a selection strategy S such that*

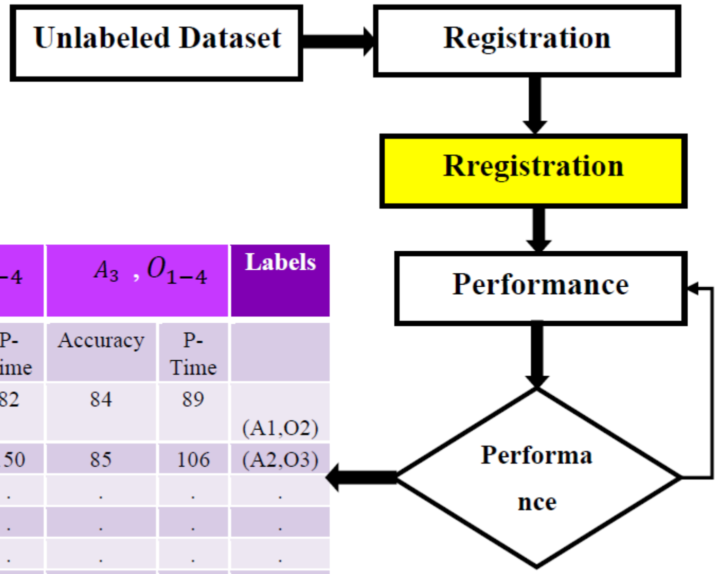
- $S(x \mid D, p(i, k, O^i): \forall d_k \in D, A_{i.} \in A, O^i \in R^i) = \{A_s, O^s opt\}, A_s \in A, O^s opt \in R^s$ *such that* $P(x, s, O^s opt, W_m) \geq P(x,i)\ \forall Ai \in (A) \& O^i \in R^i$

6.3 Problem Solution

The solution strategy is adapted from the greedy algorithm strategy, where the optimal local selection considers several criteria such as prior and expert's knowledge and registration parameters to enhance the global performance of the selection system. Furthermore, the solution strategy relies on three main activities : the creation of the supervised dataset, the training stage, and the testing stage.

6.3.1 Dataset Labelling :

The dataset was preprocessed based on prior and expert knowledge as defined in figure 1-1. Furthermore, the dataset labelling process was started by applying the dataset from dataset space to a registration algorithm space and registration parameters space. The output was the performance, registration accuracy and processing time, as shown in Figure 6-5. The best registration algorithm with the best registration parameters regarding the best performance was selected based on the ranking process. The same procedure was applied for all input datasets iteratively, and finally, all the input datasets were labelled as shown in table 1.



Dataset	A_1, O_{1-4}		A_2, O_{1-4}		A_3, O_{1-4}		Labels
	Accuracy	P-Time	Accuracy	P-Time	Accuracy	P-Time	
1	89	82	87	82	84	89	(A1,O2)
2	88	102	87	150	85	106	(A2,O3)
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
120	93	174	84	200	89	85	(A3,O4)

Figure 6-4: Dataset Labeling Process

6.4 Training Phase

The second stage is creating a learning model, and it aims to train a model for the automated choice of the best registration algorithms and best registration parameters. The development of a learning model is the primary task of the training stage. If a user applies the system to an algorithm selection assignment, the model must decide which registration algorithm is the best. The ANN is used to build the learning model. However, this does not mean that other models like SVM and K-nearest neighbour could not be used. Some learning models are widely employed in various sectors and are frequently recognized as "state of the art", such as ANN. . (Please rewrite the previous sentence.) An ANN can use many types and may be taught to use the labelled data set generated in the first stage, as shown in Figure 6-5, in a controlled learning variant of an ANN identified as a Multi-Layer Perceptron MLP, as shown in figure 6-6. ANNs can be extended in several ways, as demonstrated in our experiments, where various tasks can be modelled. The chosen classifier used 100 labelled datasets. The data are introduced to the grid on the input layer on each iteration on an instance-by-instance basis . The data are then transmitted to the output layer through the network layers. An error is computed on the network output layer, showing how it differs from the actual value. The measured error would spread across the network with the back spread (chain rule differentiation) backwards to update the net's weights to generate an output nearer to the actual value [4]. The training is called the iterative offline method.

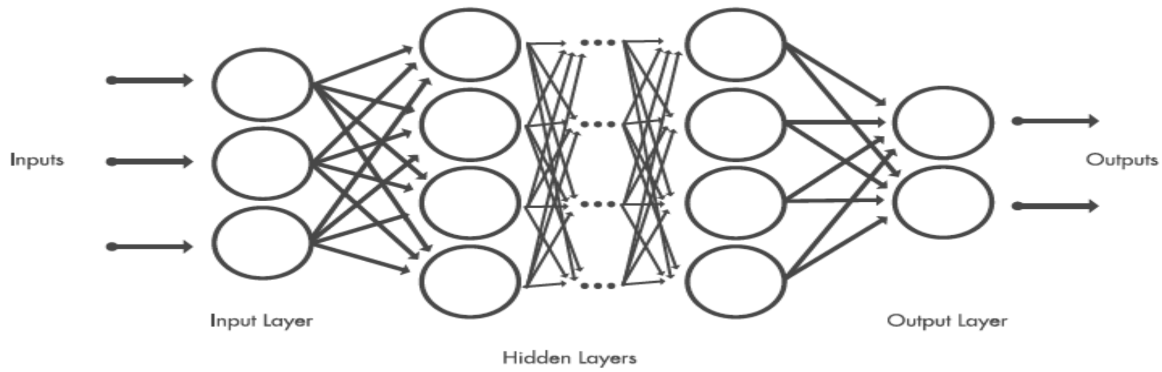


Figure 6-5: MLP Architecture

The second step is creating a learning model , as shown in figures 6-7. The learning model was developed, where the labelled dataset was mapped with an MLP classifier to classify them into three classes, as represented in table 1. As described above, registration algorithm selection is considered a classification problem. Therefore, the problem can be solved by training a classifier to discriminate among the three classes, as shown in tables 6-1.The learned model is then assessed using an unseen dataset (unlabelled dataset).

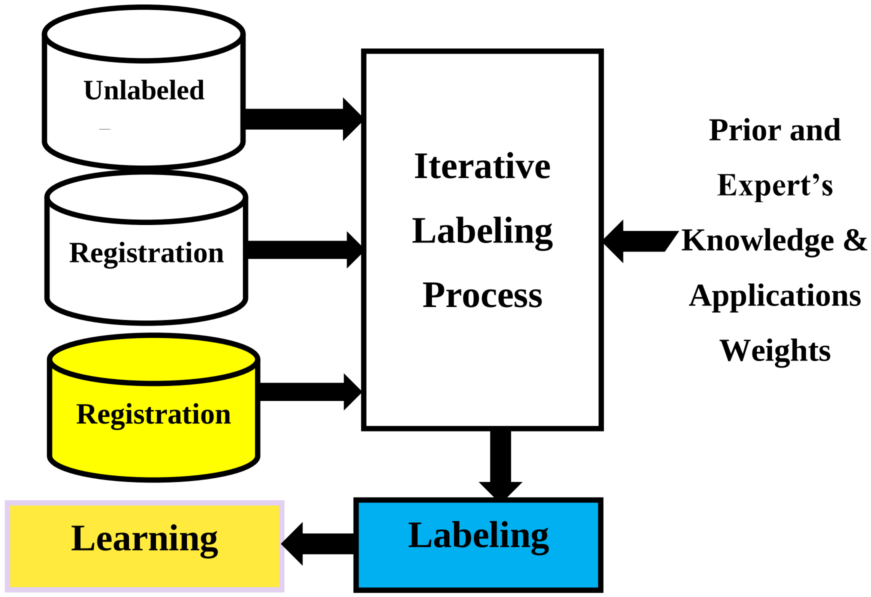


Figure 6-7:Schematic Diagram of The Learning Model

6.5 Testing Phase

The third stage involves selecting the best registration algorithm and parameters based on the prior and expert knowledge and the weighted registration algorithm's application, as shown in figures 6-8. Testing unlabelled datasets is the third step, where a set of unlabelled datasets are used with a learning modal to classify them. When the test datasets are mapped to the learned model, the output of the learned model is the labelled dataset, and that label represents the best registration algorithm and registration parameters. As a result, the best registration algorithm for the unknown dataset has been selected, as described in figure 6-8. The last stage is mapping the dataset to the chosen registration strategy to accomplish the registration process using the performance weighting based on the registration algorithm application. The created framework is used to choose the best registration algorithm based on the actual application and prior knowledge. While some applications need high speed, others need high accuracy, and some need high performance, high accuracy, and high p-time. Therefore, the framework answers the main question: "What is the best registration algorithm?" The main keyword in selection depends on the required application, as shown in the following charts representing the relationship between accuracy and processing time.

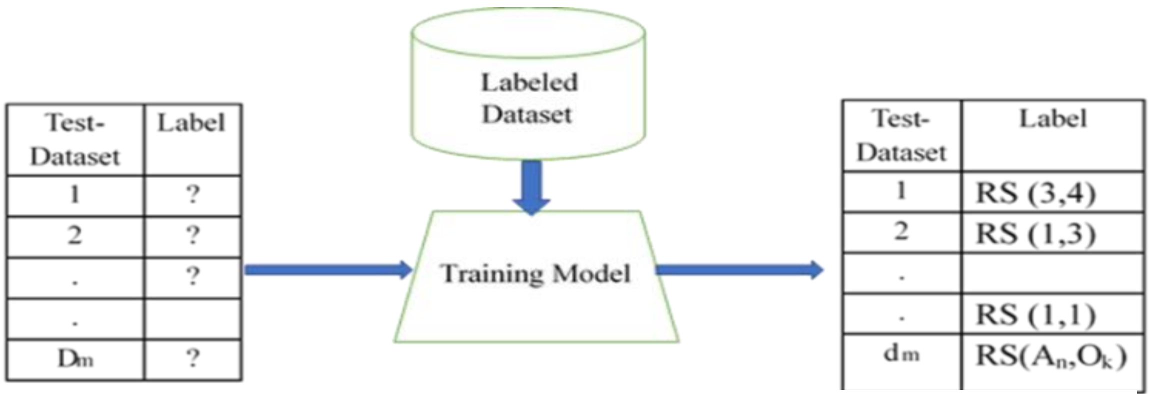


Figure 6-6: Selection Strategy for Unseen Dataset

6.6 Selection Strategy based on Image Registration

Applications of medical image registration algorithms, such as diagnosis, treatment, and surgical guide systems, are critical in choosing the optimal registration algorithm. The created framework work could select the best registration algorithm based on their application.

6.6.1 Medical Diagnosis

Medical image registration is used for several applications; one is the medical diagnosis. Furthermore, the main requirement for medical diagnosis is accuracy and any consideration of the processing time. The registration performance space weighting determines the framework's selection, as shown in Tables 6-2. Therefore, relying on the weighting vector, the framework will concentrate on the accuracy of their selection. The final selection of the involved framework is the most acceptable registration algorithm that produces the best accuracy, as presented in Figures 6-13. As is apparent, figure 6-13 explains the comparison between the three medical image registration algorithms and the created Framework. We can conclude that the selection framework is outperforming overall other used registration algorithms for all input datasets.

Table 6-1: Performance Weighting Based Applications

The performance weighting		Required Application
Accuracy	Processing-time	
1	0	Medical Diagnosis
1	1	Surgery Guide System

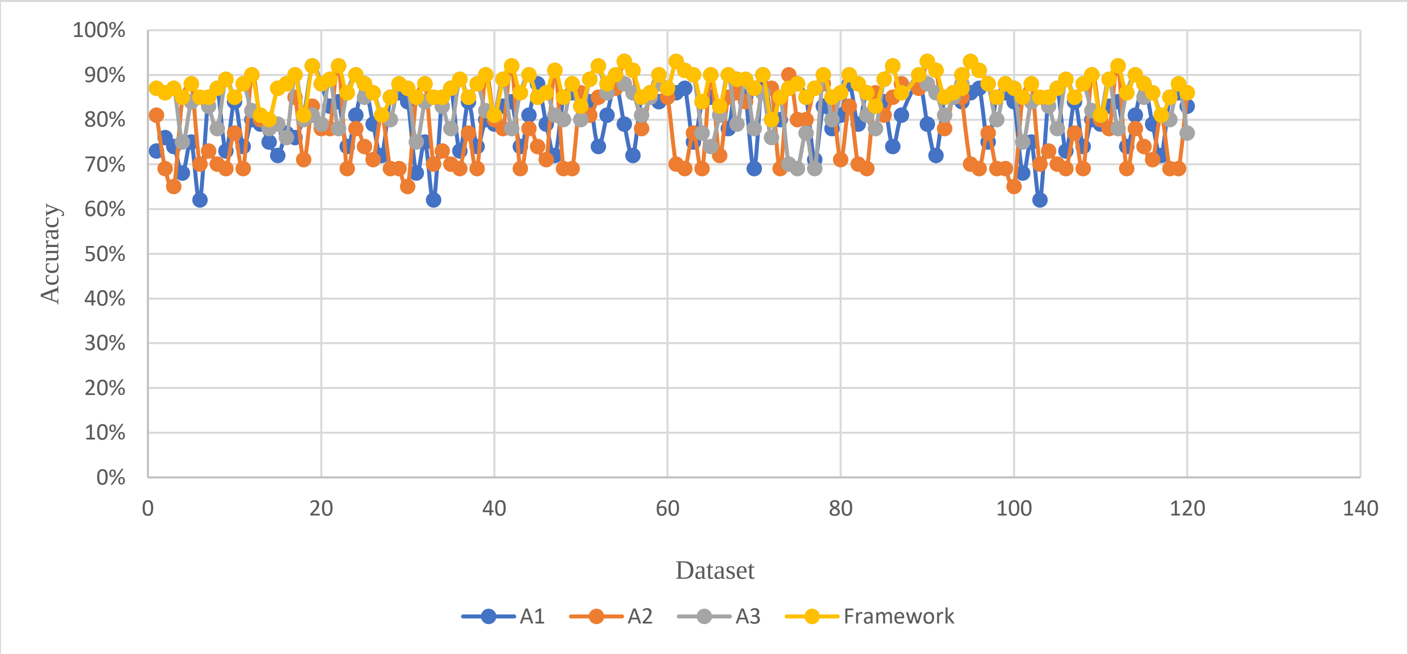


Figure 6-8: The Proposed Strategy and Candidates Comparison based Accurcy

6.6.2 Surgery Guide System:

Medical image registration is used for several applications; one is the surgery guide system. Furthermore, the surgery guide system's main requirement is the registration process's accuracy and p-time. Therefore, the framework work could opt for the best registration algorithm based on their performance weighting. The registration performance space (Rn) weighting determines the framework's selection, as shown in Tables 6-2. Therefore, relying on the performance weighting vector, the framework will concentrate on the processing time and accuracy. The final selection of the complicated system is the best registration algorithm that produces the best processing time and accuracy, as presented in Figures 6-13. As is apparent, figure 6-14 explains the processing time comparison between the three medical image registration algorithms and the created framework. We can conclude that the selection framework outperforms overall different registration algorithms for all input datasets.

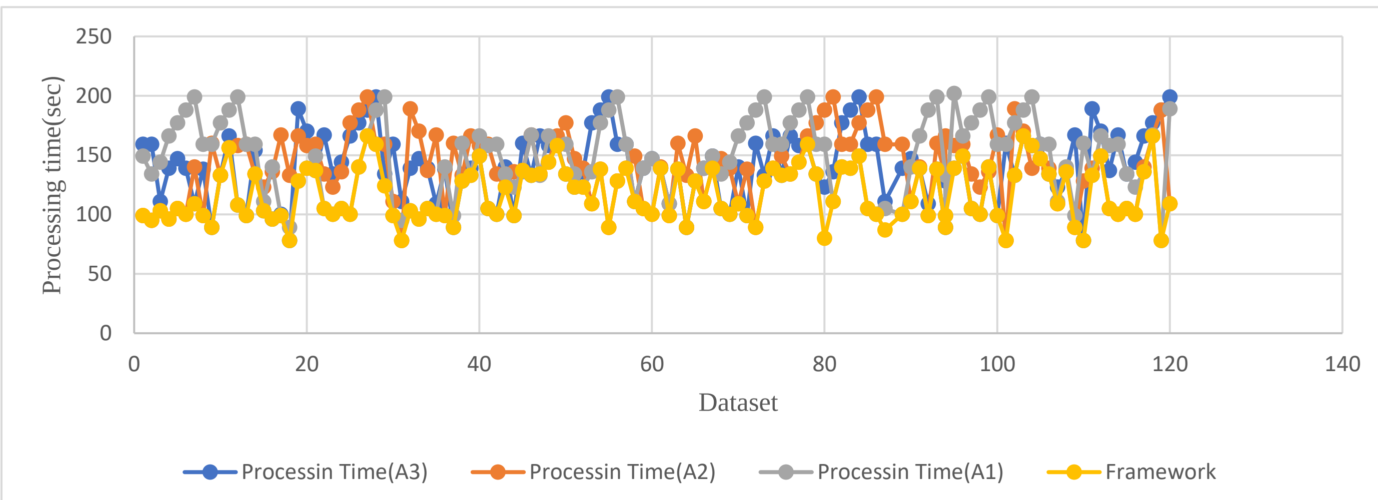


Figure 6-10: The Proposed System and Candidiates Comparison based Processing Time

6.7 Summary

Several registration algorithms have varying performance in the literature, and there is no guarantee that no single algorithm can surpass each other. Moreover, an efficient framework for algorithm selection based on the medical image registration performance and its application is developed. Two learning datasets were established: dataset with accuracy as a label and dataset with processing time as a label, as shown in table 6-1. The provided dataset is mapped in parallel with several medical image registration algorithms, and the outcomes are accuracy and processing time, as shown in figure 6-9. Selection could be made based on one of the following measures in the current implementation: (1) accuracy, (2) speed, or (3) a mixture of accuracy and processing time. The crated framework work could determine the best registration algorithm based on their performance and application weighting. The registration performance space (Rn) weighting determines the framework's selection, as shown in Tables 6-2. Therefore, relying on the performance weighting vector, the framework will concentrate on processing time, accuracy, or application required.

Chapter 7
Experimental Work and Results

7.1 Experimental Setup

As discussed in the previous chapter, experiments were conducted to investigate how the proposed system would work. Given the system requirements, the experimental work was divided into the following stages:

7.1.1 Dataset Collection:

In this work, approximately 400 (preprocessed) MRI/PET/CT datasets of the brains of different subjects (patients) were acquired from the Retrospective Image Registration Evaluation (RIRE) dataset website [44]. Dr. Michael Fitzpatrick prepared them to examine the accuracy of several different registration algorithms**.**

Table 7-1: Dataset setup

Medical Image	Patients	Training Data	Test Data
CT	180	120	60
MRI			
PET			

7.1.2 Registration Algorithms

The algorithm space contains the selected registration algorithm utilized in this research, as demonstrated in figure 7-1. The head-and-hat algorithm [40], the iterative closest point algorithm (ICP) [45], and the shared information-based registration algorithm [51] are all used for medical image registration in this work.

1	Insight Segmentation and Registration Toolkit (ITK)
2	Medical Imaging Toolkit (MITO)
3	Medical Image Registration Tool Kit(MITK)

Figure 7-1: Registration Algorithms Space

The head-and-hat algorithm is used to identify two identical surfaces in the images. The first is the head, which is portrayed as a stack of discs in the higher-resolution modality. An array of disconnected three-dimensional points defines the second surface. Iteratively compute the registration transformation by altering the (stiff) hat surface related to the skull surface till the hat fits the skull perfectly. Iterative nearest point approaches are optimized for various surface data formats, including point sets, parametric and curve surfaces, and implicit surfaces. Iterative in nature, the algorithm contains two stages. The first stage finds the image point closest to each data point, and the second phase finds the least-squares rigid body conversion connecting these point sets. The technique then locates the nearest point set and maintains it till the algorithm locates the locally optimum matches among contact objects, as defined by a tolerance level. Finally, mutual information register techniques are characterized by the fact that the info included in each image is just the entropy of the part of the spectrum that corresponds to the volume data in the other images. Mutual knowledge, most significant at optimal alignment, may be thought of qualitatively to quantify how well one image explains the other. The registration approaches are being used to match a fixed target image with a distorted moving source image. The data are provided in phases to aid in visualizing the process qualitatively.

7.1.3 Dataset Labelling Based on Registration Algorithms:

According to the conventional definition of labelling, “labelled data takes an unlabeled set of data and augments each item of unlabeled data with some meaningful ‘tag,' ‘label,' or ‘class' that is either instructive or desirable to know” [17]. Medical Imaging Interaction Toolkit (MITK) was utilized to conduct the registration processes. Three medical image registration algorithms were employed:

a. A points-based registration algorithm
b. An iterative closest point (ICP) registration algorithm
c. External points registration based on alignment

The labelling process was carried out by mapping each dataset (a pair of MRI/PET/CT images) into three registration algorithms; the results were levels of registration accuracy. As presented in Table 7.2, the registration algorithm that produced the highest accuracy is selected as a label for that input dataset. The result was a registration algorithm based on the labelled dataset.

Table 7-2: Dataset Based Accuracy and Processing Time

Dataset	A1		A2		A3		Labels
	Accuracy	P-Time	Accuracy	P-Time	Accuracy	P-Time	
1	89	82	87	82	84	89	(A1)
2	88	85	87	76	85	93	(A2)
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
121	**93**	87	84	90	89	85	(A3)

7.1.4 Learning Model:

First, the labelled dataset was obtained from the former stage. Secondarily, the machine-learning system is utilized to the labelled data, and the learning model is established. Finally, the unseen dataset could be presented to the model, and a likely label could be predicted for the unseen data. A Waikato framework for Knowledge Analysis (Weka) framework tool was used for creating a learning model based on the learning of the appropriate MLP classifier that would predict a label for the test dataset. The MLP has been trained with algorithm performance on the input datasets. The MLP classifier was applied to create a learning modal and K-fold cross validation used for validation. The average standard metric values were measured and are displayed in Table 7-2. For this work, the classification concept means that the datasets are classified based on the registration algorithm for which the algorithm achieves the best performance. Each couple of images was allocated to the registration algorithm class for which the algorithm gave the best performance for those images

Table 7-3: MLP 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
Accuracy	96%	95%	95%

7.1.5 K-fold cross-validation

The dataset (N=100) based on the K value is divided into 10 sections. After that, the sequence is trained on the remainder of the tenth fold, on k = nine folds. K = 10 folds were applied to data from N = 100 cases. On the remaining 10th fold, the pattern is then trained in k − 1 = 9 plates. Ten times until all sections are accurately counted once in a row. This repeat ensures that any data example is executed and tested precisely once. The exactness of a selection model assesses how the predictor can make accurate predictions. The model is also trained in predicting the given performance on a classification time basis to optimize its accuracy.

7.2 Discuss and Analyze the Results

The findings derived from the methodology suggested in the third strategy will be discussed. Firstly, implement the experimental configuration and equipment. Then, the evaluation of the results will be addressed and discussed in the proposed Framework.

7.2.1 Preliminary Investigation

Several experiments were conducted to assess the novel selection system. The first trial is conducted to assess the training datasets based on the candidate performance, accuracy and processing time, as shown in table 7.1.

As a result, two learning datasets are created based on labelling performance: the first is labelled on the basis of accuracy, while the second is labelled on the basis of processing time.

$$P(i, k, O^{i}opt, W_{m}) \geq p(i, k, \forall O^{i} \in R^{i}) \qquad \textbf{(7-1)}$$

The equation 7-1 is utilized to choose the best registration process on the basis of comparing the performance with application weighting consideration and without application weighting. Moreover, the (Wm) is a vector with two parameters: processing time and accuracy, and the weight of each parameter represent the importance of the desired application. For instance, if the Wm is (Accuracy, P-Time) equal (1,0.5), accuracy is more important than processing time. Thus, the best registration algorithm has the highest accuracy. Therefore, the selected registration algorithm performance with weighting should be greater than the performance without weighting, as represented in Equations7-1. Figures 7-2 and 7-3 represent the relationship between the dataset and accuracy and processing time.

Moreover, all candidates do not outperform all input datasets. Therefore, the accuracy and processing time are calculated for each dataset for all candidates, and their application is the only measure that distinguishes them. The following section explains the using the application effect on the best selection.

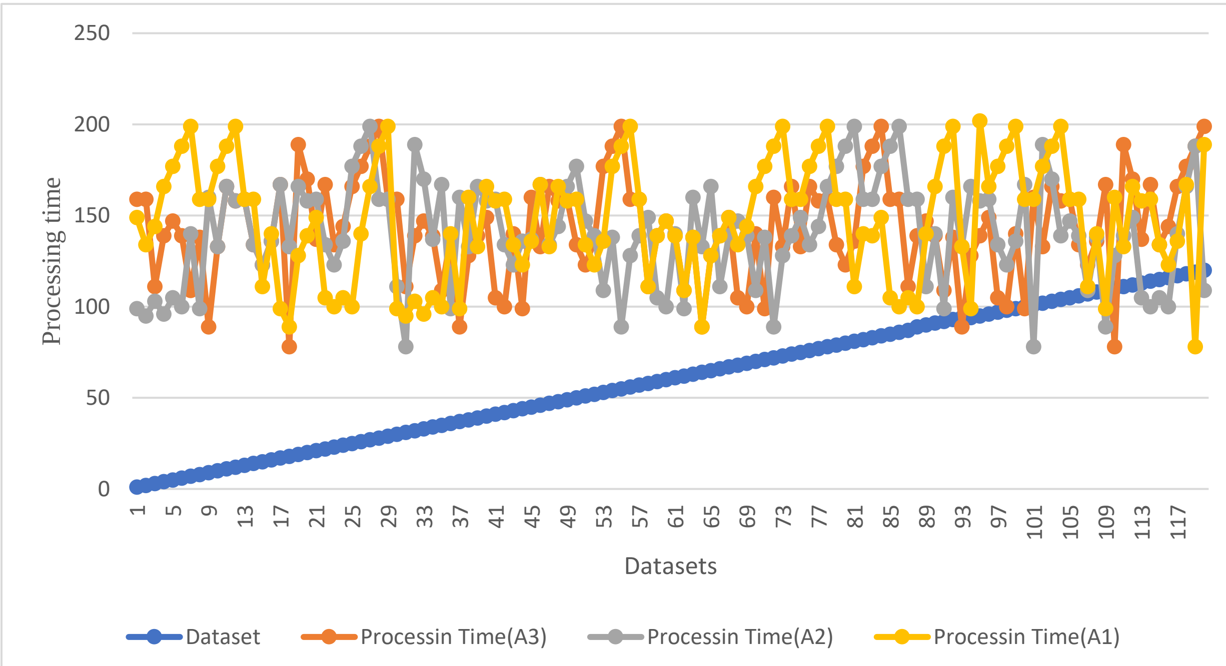


Figure 7-2: Framework and Registration Algorithms Comparison Based Processing Time

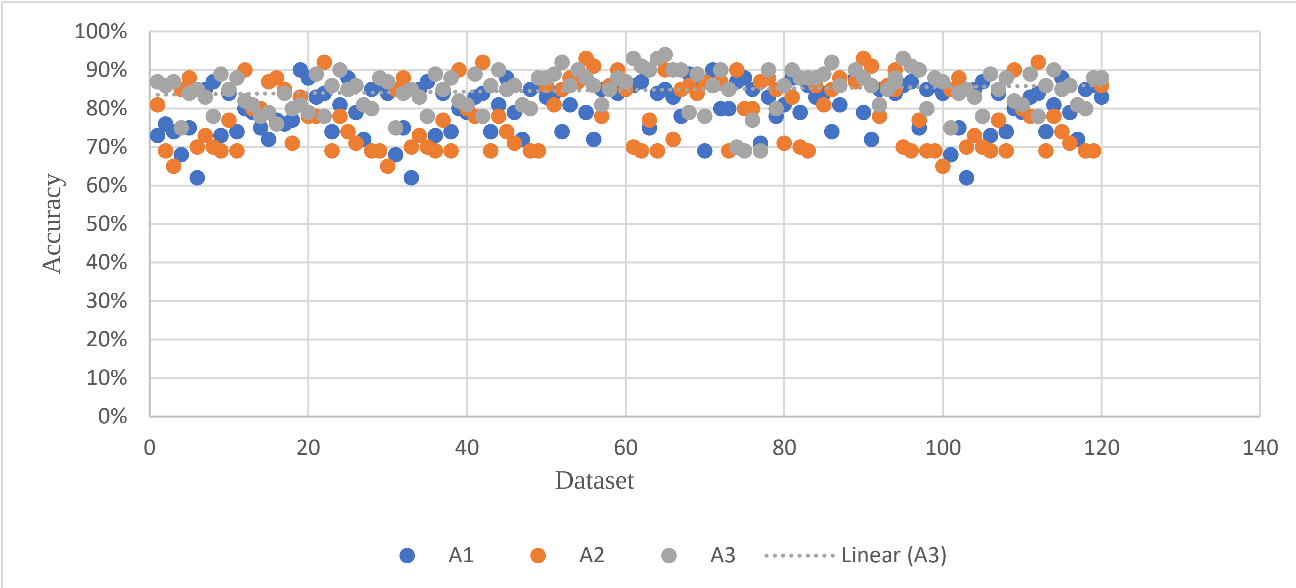


Figure 7-3: Framework and Registration Algorithm Comparison Based Accuracy

7.2.2 Algorithm Selection Based Medical Image Registration for Diagnosis

Medical image registration is used for several applications; one is the medical diagnosis. Furthermore, the main requirement for medical diagnosis is the registration process accuracy and any consideration of the speed. Therefore, the created Framework could select the best registration algorithm based on their application. The registration performance space (Rn) weighting determines the Framework's selection, as shown in Tables 7-4. Therefore, relying on the weighting vector, the Framework will concentrate on the accuracy of their selection. The final selection of the involved Framework is the most acceptable registration algorithm that produces the best accuracy, as presented in Figures 7-4. As is apparent, Figure 7-4 explains the accuracy of the three medical image registration algorithms and the created Framework. Thus, we can conclude that the selection framework outperforms different overall registration algorithms for all input datasets.

Table 7-4 : Performance Weighting Based Applications

The performance weighting		Required Application
Accuracy	Processing-time	
1	0	Medical Diagnosis
0	1	Medical Treatment
1	1	Surgery Guide System

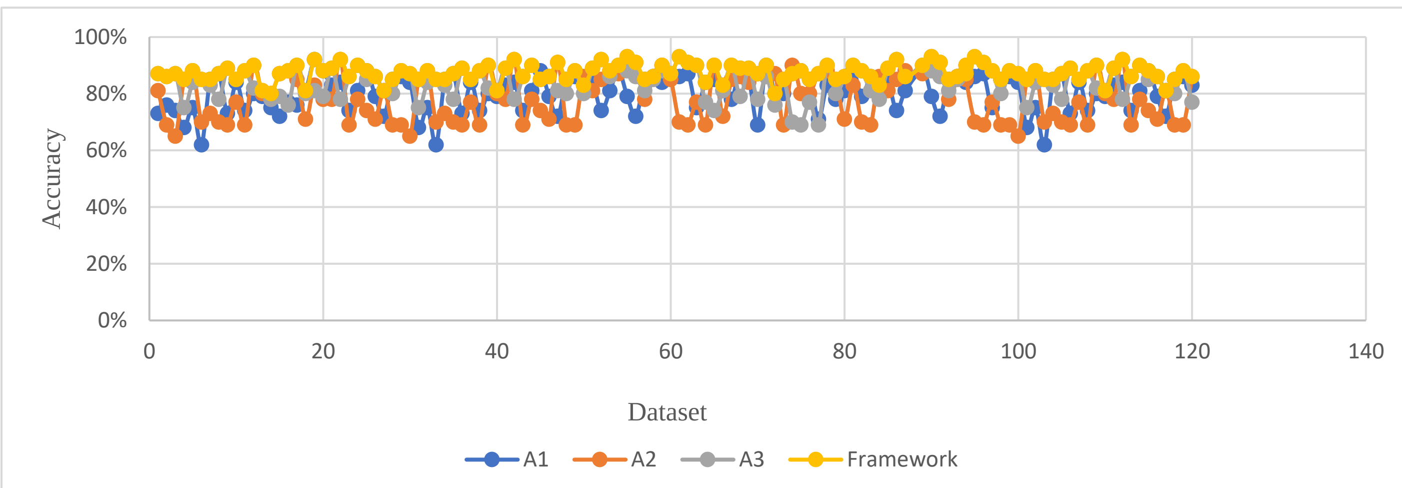


Figure 7-4: The Comparison Between the Framework and Candidates

7.2.3 Algorithm Selection Based Medical Image Registration for Treatment

Medical image registration is used for a variety of purposes in the medical area.; one is medical treatment. Furthermore, the main requirement for medical treatment is the processing time of the registration process and any consideration of the processing time. Therefore, the crated framework work could choose the best registration algorithm built on their application. The registration performance space (Rn) weighting determines the Framework's selection, as shown in Tables 7-3.

Therefore, relying on the weighting vector, the Framework will concentrate on the processing time. Thus, the final selection of the involved Framework is the most suitable "best" registration algorithm that produces. The best processing time, as presented in figure 7-4. As is evident, figure 7-6 explains the comparison between the three medical image registration algorithms' processing time and the created Framework. Thus, we can conclude that the selection framework outperforms different overall registration algorithms for all input datasets.

7.2.4 Algorithm Selection Based Image Registration for Surgery Guidance

Medical image registration is used for several applications; one is the surgery guide system. Furthermore, the surgery guide system's main requirement is the error and processing time of the registration process. Therefore, the crated framework work could opt for the best registration algorithm based on their performance weighting. The registration performance space (Rn) weighting determines the Framework's selection, as shown in Tables 7-3. Therefore, relying on the performance weighting vector, the Framework will concentrate on the processing time and accuracy. The final selection of the involved Framework is the best registration algorithm that produces the best processing time and accuracy, as presented in Figures 7-5. As is apparent, Figure 7-6 explains the processing time comparison between the three medical image registration algorithms and the created Framework. We can conclude that the selection framework outperforms overall different registration algorithms for all input datasets.

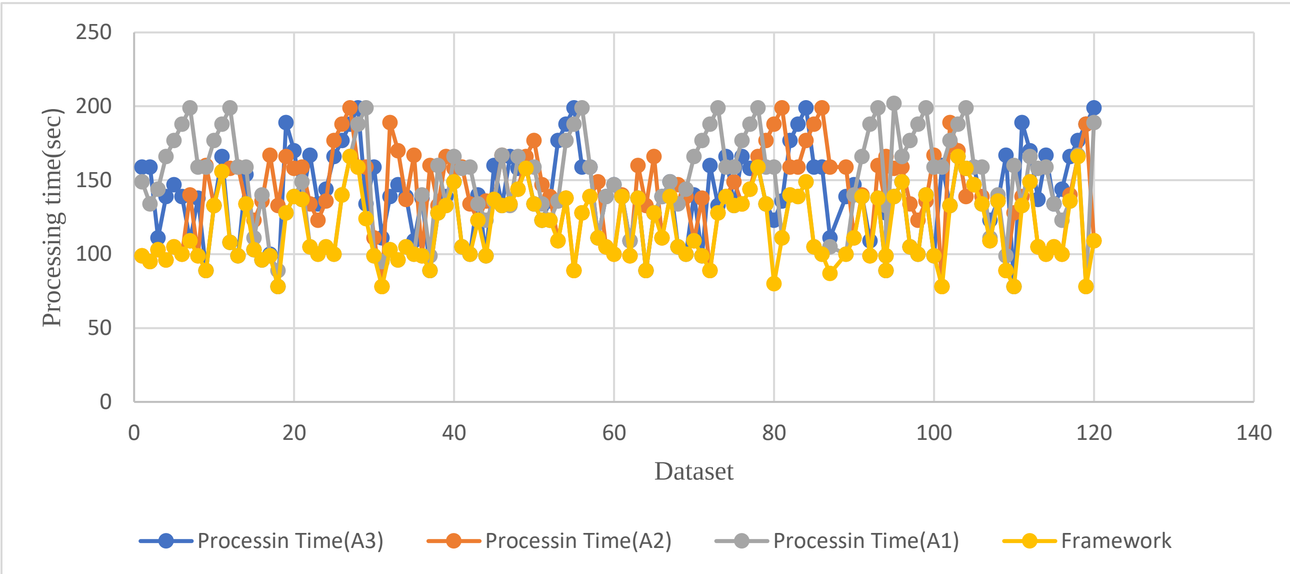


Figure 7-6: Comparison Between Framework and Candidates Based Processing Time

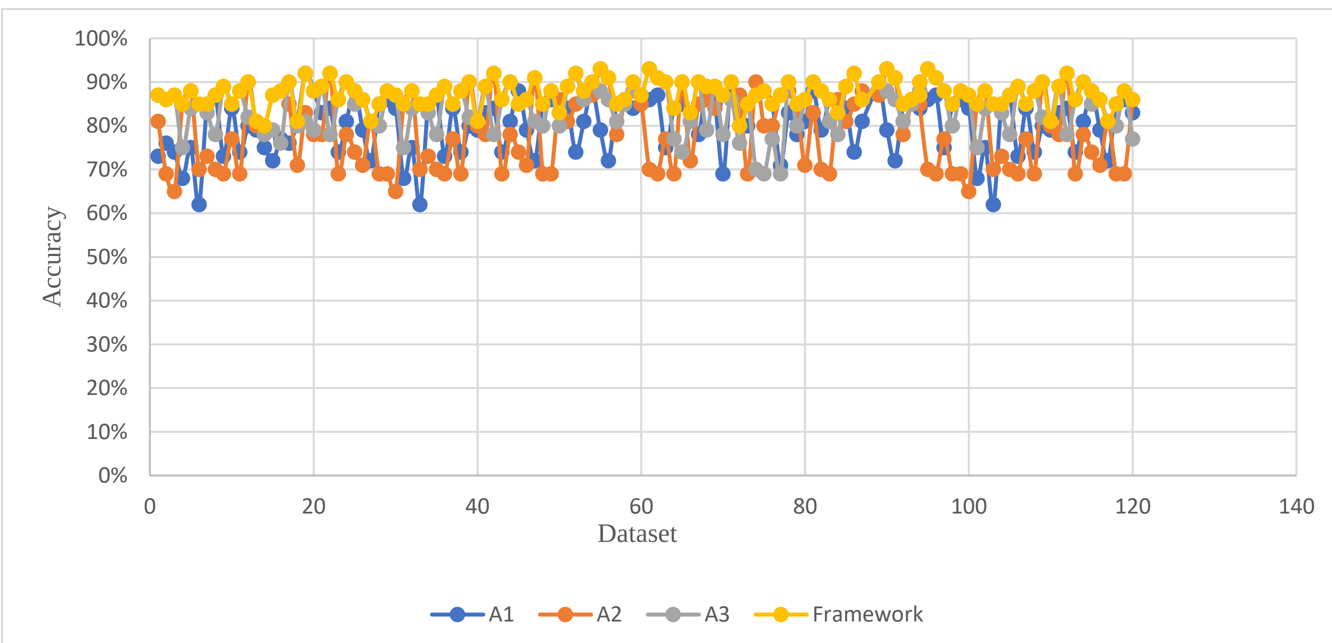


Figure 7-5: Framework and Candidates Comparison Based Accuracy

7.2.5 Registration Algorithm Performance Analysis:

The following graphs illustrate the link between the performance and each candidate's error and processing time to construct the data. Figure 7-7 represents the registration algorithm A1's performance, where the axis-Y characterizes the accuracy and the x-axis represents the processing time. Overall, there are three categories which are (Low Accuracy, High p-time), (Low accuracy, L- P-time) and (H- accuracy, L- P-time), (H- Accuracy, H- P-time). The accuracy range from 80% to 90% represents the highest accuracy and the processing time ranged from 75sec to 120sec is the lowest P-time, as shown in Figure 7-8.

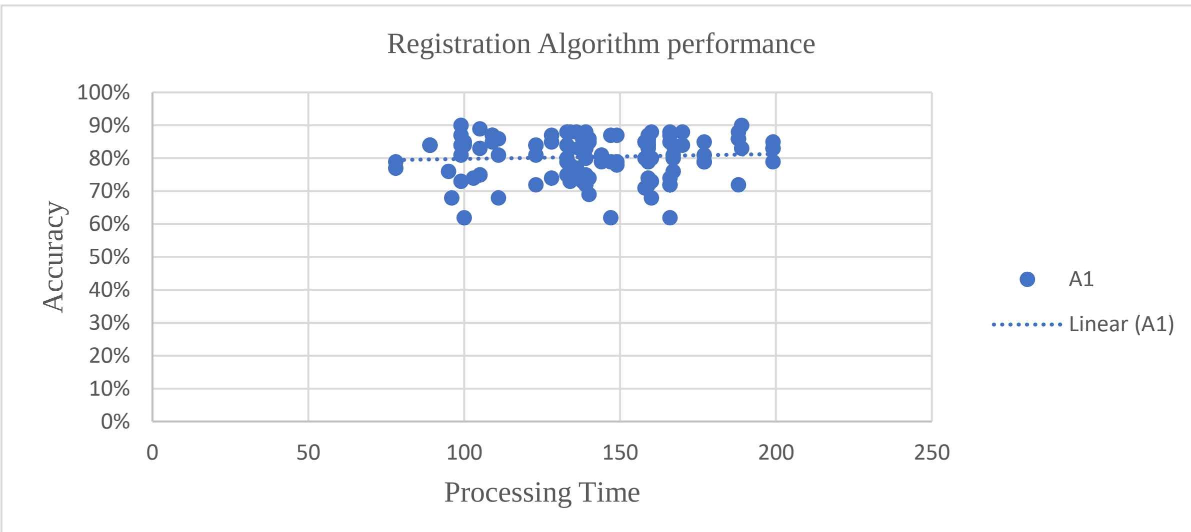


Figure 7-7: The Accuracy Versus Processing Time - A1

The scatter chart in Figures 7-8 shows the performance of registration algorithm A2. The Figure shows that the high accuracy ranged from 78% to 93%, and the low P-time varied from 80sec to 130 sec.

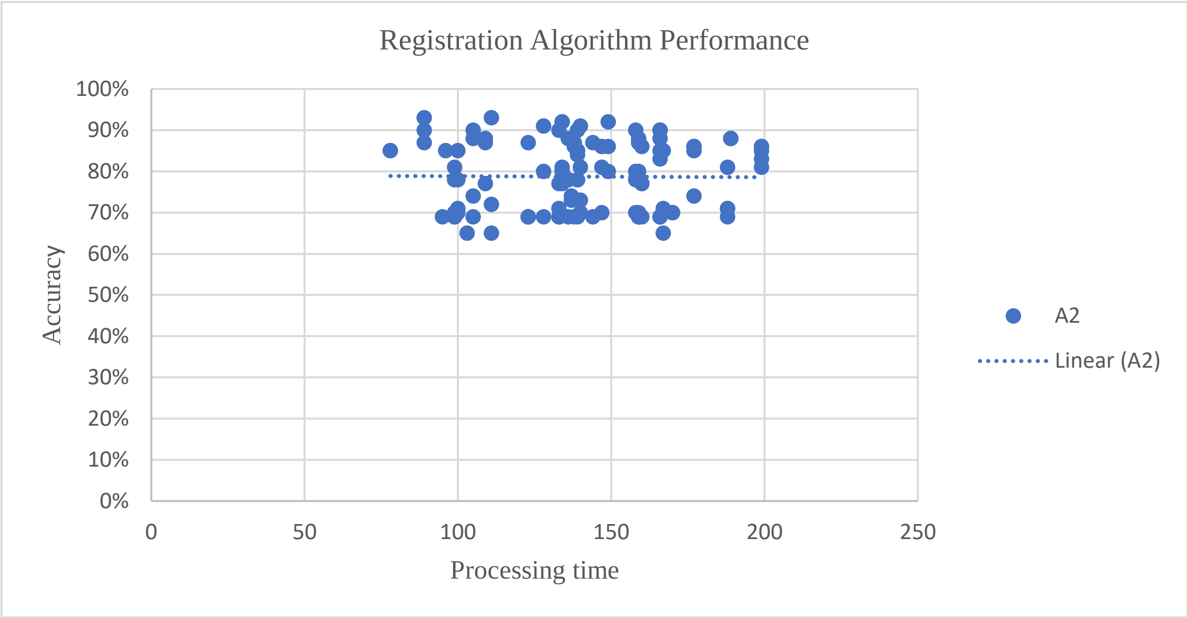


Figure 7-9: Accuracy Versus Processing Time - A2

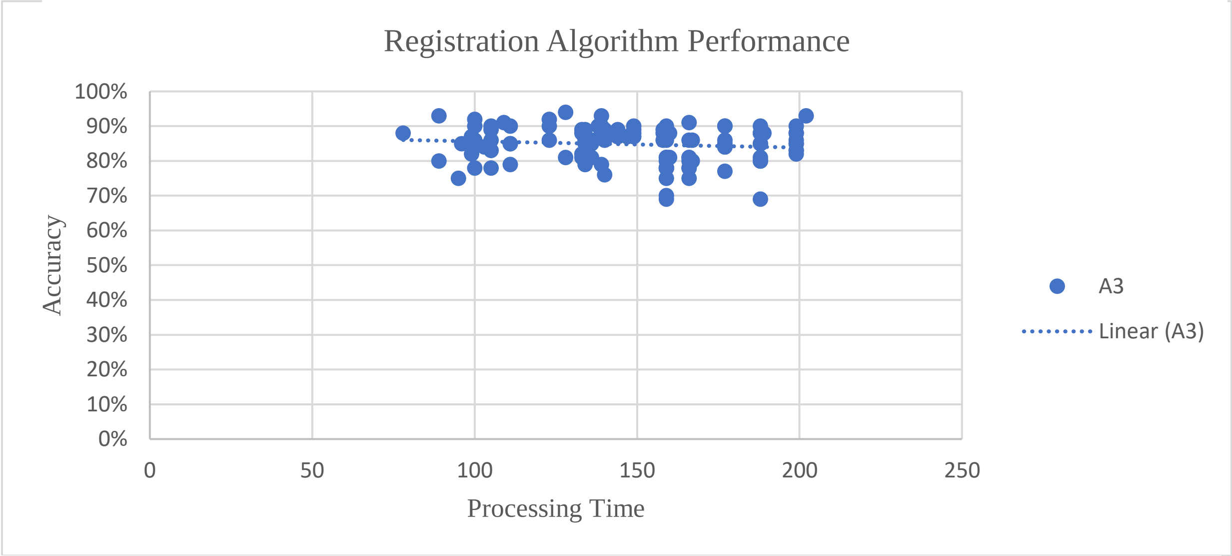


Figure 7-8:Accuracy Versus Processing Time - A3

The registration algorithm A3 provides a higher accuracy average, which is 87%. However, the accuracy varied from 80% to 93%, and the low P-time fluctuated from 80 sec to 110sec, as presented in figure 7-9.

Therefore, there are four regions of Processing time and two regions of accuracy for all candidates. Each application has a specific required region. For example, the registration algorithm used for diagnosis needs high accuracy and low P-time, and the indifferent way the registration algorithm used in the surgery guide system needs high Accuracy and Low P-time. Finally, detailed descriptions were made of the overall structure and the two phases of the Framework, the training phase and the test stage. The following section explores and analyses findings based on the proposed structure.

Table 7-5: Results Summary

Selection Strategy	Training result (MLP)	Testing result	Function Formulation
Greedy Selection Strategy	The proposed solution outperform for all input dataset where the accuracy average is 88 %	Unsuccess for number of input dataset and the accuracy average is 85%	$P = S(A_n, d_j)$ $A_x \in A$ maximizes the performance $p \in P$
Optimal registration parameters guided selection strategy	The proposed solution outperform for all input dataset and the accuracy average is 92%	Success for input test dataset and the accuracy average is 86%	$P = S(A_n, O_k, d_j)$ $A_n \in$ A, $O_k \in$ O maximizes the performance p ∈ P
Task driven algorithm selection	The proposed solution outperform for all input dataset and the accuracy average is 92%	Success for input dataset, and the weight of diagnosis application is (1)and Processing time is (0). The accuracy average is 86%	$P = S(A_n, O_k, d_j, W_m) \geq$ $P = S(A_n, O_k, d_j)$ $A_n \in$ A, $O_k \in$ O and W_m maximizes the performance p ∈

Chapter 8
Contributions and Concluding Remarkers

The primary focus of this thesis is concerned with algorithm selection as it pertains to image registration. The main contributions of this research could be encapsulated as follows:

8.1 Contributions

1- The supervised dataset is created based on the registration algorithm and optimal registration parameters.
2- Develop and implement a generic framework for registration algorithm selection. The framework aims to support the physician in selecting the most appropriate algorithm.
3- Develop insight into how different evaluation criteria, such as Processing time and accuracy, affect selecting the best registration algorithm for a given dataset.

8.2 Concluding Remarkers

A multi-selection algorithm is represented in this work.

The multi-selection algorithm has three manifestations:

1- Greedy selection strategy: Best algorithm registration parameter
2- Optimal registration parameters guided selection strategy: Optimal selection strategy with optimal registration parameters
3- Task-driven algorithm selection strategy: Optimal selection strategy based on prior and expert knowledge and applications weight.

The developed framework is much faster than the traditional analysis method.

The multiselection algorithm strategy consistently outperforms individual algorithms for different modalities.

8.1 Solution Summary

Numerous real-world scenarios are classified as a particular issue, which means that no efficient solution exists to handle them in the worst-case scenario exactly. Rather than that, the particular literature contains a range of empirical methods that have demonstrated acceptable performance. Even Though the scientific community's efforts to discover new techniques, there is no optimal algorithm in all potential cases. As a result, establishing a broad framework is frequently the best course of action. As a result, numerous approaches to the algorithm selection problem have emerged. As discussed in Chapter 3, the proposed solution's central concept is to use a meta-learning technique to create a learning model to evaluate the new unlabeled dataset. Therefore, the proposed solution framework creates three phases to obtain a labelled dataset. The initial phase of the proposed solution system has three steps, and the first step is to find a set of registration algorithms with different techniques in the algorithm space and find a dataset in the dataset space. The next step is to map all the algorithm space registration algorithms with all datasets in the dataset space to measure their performance. So, the registration algorithm that generates the maximum level of accuracy is designated as a label for the input dataset. The second phase is creating a learning model whereby an MLP classifier is selected and learned using the generated training dataset created during the first phase. The third phase entails selecting the best registration algorithm, where an unlabeled dataset is entered into the learned model, and the output is a labelled dataset that enables the best registration algorithm to be determined from the labels. In more detail, three strategies were generated to choose the best registration algorithms created on several principles. The first strategy is the algorithm selection strategy, which transforms algorithm selection into a classification problem. Therefore, to accomplish that, a supervised machine learning technique was used. Moreover, a supervised dataset was created to establish a learning model, where candidates' algorithms represent the dataset labels. The second strategy is algorithm selection optimization, which investigates the effect of various characteristics, such as optimization control points, on the optimal selection. Despite the first strategy's success in selecting the suitable registration algorithm but it has some disadvantages. (i) the first strategy is the best if that tested image is the same data point in the learned model. (ii) The system's performance is determined by the learned dataset. (iii) due to the extraction of erroneous landmarks, the local maxima of the similarity measure also impair registration accuracy in the elastic transformation. Therefore, optimization measures are critical for improving MIR performance. The second strategy was created to overcome the problems in the first one, and from the literature review conducted on the MIR, the optimization strategies have a crucial effect on the performance. Therefore, the roulette wheel selection approach improved the accuracy, reliability, and robustness of the selected registration strategy.

The third strategy is algorithm selection for image registration, which is contended that the concept of "best registration" is meaningful only in the context of application and performance measures. Additionally, we expressed that we could increase the application's efficiency by taking the application and performance type into account when registering. This strategy presents a framework for determining the ideal registration procedure for a particular registration dataset using two significant criteria: registration algorithm applicability and performance. The strategy discussed here is based on weighting two parameters: the MIR application and its performance. Also, a machine-learning algorithm that determines which candidate is the best.

8.2 Results Summary

Several medical image registration methods are present in the literature today, each with a unique set of abilities and performance characteristics. No single registration process, however, is guaranteed to beat all others in all input datasets. Machine-Learning and Neural Networks (ANNs) were utilized in this thesis to manage algorithm selection. The built framework was evaluated in various settings using various registration method performance measurements and algorithms. When applied to algorithm selection for registration algorithms on a set of 100 datasets, encouraging results have been obtained. The framework was capable of producing satisfactory results with a high level of precision and stability. The framework also produced good performance when the registration algorithm's objective was modified from minimizing processing time to minimizing processing time while maintaining the same learning model and evaluation criteria. The study enabled the advancement of a novel generic framework for the efficient and automatic selection of registration algorithms. The system can be utilized in more expansive sectors to select algorithms from diverse datasets automatically. While preserving flexibility in how performance measurements and the guidance model are deployed, an empirical demonstration of the model's strength was conducted. When evaluated in various contexts, the framework demonstrated correct algorithm suggestions by utilizing machine learning techniques to learn algorithm performance from previously reported situations.

8.3 Future Work

Various enhancements can be made to extend the work accomplished in this work. Improvements could include but are not limited to improving the framework itself or broadening the technical study to incorporate more performance measures.

8.3.1 Dataset challenges

The dataset is available on Kaggle (Find Open Datasets and Machine Learning Applications | Kaggle). The dataset's size and accessibility impose constraints on the researchers. The issue arises from the confidentiality of patients' medical records, which makes them inaccessible. As a result of this obstacle, the suggested works cannot be generated, revised, or compared to other researchers' works. Numerous studies have been performed to solve this issue.

8.3.2 Medical Image pre-processing

Medical image scanners created various difficulties, including noise and outliers, which significantly affected the achievement. As a result, additional preprocessing on the input photos may affect the final product. However, the clean photos can contribute to an impressive outcome.

8.3.3 Enhancements to the Framework

As an essential characteristic of robustness, the created framework can accept a variety of machine learning models. The influence of alternative learning models such as a decision tree (DT) or other variations of the Artificial Neural Network on algorithm selection accuracy may be explored.

8.3.4 Performance Metrics

Extensions Additional research on the efficiency of creating a medical image registration learning model using different classifiers may be conducted using criteria other than those used in this research. These measurements may include other purposes, such as ranking factors according to their scalability or updating ability. Additionally, multi-objective metrics can score the algorithm corresponding to a weighted pattern of two or more criteria.

8.3.5 Estimation of the Algorithm's Performance

The further work in the Outcomes chapter demonstrates that the framework is easily extensible to address various challenges, such as processing time. This primary examination leads to a more extensive examination of the framework's suitability for addressing such issues. Additional improvements can be gained by employing ANN-based architectures other than the one employed in our study. Using non-ANN models might potentially be a study path.

List of Published Work

This research work was disseminated in the form of Journal Publications, as follows:

1- Elkeshreu, H., Basir, O. (2020). Optimal Algorithm Selection in Multimodal Medical Image Registration. IRA. International Journal of Applied Sciences (ISSN 2455-4499), 15(4), 55-72. doi:http://dx.doi.org/10.21013/jas.v15.n4.p1

2- Elkeshreu, H., Basir, O. (2019). Algorithm Selection in Multimodal Medical Image Registration. IRA. International Journal of Applied Sciences (ISSN 2455-4499), 14(2), 10-21. doi:http://dx.doi.org/10.21013/jas.v14.n2.p1

3- Elkeshreu, H., Basir, O. (2020). An Effective Framework for Automatic Algorithm Selection using Registration algorithms. IRA. International Journal of Applied Sciences (ISSN 2455-4499), 15(4), 55-72. doi:http://dx.doi.org/10.21013/jas.v15.n4.p1

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