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Alzheimer image registration using hybrid random forest and deep regression network algorithm

Ramakoteswararao Siddabathuni[1], Sivagurunathan Palanivel[1], Godavarthi Lakshmi Narasimha Murthy[2]
[1]Department of Electronics and Instrumentation Engineering, Annamalai University, Chidambaram, India
[2]Department of Electronics and Communication Engineering, Lakireddy Bali Reddy College of Engineering, Mylavaram, India

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ABSTRACT

Image registration involves superimposing images (two or more) of similar background obtained at various periods of time, at different angles, and/or with various detectors. Geometrical alignment of two scans, reference image as well as capture image. The current dissimilarity between images is because of distinct image conditions. Image registration is difficult step in image analysis works on change detection, image fusion as well as multi-channel images recovery to obtain concluded data from integration of different sources. In this analysis image registration using hybrid random forest (RF) and deep regression network algorithm for magnetic resonance imaging (MRI) applications is implemented. The Alzheimer's disease neuroimaging initiative (ADNI) database provided by the dataset utilised in this implementation. From results it can observe that compared with individual random of forest, Hybrid RF and deep regression network algorithm improves the accuracy, precision and F1-score in effective way.

Corresponding Author:

Ramakoteswararao Siddabathuni
Department of Electronics and Instrumentation Engineering, Annamalai University
Chidambaram, Tamil Nadu, India
Email: koram419@gmail.com

1. INTRODUCTION

Image registration is nothing but determination of different points which transforms the data in geometrical way. In space, physical arrangement of an object is utilized based on the three-dimensional image and a two-dimensional image. Based on the different imaging conditions both input images and reference images provide highest values [1]. With the expansion of computational resources, algorithmic complexity, and algorithmic capabilities, the area has seen significant development. Image registration is used in many clinical applications such as post-operative evaluation, image-guided treatment management, and disease diagnosis and monitoring. Since variations in the spatial resolution of medical images are common, it is also frequently used as a tool to preprocess data for later tasks like object recognition, segmentation, or classification. As such, fixed size and resolution, as well as the quality of the image registration technique used to bring the images to a common coordinate frame, have a significant impact on the latter's performance [2].

Analysis of multi view: in this various view points are acquired in the same scene in the image. Based on the scanned scene the representation of 2D view or a 3D view is gained larger. This is mainly used in the applications of remote sensing applications [3].

Analysis of multi temporal: based on the different conditions same scene is used for different times in the image. Based on the consecutive images acquisitions the image is used to evaluate changes in the scene. The multi temporal analysis is mainly used in the applications of landscape planning, global land usage, and tumor evolution monitoring and medical image monitoring [4].

Analysis of multi modal based on different sensors: by using different sensors same scene is acquired in the image. Different representations are obtained based on the different source streams [5]. This is mainly used in the applications of remote sensing, spectral resolution, solar illumination, magnetic resonance spectroscopy (MRS) and positron emission tomography (PET). Due to the prevalence of soft tissues, magnetic resonance imaging, or MRI, may be a widely recognised technique for cancer diagnosis and radiation target outline. Bone and air segmentations are imperative works for MR scans as well as laboratorial research [6].

A MR scan-based medication method is desirable because that can divert computed tomography (CT) scan, avoiding MR scan-CT enrollment faults and ionized radiation, reducing healthcare costs and laboratorial work [7]. Anyhow, this is impractical in present medical practices because MR scans will not produce electron density data for dosage calculations or references image for patient's configuration. Neglecting non-uniformity results in a dose error of 4-5% [8]. When using synthetic CT, which allows continuous estimation of electron density to improve the accuracy of dose calculations, the distinction between bone and air was consider element for rectification of non-uniformity and therefore approximate dosage is calculated. Hybrid positron emission tomography/MR scan systems have combined as better scanning method because unprecedented soft-tissues data produced by non-ionized scan modalities. Accurate segmentation for various kinds of tissues affects calculated accuracy of attenuations maps [9]. Bone segmentation in MR scan makes easier for rapidly enhancing technique for image guide and it needs ultrasound beam to be refocused to requite the distortions and shifts generated by attenuations as well as scatter by bone [10]. Because several techniques usage is depended on MRI, it may be needed to distinguish between bone and scan.

Unlike CT, outstanding bone and air contrast, standard MRI are low signals in areas, making bone-air segmentations especially complex. A simple approach to approximately describe the structures to transfer the atlas template is MRI. This allows us to take advantage of bone-to-air contrast on CT scans to detect related areas on MRI [11]. The huge diverse Atlas datasets can support to enhance registration accuracy. Anyhow, organ morphology and large patient-to-patient variability makes it complex to convince for entire feasible frameworks. Additionally, larger atlas templates typically require primarily more computation [12]. Here it initializes the segmentation using the Atlas dataset. An expectation–maximization (EM) method is implemented to create complete pattern of a given object. Lastly, refine segmentation using the level set method. Dedicated MR sequences, like ultra-short echo time (UTE) pulse series, which is researched on bone visualize and segmentations. Implementation restricted by noise as well as scan artifacts. Skull segmentation using MR scans is challenging because it is classified by short lateral relaxations time as well as normally does not produce a signal by utilizing standard MRI patterns [13].

The related CT segmentation marker at the central location of this patch was taken as learning-based classification target. The initial convolution obtains function voxel-wise, for example by pairwise difference (PD) implemented on two voxels [14]. The later convolution obtains features through the subregion method as follows: Sub-regions of the patch are used to apply the features extraction techniques of local binary pattern (LBP) and discrete cosine transform (DCT), and pairwise difference extracts feature implemented on the average of two sub-regions of the patch. A multi-scale strategy was utilized for further expand the range of features. Feature extraction was performed on full-scale MRI as well as three rescaled MRIs (scale factors 0.75, 0.5, and 0.25) [15]. The extracted characteristics will contain noisy and non-informative elements that can affect the implementation of categorization technique, so it uses feature selection to decrease these elements and also performed by logistic least absolute shrinkage and selection operator (LASSO) [16]. They used auto-context strategies for repeated enhancement of segmentation output. This means that the initial categorization technique is trained only on extracted characteristics, and other techniques are trained on features extracted from MR scans as well as segmentation outputs [17].

Development frequently focuses on enhancing the similarity metric in traditional medical image registration techniques in order to achieve greater registration accuracy. When dealing with images from different modalities (also known as multimodal image registration), most similarity measures have many local optima surrounding the global one. As a result, they lose their effectiveness and can lead to premature convergence or stagnation, two common confining problems in the optimisation field. The most powerful methods in the field of machine intelligence, deep neural networks (DNN) and machine learning, have been used in a wide range of image processing applications. Neural networks have been utilised in a number of studies as data-driven and learnable analyzers of similarity metrics, providing a framework that can be adapted for various applications and image modalities. In order to evaluate Accuracy, Precision, Recall, and F1-score values for MRI applications, this research proposes image registration utilising a hybrid random forest (RF) and deep regression network technique. The rest of the paper is arranged as follows: the literature review is presented in section 2, the image registration model is explained in section 3, the results and their discussions are shown in section 3, and the paper is completed in section 5.

2. LITERATURE SURVEY

A hybrid deep learning (DL) method for developing an intelligent system for detecting pneumonia in chest x-ray images is reported in [18]. To automatically diagnose pneumonia from chest X-ray images, three types of classifiers were utilised: RF, k-nearest neighbour (KNN), and support vector machine (SVM). The traditional convolutional neural network (CNN) classification technique, called softmax, was also used. With the exception of the RF hybrid system, which performed less than the others, the accuracy, precision, and specificity of the hybrid systems were on par with the traditional CNN model with softmax. On the other hand, the best consumption time was recorded by the KNN hybrid system, which was followed by the SVM, softmax, and RF systems. In a short amount of time, the new system demonstrated highly efficient performance in categorization.

Tan *et al.* [19], showed a method for engineer image-based features when used with a RF classifier to identify artificial speech by use of data transformation techniques. The two goals are as follows: i) from the mel-frequency cepstral coefficients representation of the speech signal, extract image-based features; and ii) compare the effectiveness of using RF and the extracted features with the existing approaches to determine the authenticity of voices. To determine an appropriate combination of the classifier and engineer attributes, an experiment was carried out. The results of the experiments demonstrated that the suggested method could accurately and with an identical error rate of 0.10% identify voice conversion and speech synthesis attacks.

It is suggested to classify cytology image data in [20]. Because of its high classifying cytology images has always been a challenging task for the various image analysis algorithms. The DCT and the Haar transform coefficients are used as features in the suggested study. Seven different machine learning algorithms are trained using these characteristics in order to classify normal and abnormal pap smear images. Fractional coefficients are utilised to create the five different feature vector sizes in order to optimise the feature size. The DCT transform has produced the best classification accuracy of 81.11% in the suggested study. When comparing the various machine learning methods, the RF classifier has the greatest overall performance.

Registration of multi-world remote detecting pictures will broadly implemented in military as well as regular citizen regions, for example, ground target ID, metropolitan advancement appraisal and geographic change evaluation. Ground surface change difficulties highlight the point discovery in sum and quality, which is a typical quandary based on enrollment calculations. This work presents CNN highlight based multi temporal remote detecting picture enrollment strategy with two cases: i) it utilize CNN to create hearty multi-scale include descriptors; and ii) a plan of progressively expanding choice of exception to work on vigor of component focuses enlistment. Broad investigations are based on coordinating and picture enrollment is performed by multi-fleeting satellite picture dataset and multi-transient unmanned aerial vehicle (UAV) picture dataset [21].

An ant colony system (ACS) is used in the [22] work to propose a new feature selection technique that separates important characteristics from the retrieved data. The methods were assessed using KNN, decision tree (DT), RF, multilayer perceptron (MLP), SVM, and kernel SVM. The suggested model is tested on four datasets: greatest common divisor, medical graphics corporation (MGC) diagnostics corporation, Singapore whole-sky imaging categories, and Kiel. Six bioinspired benchmark feature selection techniques are compared with the self-adaptive ACS (SAACS) algorithm. The SAACS method outperformed all benchmark feature selection algorithms, with a classification accuracy of 95.64%. Furthermore, the suggested algorithms' efficiency is statistically assessed using the Friedman test and Mann-Whitney U test.

A DL model based on CNNs is presented in [23] as a potential method for classifying images of breast cancer histopathology as benign or malignant. In addition, the performance of the model to handle this task has been examined using five different types of pre-trained CNN architectures: remaining neural network-50 (ResNet-50), visual geometry group-19 (VGG-19), Inception-V3, and AlexNet. Although the ResNet-50 may also be used as a feature extractor to extract information from images and send it along to machine learning techniques, here categorization is done using a RF and KNN. The research conducted in this study make use of the BreakHis public dataset. Consequently, the best test accuracy of 97% for classifying images of breast cancer is achieved by the ResNet-50 network.

A method for classifying and segmenting MR brain pictures in order to distinguish between normal and abnormal images is provided in [24]. To extract image attributes in the first step, a 3-level discrete wavelet transform (DWT) is applied. The principle component analysis (PCA) is used in the second step to minimise the size of the features. Lastly, feature selection was used with a RF classifier to identify the data. A total of 181 MR brain images (81 normal and 100 abnormal) were gathered. The experimental results demonstrated the efficacy of the suggested technique when compared with various types of literature, generating an accuracy of 98%, sensitivity of 99.2%, and specificity of 97.8% in identifying normal and abnormal tissues. These results demonstrate that the best classification results were still obtained by the 3L-DWT+PCA+RF.

Image alignment is classic issue that involves detecting geometrical transforming of two images alignment. As amount of multi-sensor remote sensing images increases significantly, finding a transformation that matches the mutual data is time utilizing and unvarying, the rapid and tedious processing of images from various sensors is becoming increasingly difficult. Therefore, it is necessary to consider implementing automatic image registration techniques based on mutual information on high-performance equipments. First, we present a parallel implementation of the mutual information-based image registration algorithm. Take benefits of cluster equipments by dividing information according to method specificity [25].

3. HYBRID RANDOM FOREST AND DEEP REGRESSION NETWORK ALGORITHM

Figure 1 shows the work flow for image registration using hybrid RF and deep regression network algorithm for MRI applications. The ADNI database provided by the dataset utilised in this investigation. All individuals T1-weighted MRI scans were registered using affine registration to the Montreal Neurological Institute (MNI) space. A 3D bounding box measuring 32 by 48 by 48 was then used to extract the hippocampus regions for each subject. From the ADNI harmonised segmentation procedure project, 100 T1 images with labels indicating hippocampal segmentation were acquired. Based on an overlap measure between the hippocampus labels of registered images, the performance of image registration was assessed using these images labelled with the hippocampus.

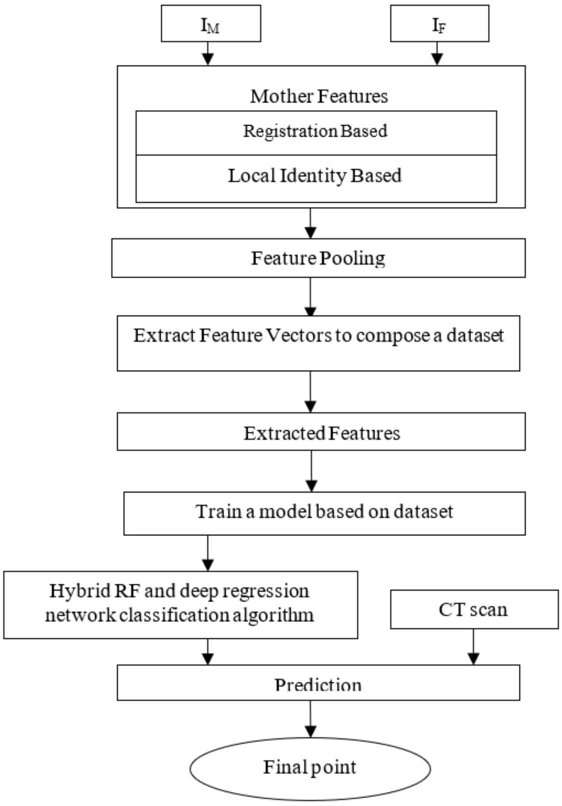

Figure 1. Flow chart of hybrid random forest and deep regression network algorithm

The first step involves utilising the FMRIB software library (FSL) (functional magnetic resonance imaging (FMRI) based software library) utilities raw images to standard space and crop them to eliminate the neck area. Moreover, the cropped pictures undergo bias-correction using the N4 approach from advanced normalisation tools (ANTs) to eliminate low-frequency intensity changes caused by the scanner magnetic field’s variations. Finally, using the FSL flirt interface, the images are both rigidly and affinely aligned to the

$1 \times 1 \times 1$ mm^3 standard T1-weighted FSL template. The photos are personally examined after registration to ensure proper alignment with the template.

Hybrid model is more effective in image registration process. Among the supervised learning methods is the well-known machine learning algorithm RF. It may be applied to machine learning issues involving both classification and regression. It is basis is the idea of ensemble learning, which is the act of combining several classifiers to solve a challenging issue and enhance the model's functionality. To predict the continuous values by solving tasks then it is known as deep regression techniques. Deep regression network mainly used in applications of image registration, facial landmark detection, human pose estimation and head-pose estimation. The DNN's input layer processes the input features before the hidden layers, which utilise non-linear activation functions to discover complex relationships in the data, handle them. Lastly, the F1-score, accuracy, precision, recall, and single performance characteristics are used to quantify performance.

3.1. Algorithm

The Alzheimer's images are taken as points which are expressed as I_M and I_F. Next, mother features are applied on Alzheimer's image. The mother features are divided into two ways, one feature will register the image and another feature will perform local density which means derived from the registered images. Next the features are extracted from feature vector composed dataset and model is trained with the hybrid RF and deep regression network classification algorithm.

STEP-1: initially moving images and fixed images are taken as points which are expressed as I_M and I_F.

STEP-2: next, mother features are applied to both fixed image and moving image. The mother features are divided into two ways, one feature will register the image and another feature will perform local density which means derived from the registered images.

STEP-3: next, dataset is composed to evaluate the features of registered images.

STEP-4: now, features are extracted and model is trained based on dataset.

STEP-5: apply the hybrid RF and deep regression network classification algorithm.

STEP-6: after that from classified data prediction is done.

4. RESULTS AND DISCUSSION

To evaluate the performance of various metrics classification results are discussed in this section based on machine learning and DL algorithms. The below shows the parameters which are evaluated based on hybrid RF and regression technique:

– Accuracy: based on the observed values, correct number of predictions is done in this model which is nothing but accuracy. True or accepted value is measured for defined values. The (1) shows the accuracy measurement. It is measured on true positive, true negative, false positive and false negative statements.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

– Precision: to measure the sensitivity and success in classification model, precision is introduced. It is measured using true positive and false positive statements. In this classifier probability is given result as positive and it is calculated as given in (2):

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

– Recall: is nothing but when the classification results are given as negative based on classifier probability. It is measured using true positive and false negative statements. The (3) shows the calculation of recall.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

– F1-score: the F1-score is used to calculate prediction performance. The F1-score is the weighted average of recall and precision. It is measured based on the precision and recall. The (4) shows the calculation of F1-score.

$$\text{F1Score} = \frac{2*Precision*Recall}{Precision+Recall} \tag{4}$$

Table 1 shows the comparison table RF classification and hybrid RF and deep regression network algorithm. Here, the classification results are measured using F1-score, accuracy, precision, and recall. Compared with RF classification and hybrid RF and deep regression network algorithm improves accuracy, precision, recall and F1-score in effective way.

Table 1. Comparison table

S.no	Parameter	RF classification	Hybrid RF and deep regression network algorithm
1	Accuracy	43%	92%
2	Precision	67%	95%
3	Recall	53%	89%
4	F1-Score	78%	97%

The Figure 2 shows the accuracy comparison graph for RF classification and hybrid RF and deep regression network algorithm. Compared with RF classification, hybrid RF and deep regression network algorithm improves accuracy in effective way. Figure 3 shows the precision comparison graph for both RF classification and hybrid RF and deep regression network algorithm. Compared with RF classification, hybrid RF and deep regression network algorithm improves in effective way.

Figure 4 shows recall comparison graph for RF classification and hybrid RF and deep regression network algorithm. Compared with RF classification, hybrid RF and deep regression network algorithm improves recall in effective way. Figure 5 shows F1-score comparison graph for RF classification and hybrid RF and deep regression network algorithm. Compared with RF classification, hybrid RF and deep regression network algorithm improves F1-score in effective way. From results it can observe that compared with individual RF, hybrid RF and deep regression network algorithm improves the accuracy, precision and F1-score in effective way.

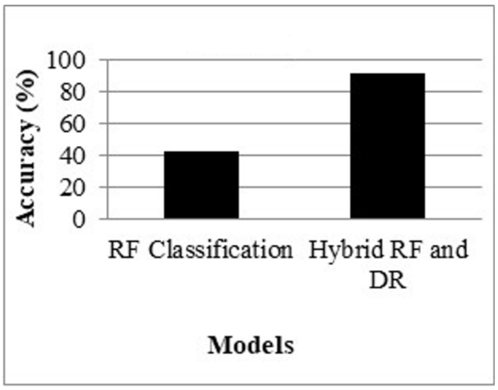

Figure 2. Comparison of accuracy

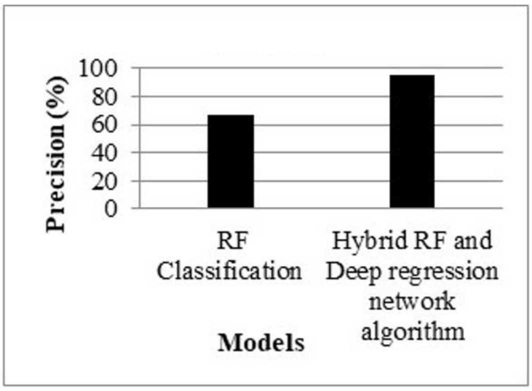

Figure 3. Comparison of precision

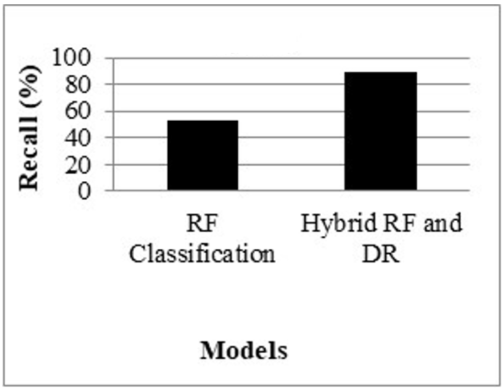

Figure 4. Comparison of recall

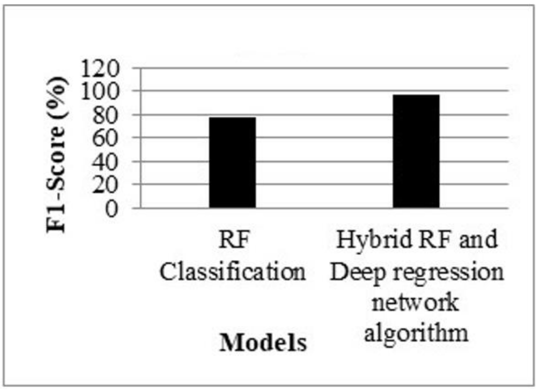

Figure 5. Comparison of F1-score

5. CONCLUSION

In this paper image registration using hybrid RF and deep regression network algorithm for MRI applications is implemented. In computer vision and image processing, image registration is a crucial operation that is frequently used to medical imaging. The ADNI database provided by the dataset utilised in this investigation. Initially moving images and fixed images are taken as points which are expressed as IM and IF. Next, mother features are applied to both fixed image and moving image. The mother features are divided into two ways, one feature will register the image and another feature will perform local density which means derived from the registered images. Next the features are extracted from feature vector composed dataset and model is trained with the hybrid RF and deep regression network classification algorithm. Hybrid model is more effective in image registration process. After that from classified data prediction is done. Performance evaluation is measured by performance parameters as accuracy, recall, F1-score, and precision. From results it can observe that compared with individual random of forest, hybrid RF and deep regression network algorithm improves the accuracy, precision and F1-score in effective way. Rather of utilising continuous values, spiking neural networks (SNNs) function by using spikes, which are discrete events that happen at time instances. In basic terms, an SNN differs from traditional neural networks as understood by the machine learning community. The location of a spike is determined by differential equations representing several biological processes, among which the membrane potential is the most significant. In general, a neuron spikes and resets its potential when it reaches a particular potential. SNNs, frequently have sparse connections and will eventually benefit from sparse network topologies.

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BIOGRAPHIES OF AUTHORS

Ramakoteswararao Siddabathuni is a research scholar at Annamalai University in Chidambaram, India's Department of Electronics and Instrumentation Engineering. Machine learning and image processing are two areas in which he is interested. He graduated from Sathyabama University in Chennai with an M.E. in Applied Electronics. He graduated from JNTUK with a B.Tech. in the ECE Department. He can be contacted at email: koram419@gmail.com.

Sivagurunathan Palanivel he works as an associate professor at Annamalai University in Chidambaram, India, in the Department of Electronics and Instrumentation Engineering. He has been a teacher for 23 years. He graduated from Annamalai University with a Ph.D. in E&IE, with a focus on industrial automation, process control, transducers, and measurements. His areas of interest are machine learning and image processing. He is the author of over 10 publications, both alone and with others. He can be contacted at email: spalaanivel@gmail.com.

Godavarthi Lakshmi Narasimha Murthy is working with Lakireddy Balireddy College of Engineering and Technology as a professor in the ECE Department. He has been a teacher for twenty years. He graduated from SV University in Tirupathi with a Ph.D. in ECE with a focus in image processing. Image processing, signal processing, and biochemical signal processing are the topics of his study. He is the author of over 16 works, both alone and with others. He can be contacted at email: murthyfromtenali@gmail.com.