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A Novel Software Platform for Medical Image Processing and Analyzing

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Abstract:

Image segmentation is a technique for extracting important features from a digital photo. It's a must-have for any serious image analyst. It may be used for medical diagnosis, analysis of satellite images, identification of faces and fingerprints, management of traffic, and many other tasks. It is a fresh, rapidly developing area of contemporary science. Since most diseases can be diagnosed and analysed with the help of medical imaging methods, image segmentation is particularly important in medical image analysis. Imaging techniques including X-rays, CT scans, ultrasounds, mammograms, and MRIs are routinely employed to acquire medical pictures. Image segmentation algorithms are crucial for transforming medical pictures into a form that can be understood by humans. Model training, data visualisation, human-computer interaction, and GUI development are only few of the many phases involved in developing an algorithm for medical picture analysis. Algorithm developers may save time and energy by using a software tool that handles the tedious details of the development process while they concentrate on writing the algorithm itself. Annotation of training data and graphical user interface (GUI) creation software is especially sought after for the creation of deep learning (DL) algorithms.

Keywords: medical disease diagnosis .X-ray, computed tomography, ultrasound scan mammography and magnetic resonance imaging

Introduction

Recent decades have seen a dramatic increase in the practical effect of picture segmentation. picture segmentation is a method for systematically extracting useful features of a digital picture for use in subsequent analysis and decision-making. Grayscale and category-similar pixels are connected together to form an area in the foundations of picture segmentation. The three main ideas in picture segmentation are the edge based approach, the thresholding, and the region based methods. Image segmentation now has a wide variety of practical uses, including but not limited to the following: video surveillance; fingerprint identification; satellite communication; medical diagnosis; artificial eye; robotic vision; crop disease detection. When compared to other methods for image segmentation, thresholding stands out as the most flexible and reliable. Suppose a pixel is located at coordinates (i, j), and its grey level, denoted by f(i, j), is X, where X is the threshold. If f(i, j) is less than X, then group 1 owns that pixel; otherwise, group 2 gets it. In threshold-based picture segmentation, the choice of threshold value X is crucial. The best segmentation outcomes can only be achieved by pinpointing the optimal threshold value. When it comes to image segmentation, the idea of optimisation algorithms enters the picture. Only with a superior segmentation algorithm can we hope to get useful results in any area requiring segmentation. The research in this study is broken down into two parts. This study examines four different types of medical imaging data, including a CT scan of the lungs, an ultrasound of the ovaries, an ultrasound of the breasts, and an MRI of the brain. In this study, we examine how different optimisation strategies affect segmentation precision. The findings of the best optimisation algorithm are compared to those of the bat optimisation algorithm, the pigeon optimisation algorithm, and the suggested hybrid approach in this study of picture segmentation. As a consequence of this study, it was suggested to combine the pigeon optimisation method with the bat algorithm to create a hybrid optimisation algorithm. The suggested strategy clearly provides a superior answer compared to the methods studied in this study. Optimising an algorithm that aids in extracting information from a picture efficiently is shown to improve segmentation accuracy in this study. The study on medical image preprocessing to denoising has included a thorough assessment of different noises and filters in addition to picture segmentation approaches. It has been shown that filter choice aids in improving picture segmentation results. Additionally, the robustness of the proposed method has been demonstrated by comparing the segmentation accuracy of the two methods. Positive results from the experimental study show promise for the suggested segmentation approach. The segmentation technique for detecting lung cancer with the best accuracy (93.6473%) uses assured convergence particle swarm optimisation. Breast cancer identification from ultrasound breast images is most accurate when using the chaotic particle swarm optimisation method, which achieves an accuracy of 93.5793. Using Gaussian pigeon inspired optimisation, the greatest accuracy for follicle recognition in an ultrasound picture of the ovary was found to be 90.6515. The cockroach swarm optimisation algorithm achieves higher accuracy (96.3929) in the diagnosis of Alzheimer's disease than any of the other approaches. Our approach is compared to those of other popular optimisation techniques in the field of medical picture segmentation. This study demonstrates that the proposed method has an accuracy of 98.9436 for detecting lung cancer from CT images, 98.9766 for detecting breast cancer from ultrasound images, 96.9713 for detecting ovarian follicles from ultrasound images, and 97.7653 for detecting Alzheimer's disease from MRI brain images. There are three different algorithms that have different convergence rates: the bat algorithm (

0.58), an optimisation algorithm inspired by pigeons (0.54), and the suggested hybrid approach (0.51). These numbers prove beyond a reasonable doubt that the suggested hybrid technique outperforms the alternatives.

Noise Removal

By using predetermined criteria, image segmentation may separate an image into distinct parts. The starting point for medical image segmentation is a picture of a patient taken by medical equipment. Computer tomography, mammography, X-ray, positron emission tomography, ultrasound scanning, and magnetic resonance imaging are only few of the imaging modalities used in medical diagnostics to capture images of the human body's

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interior organs. When dealing with human lives, precision in medical image segmentation is crucial. The success of a diagnosis and subsequent treatment plan depends on the precision of picture segmentation. There is always the chance of making a mistake while using imaging equipment to capture photos, whether due to operator error or improper setup. The main kind of noise added in medical imaging that degrades image quality is called speckle noise. The segmentation accuracy suffers and fault identification is the result when these photos are used for segmentation. In order to improve the accuracy of the segmentation, picture segmentation often employs preprocessing methods, most notably image denoising utilising filters.

Contrast Enhancement

After image denoising, contrast enhancement can be used to further improve image quality. In the case of medical image segmentation, contrast enhancement allows for a more thorough examination of the picture. The likelihood of accurately diagnosing illnesses will improve as a result. In this case, histogram equalisation is a common technique, in which pixels are mapped in accordance with their rank relative to neighbouring pixels. In this study, we used the histogram equalisation and adaptive histogram equalisation techniques to improve contrast and found them to be effective.

Image Segmentation Techniques

In order to get meaning from a digital picture, segmentation is an essential step in the image processing workflow. Segmenting a picture may be done in a million different ways. Thresholding is the most common and straightforward approach. It does this by comparing the pixel intensities to a threshold value and separating the foreground from the background. Choosing a threshold value is the primary challenge of thresholding. Segmentation of images finds features and borders in an image. Each pixel in a picture is assigned a type based on its hue, texture, and brightness. Unsupervised approaches, which often include the use of clustering algorithms, have been more popular in recent years for picture segmentation. The segmentation of colour images is performed using a fuzzy classification method. This fuzzy categorization uses a set of fuzzy rules that were built by hand. It is feasible to acquire the area of interest by modelling swarm dynamics. Particle swarm optimisation enhances the local optimal solution found by the k-means clustering technique, which was utilised by the original researchers. Fuzzy c means plays an important part in machine learning and data mining. It's clear that several methods for picture segmentation exist, each with its own set of advantages and disadvantages based on the specific use case. As a result, it's crucial to advocate for a preferred approach for broad implementations.

Literature Review

David Lacalle et.al.,(2021) cancer spheroids are the most popular 3D model for evaluating the impact of microenvironmental factors on cancer behaviour and for testing potential therapies before they reach the clinic. Imaging technologies that automatically segment and measure spheroids are useful for accelerating spheroid research, and a number of methods for automated segmentation of spheroid pictures have been proposed. However, such approaches cannot be applied to a wide range of experimental settings. The goal of this research is to provide a suite of flexible tools for spheroid segmentation.

Qifei Dong et.al.,(2020) For medical picture classification, segmentation, and object recognition using modern supervised machine learning techniques, a large number of annotated examples is often required. An efficient software programme may help facilitate and speed up the annotation process since human annotation is often labor-intensive and time-consuming. This software should ideally be adaptable to different annotation tasks, display images in the Digital Imaging and Communications in Medicine (DICOM) format, and allow for the efficient placement of multiple types of annotations on an image or a region of an image. There isn't any open-source software available that can do what we need right now. To address this need, we built DicomAnnotator, an adaptable open-source software application for annotating DICOM images. The aforementioned needs are met, and the annotating process is facilitated by the program's user-friendliness. In this article, we detail the process of creating DicomAnnotator and how it operates. Our examination of DicomAnnotator's ability to annotate DICOM images rapidly using spine image annotation as a use case shown that annotators from a wide range of backgrounds can effectively utilise the tool..

Kenneth A. Philbrick et.al.,(2019) To "learn" from labelled data, deep-learning algorithms are often classified as a subset of supervised AI. For optimum model convergence, deep-learning models need access to vast, varied training datasets. It is generally agreed that the time and energy required to curate large datasets is a major roadblock in the advancement of deep-learning systems. To expedite medical picture annotation for and using deep learning, we created RIL-Contour. The programme was built with the intention of providing a setting where clinically-focused users may easily use deep-learning models to speedily annotate medical imagery. RIL-Contour allows for the voxel and/or text annotation of medical images utilising fully automated deep-learning techniques, semi-automated approaches, and human methods. RIL-Contour encourages dataset-wide consistency in picture annotations to cut down on human mistake. The iterative deep learning (AID) approach used by RIL-Contour expedites the annotation of medical images. The idea of AID is to construct and use deep-learning models iteratively throughout the annotating and using of datasets. This is made possible by RIL-Contour's support for workflows including the annotation of medical images by different image analysts, validation of those annotations by radiologists, and finally, use of those annotations by data scientists for the purpose of training deep learning models. RIL-Contour offers ways for data scientists to "push" freshly trained deep-learning models to other users of the programme, automating the feedback loop between data scientists and image analysts. The quick cooperation between analysts, radiologists, and engineers made possible by RIL-Contour and the AID approach speeds up dataset annotation and model building.

Methodology

The field of medicine is a promising application area for image segmentation. In most cases, thresholding, edge-based, or cluster-based approaches are utilised for segmenting images. In comparison to the other ways, the cluster-based approach has the advantages of being easy to implement and quick to run. However, the best results cannot be achieved without first initialising a suitable cluster centre. In this study, four medical issues are used to validate the results of an investigation on the accuracy of medical picture segmentation algorithms. They constitute,

1. Alzheimer disease detection from MRI brain image
2. Cancer detection from CT lung image.
3. Detection of cancer from ultrasound breast image
4. Follicle detection from ultrasound ovarian image

The intensity of brain tissue is the most crucial factor in brain MRI segmentation. Intensity-based brain MRI segmentation may be broken down into four main categories. The four methods are thresholding, expanding regions, categorising, and clustering. Incorrect results may be obtained via segmentation due to intensity value corruption brought on by noise, bias field effect, and partial volume impact. Thresholding does not pay much attention to the spatial details of a picture. Consequently, thresholding is sensitive to noise and intensity homogeneities. Seed point is the basis for regional cultivation techniques. Because of the potential for error when using a manually chosen seed point, an algorithm is required for usage in this procedure. The clustering algorithms partition the picture by centroid, classifying each pixel according to its proximity to the nearest centroid. In each cycle, the clustering algorithm ensures that every pixel belongs to exactly one category. Intrinsic speckle noise and other artefacts, such as shadow attenuation and signal dropout, make ultrasound picture segmentation a challenging challenge. The finest threshold in CT image segmentation depends on the amount of tissue and air, the tissue density components, and the method used to acquire the picture.

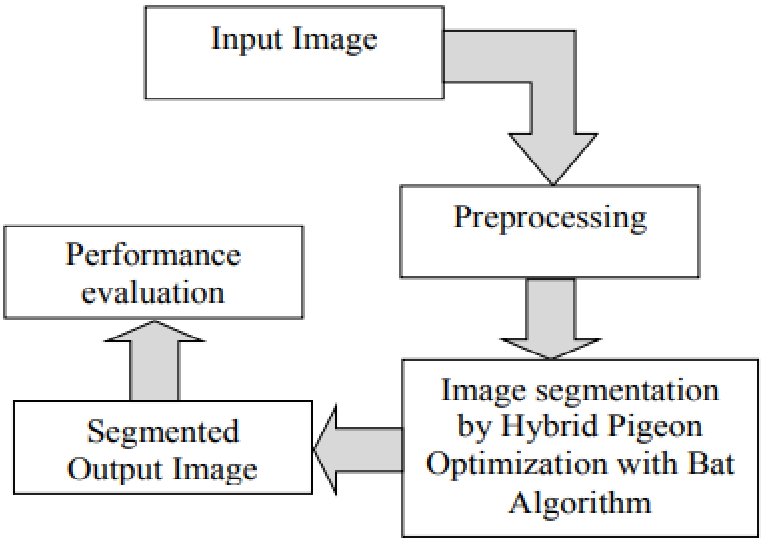

Figure 1 Block diagram of the proposed method

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The authors of this study hypothesise that modifying the velocity equation for pigeon-inspired optimisation might have a major effect on the reliability of the optimisation process and the rate at which it converges. The optimisation technique used in our study is based on the velocity equation of bats rather than pigeons. Four distinct kinds of inputs, including an ovarian picture for follicle identification, an MRI brain image for Alzheimer disease detection, an ultrasound breast image for cancer detection, and a CT lung image for cancer detection, have been used to evaluate the effectiveness of the suggested technique. The results of the practical validation show that the suggested technique has a high accuracy for identifying the illness in the input photos.

Segmentation as an optimization problem

The pixels are segmented into two additional groups depending on their intensity levels throughout this phase. Clustering and thresholding is a common and effective technique for this. The effectiveness of segmentation relies heavily on the choices made on the threshold value to use and which groups to use for clustering. These strategies exhaustively look for the best possible values in order to maximise the fitness function. To find the best possible threshold or cluster centre in such a big data environment, researchers have turned to evolutionary optimisation algorithms. The segmentation power of clustering relies heavily on the inter and intra cluster distances. Inter cluster distance is the distance from the centre of one cluster to the centre of another cluster, measured in pixels. Whereas intra cluster distance refers to how far a pixel is from the centre of its own cluster. If the distance between the clusters is greatest and the distance inside the clusters is smallest, then it is clear that the clusters are separate. Clustering relies on the maximisation or minimization of an objective function to construct its clusters. The goal is to minimise the squared error from any given pixel to the centre of the nearest cluster..

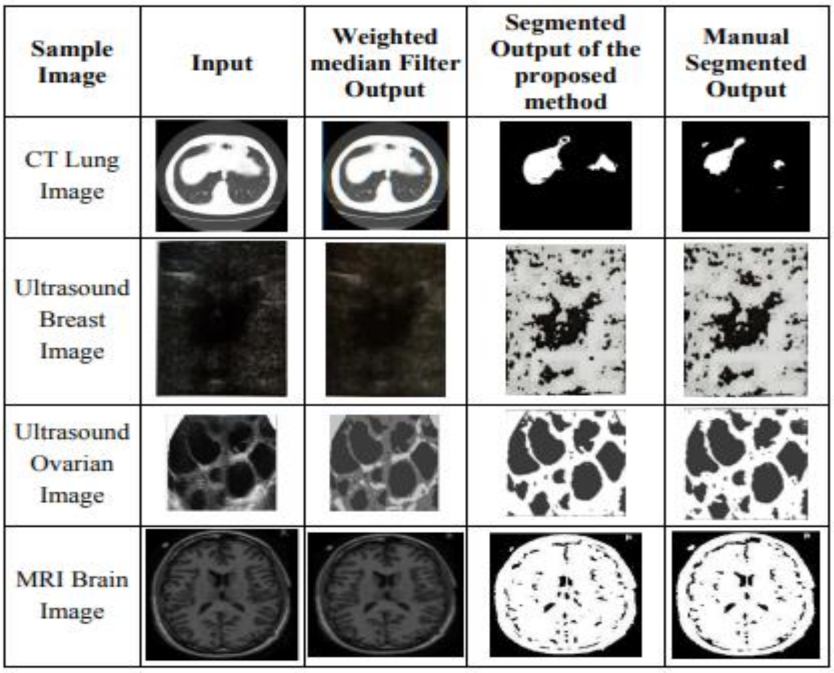

Figure 2 Resultant Images

Tables 1 and 2 give the average values for the test pictures' true positive rate, true negative rate, false positive rate, false negative rate, and accuracy measures, respectively. As can be seen in Tables 1 and 2, the suggested technique has a high degree of accuracy for the various kinds of inputs we used for this study. Since true positive is the measure for correct foreground segmentation and true negative is the measure for correct background segmentation, it stands to reason that the two values should be as high as possible for optimal image segmentation results.

Table 1 Accuracy results for tested input

Image	True Positive	True Negative	False Positive	False Negative	Accuracy
CT Lung Image	122738	172386	2833	318	98.9436
Ultrasound Breast Image	348521	101484	2387	2266	98.9766
Ultrasound Ovarian Image	6968	5743	117	280	96.9713
MRI Brain Image	24363	10986	564	244	97.7653

Table 2 Measurement results of tested input

Image	True Positive Rate	True Negative Rate	False Positive Rate	False Negative Rate
CT Lung Image	99.7416	98.3832	1.6168	0.2584
Ultrasound Breast Image	99.3540	97.7020	2.2980	0.6460
Ultrasound Ovarian Image	90.2106	9.7894	91.0550	8.9450
MRI Brain Image	99.0084	95.1169	4.8831	0.9916

Conclusion

Noise, intensity inhomogeneity, and porous boundaries in medical pictures need a sophisticated method for segmentation. Sensing modalities and artefacts might differ greatly across images of different organs. It is quite challenging to develop a general optimisation technique applicable to all medical pictures. The limitations of an optimisation method might change with its intended use. An optimisation method inspired by pigeons has a fast rate of convergence, but it gets stuck at the local maximum. This limitation of pigeon-inspired optimisation algorithms is addressed by the suggested strategy. This study proposes a universal optimisation strategy to address this issue across a wide range of imaging modalities. Sample inputs including images of the ovary, the breast, the lungs, and the brain were used to evaluate the performance of the proposed algorithm. When compared to standard practises, the proposed method achieves the highest levels of accuracy and has the best true positive and true negative rates.

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