Original Article

Medical Image Processing For Brain Disease Prediction Using Improved Fuzzy Clustering Model

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Abstract

The present work plans to investigate the performance of fuzzy system-based medical image processing for predicting the brain disease. The imaging component of NMR (Nuclear Magnetic Resonance) and the intricacy of human brain tissues cause the brain X-ray (Magnetic Resonance Imaging) images to introduce differing levels of commotion, powerless limits, and curios. Thus, enhancements are made over the fuzzy clustering algorithm. A brain image processing and brain disease conclusion forecast model is planned based on improved fuzzy clustering to guarantee the model security execution. The proposed model would utilize medical images of the brain to recognize examples and highlights demonstrative of various brain diseases. These images would be handled utilizing Improved Fuzzy Clustering model algorithm (IFCM) to segment the brain into various districts based on their attributes. In general, this proposed model can possibly fundamentally work on the accuracy and speed of brain disease utilizing medical imaging.

Keywords: Fuzzy system, Medical Images, Brain Disease, Image processing, fuzzy clustering;

1. Introduction

Medical image compression assumes a vital part as hospitals move towards filmless imaging and go totally digitally. Image compression will permit Picture Archiving and Communication Systems (PACS) to lessen the document sizes on their capacity necessities while keeping up with significant diagnostic information. Teleradiology destinations benefit since decreased image document sizes yield diminished transmission times. Indeed, even as the limit of capacity media keeps on expanding, it is normal that the volume of uncompressed information created by hospitals will surpass limit and drive up costs. Really arranging medical images assume a fundamental part in supporting clinical consideration and therapy. For instance, Examination X-ray is the best way to deal with diagnoses pneumonia which makes around 50,000 individuals bite the dust each year in the US, however characterizing pneumonia from chest X-rays needs proficient radiologists which is an uncommon and costly asset for certain regions.

Now that economy grows remarkably, health has turned into the main concern that influences individuals' expectations for everyday comforts. As a typical disease that influences human health, brain diseases are characterized based on their seriousness. Brain tumors are without a doubt the brain diseases that represent the best danger to human health. Brain tissue is a practical organization with confounded construction and unpredictable shape. The precise segmentation of brain images gives rich and significant information to clinical medical procedures. In any case, medical images of brain tissues are normally defenceless to obstruction, for example, commotions, lopsided grayscale, neighborhood volume impacts, and antiques. Meanwhile, there are extraordinary troubles in perceiving and segmenting brain images because of the frail difference in the image edges and the confounded brain tissue structure.

The medical images are difficult to gather, as the gathering and marking of medical information went up against with the two information protection concerns and the prerequisite for tedious master clarifications. In the two general settling bearings, one is to gather more information, for example, publicly supporting or diving into the current clinical reports. Another way is concentrating on the most proficient method to expand the presentation of a little dataset, which is vital on the grounds that the information accomplished from the examination can relocate to the exploration on large datasets. Furthermore, the main distributed chest X-ray image dataset (Chest X-ray 14) is still far more modest than the greatest general image dataset-ImageNet which has arrived at 14,197,122 examples at 2010

Diagnosis is the specialty of finding or recognizing the idea of a sickness through mixture and assortments of information which permits them to characterize the disease and refers the medical therapy precisely. Human diagnosticians accomplish a satisfactory accuracy in characterizing the disease by rehearsing on clear medical cases in the regulated diagnostic cycle. Medical imaging has been viewed as the huge wellsprings of diagnostic, yet it is dependent on human clarification. The requirement for, and availability of, diagnostic medical images is quickly surpassing the capacity and ability of the accessible healthcare subject matter experts, particularly in low and center pay nations. Automated cycle of disease diagnosis from medical imaging through the shrewd devices of simulated intelligence, fundamentally in the field of transfer learning, could possibly settle this quandary. Reports of pre-prepared algorithms surpassing people in diagnostic appraisal have produced significant happiness.

2. Literature Survey

1. Yadav SS et.al proposed deep convolutional neural network based medical image classification for disease diagnosis. Medical image classification assumes a fundamental part in clinical therapy and educating undertakings. Nonetheless, the conventional technique has arrived at its roof on execution. In addition, by utilizing them, much time and exertion should be spent on extricating and choosing classification highlights. The deep neural network is an arising AI strategy that has demonstrated its true capacity for various classification assignments. Thusly, this paper researches how to apply the convolutional neural network (CNN) based algorithm on a chest X-ray dataset to characterize pneumonia. Three methods are assessed through experiments. Information increase is an information pre-processing technique applied to every one of the three strategies. The results of the experiments show that information increase for the most part is a successful way for every one of the three algorithms to further improve performance..

2. **Rajalingam B** et.al proposed a novel approach for multimodal medical image fusion using hybrid fusion algorithms for disease analysis. Multimodality medical image fusion technique plays out a crucial job in biomedical research and clinical disease analysis. The medical image fusion is utilized to work on the nature of multimodality medical images by blend the two multimodal medical images of a similar patient. This paper, proposed a novel multimodal medicinal image fusion approach based on hybrid fusion techniques. This work explored the exhibition of both the customary and hybrid multimodal medical image fusion techniques utilizing a few assessment measurements. It has been shown that the best multimodality medical image fusion technique is carried out utilizing proposed hybrid technique. This hybrid algorithm (Curvelet Transform-Pulse Coupled Neural Network) acquainted an unrivaled execution contrasted and the wide range of various conventional techniques. It gives substantially more image subtleties, higher image quality, the most limited processing time and a superior visual investigation. This multitude of benefits pursue it a decent decision for a few applications, for example, for helping medical diagnosis for a precise treatment.

3. Woźniak M et.al proposed Bio-inspired methods modelled for respiratory disease detection from medical images. Medicine is a significant setting for practical utilizations of science. A fusion of mathematical modeling and programming into computer methods makes an extraordinary help for productive treatment and diagnosis. Computational Intelligence is one of these sciences which acquire important assist choice with supporting. In this article we present gave methodology executed to mimic medical assessments of pulmonary diseases. They propose Bio-Roused Methods modelled to function as the computerized choice help in a course of diseased tissues detection over input x-ray images. Mathematical model of medical skill is planned as a capability used to look for unique highlights of pixels that are addressing respiratory diseases like pneumonia, lungs sarcoidosis and cancer. In benchmark tests, for a bunch of unique x-ray images from different centers, applied methods were inspected to exhibit advantages of utilizing carried out arrangement. Results show that proposed methodology is productive and promising for pulmonary diseases detection.

4. Chan HP et.al proposed artificial convolution neural network for medical image pattern recognition. An unconventional method of utilizing turn and shift invariance is additionally proposed to upgrade the neural net presentation. The construction of the artificial neural network is a worked on network design of the neocognitron. Two-layered neighborhood association as a gathering is the essential design for the sign proliferation in the convolution neural network. Weighting arrogances of convolution parts are framed by the neural network through back proliferated preparing for this artificial neural net. This work has shown two effective medical diagnostic applications utilizing an artificial visual neural network and master prepared computer systems rather than a non-convolution neural network or other customary characterization method. This technique endeavoured to recreate the radiologists' understanding example: pre-screen and order for translation. We accept that the proposed convolution neural network and its related preparation techniques can be stretched out to numerous diagnostic imaging regions, for example, the detection of low differentiation mass in mammography and the example acknowledgment of interstitial lung disease in chest radiography. As a matter of fact, the proposed CNN technique ought to have the option to be prepared to identify practically all disease designs detectable by a prepared radiologist.

5. W. Yang et.al proposed Predicting CT Image from MRI Data through Feature Matching with Learned Nonlinear Local Descriptors. Attenuation correction for PET/MR hybrid imaging systems and portion making arrangements for MR-based radiation therapy stay testing because of lacking high-energy photon attenuation information. We present a novel methodology that utilizes the learned nonlinear local descriptors and feature matching to predict pseudo CT images from T1w and T2w X-ray information. The nonlinear local descriptors are acquired by projecting the direct descriptors into the nonlinear high-layered space utilizing unequivocal feature guide and low-rank estimation with managed manifold regularization. The closest neighbors of every local descriptor in the info MR images are looked through in a compelled spatial scope of the MR images among the preparation dataset. Then the pseudo CT patches are assessed through k-closest neighbor relapse. The proposed method for pseudo CT prediction is quantitatively examined on a dataset comprising of matched brain X-ray and CT images from 13 subjects. Our method produces 18.05□pseudo CT images with a mean absolute error of 75.25 1.15 dB, a±Hounsfield units, a pinnacle signal-to-commotion proportion of 30.87 0.50% in PET attenuation±relative mean absolute error of 1.56 correction, and a portion relative structure volume distinction of 0.107% in D98%, when contrasted with genuine CT. The±0.055 exploratory results likewise show that our method outflanks four state-of-the-art methods.

3. Proposed Methodology

Medical imaging equipment gets refreshed consistently as computer technology progresses. Medical image segmentation is an essential connect to medical image analysis, as well as an essential and key technology for clinical medical procedures. Nonetheless, because of individual contrasts and the intricacy of human tissues, for example, the brain, the segmentation results of medical images, particularly brain growth images, are not satisfactory. Thus, endless researchers in this field overall have contributed a ton of energies to research this issue.

3.1 Fuzzy System to Brain Image Diagnosis and Prediction

How much information in images continues expanding with present day medical imaging technologies, making it fundamental for medical specialists to embrace an enormous responsibility during medical image analysis; Notwithstanding, images seem to have low differentiation, changeability between tissues, the ambiguity between various tissues or among tissues and sores because of the distinctions in the imaging standards of medical images and the characteristics of the tissues themselves. Therefore, the intricacy and assortment of medical images themselves have made extraordinary deterrents the precise processing and analysis of medical images. Thus, utilizing computer technology to help brain image recognition and brain disease prediction is of essential importance for diagnosing and treating diseases.

Medical brain images have heaps of vulnerability during diagnosis and prediction, and their substance lies in the ambiguity. There are three key indications. In the first place, the grayscale is fuzzy: brain images are obstructed by lighting conditions and spatial resolution, making the edge of the pixel grayscale between the brain image limit and the background blurry and overlap with one another. Second, it has a local body effect: because of the impact of gear factors, voxels on a limit often contain two substances: limit and object, making it challenging to precisely portray the connections among the edges, corners, and regions of the objects in the image. Third, there is vulnerability knowledge. On account of obsessive changes, brain images will have protuberances or masses that are not accessible in normal tissues, acquiring extraordinary hardships constructing the model. Moreover, there might be commotion obstruction, offset field effects, and partial volume effects in brain image processing.

Based on the above issues in brain medical image processing, this work involves the limit information of unlabeled and marked information in brain medical image as medical space knowledge to further work on the effect of brain image segmentation and diagnosis.

3.2 Improved Fuzzy Clustering Model (IFCM) for Brain Disease Prediction

The imaging mechanism of NMR and the complexity of human brain tissues make X-ray images present different levels of noise, feeble limits, and artifacts. Therefore, the fuzzy clustering algorithm is improved to extract the features of information got in the brain image. Subsequently, a brain image processing and brain disease diagnosis prediction model based on improved fuzzy clustering is planned while guaranteeing the security execution of the model.

In the proposed algorithm, an improved fuzzy clustering algorithm is proposed based on the bit distance metric with respect to serious areas of strength for the obstruction of medical images. This algorithm consolidates the portion function, participation limitations, and regularization parameter ρ based on the customary fuzzy clustering algorithm, actually taking advantage of the local spatial information of the image. This causes the algorithm to possess better segmentation accuracy and detail maintenance capacity meddled by high-intensity noise, and the image edges after segmentation have better perfection. This algorithm is recorded as IFCM (Improved Fuzzy Clustering model), described as Equation (1):

$$\mathbf{J_{SIPMFCM}\left(U, v_1, \dots v_c, \lambda_1, \dots, \lambda_n\right) = 2 \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \left(1 - \left\|x_j - v_i\right\|\right) + \sum_{i=1}^{c} \rho_i \sum_{j=1}^{n} u_{ij} \left(1 - u_{ij}^{m-1}\right) + 2 \sum_{i=1}^{c} \rho_i \sum_{j=1}^{n} \left(1 - \left\|\overline{x_j} - v_i\right\|\right)} \qquad \mathbf{(1)}$$

Algorithm 1: Improved fuzzy clustering Model (IFCM)
Step 1: Start the process
Step 2: Input: p, q, m
Step 3: Parameters: $p = 2, q = 1, m = 2$ iteration number $t = 0$, thershold $\varepsilon = 0.001, u^0$
Step 4: Output: u_{ij}
Step 5: Calculate the mean filter image and median filter image $\overline{x_j}$
Step 6: Calculate the cluster center v_i^t
Step 7: $v_i \leftarrow \frac{\sum_{j=1}^{n} u_{ij}^{m}\left(\left(\left\|x_j - v_i\right\| x_j + \rho_i \left\|\bar{x}_j - v_i\right\| \bar{x}_j\right)\right.}{\sum_{i=1}^{c} u_{ij}^{m}\left(\left(\left\|x_j - v_i\right\| x_j + \rho_i \left\|\bar{x}_j - v_i\right\|\right)\right.}$

Step 8: Calculation of membership function u_{ij}
Step 9: $u_{ij} \leftarrow \frac{1}{\sum_{k=1}^{c}\left(\frac{2\left(1-\left\|x_j-v_i\right\|\right)-\rho_i+2\rho_i\left(1-\left\|x_j-v_i\right\|\right)}{2\left(1-\left\|x_j-v_i\right\|\right)-\rho_i+2\rho_i\left(1-\left\|x_j-v_i\right\|\right)}\right)^{m-1}}$
Step 10: if $\|u^{t+1} - u^{t}\|\| < \varepsilon$ or $t > 100$
Step 11: Iteration termination then update $t = t + 1$
Step 12: Return v_i^t, u_{ij}
Step 13: end if
Step 14: end

In Equation (1), $\bar{x}$ refers to the mean filtering brain image or median filtering brain image. The primary thing here is that the customary IFCM expression is transformed from the kernel distance measurement, which maps the examples to a high dimensional space and builds the distinction between the examples. The second membership punishment thing makes the fuzzy division more distinct. The third thing here is the local space restriction thing, planning to strengthen the algorithm's heartiness to image noises. Ultimately, the spatial function is incorporated into the membership function u_{ij}:

$$\mathbf{u_{ij}^{t}} = \frac{\mathbf{u_{ij}^{p} s_{ij}^{t}}}{\sum_{k=1}^{c} \mathbf{u_{ij}^{p} s_{ij}^{q}}} \qquad \textbf{(2)}$$

In Equation (2), s_{ij} is like the membership function, addressing the likelihood that a pixel has a place with a classification, and parameters p and q are the weight parameters that control the membership function and the spatial relationship function, respectively. Here, u_{ij}^{t} is the last participation function shows the improved fuzzy clustering algorithm IFCM.

Furthermore, the brain image features are extracted. The U-Net algorithm just purposes the features of the last convolution all Layer, the information is basic, and containing rich nitty gritty information isn't sufficient. Subsequently, the accompanying enhancements are made. To start with, the introduction of the feature fusion permits the model to combine information of multiple scales to aid the image feature extraction. Second, intertwining features of multiple scales assists with melding semantic and location information, supplements multiple feature information, and works on the accuracy of feature extraction. In addition, information of various scales is coordinated to accomplish effective and quick image segmentation.

This neural network means to gain proficiency with the information distribution. Parameters are adopted to recreate information distribution to portray the first information and predict the obscure information. During training, the mean worth μβ of the inward information distribution of each bunch is determined first as Equation (3):

$$\boldsymbol{\mu_{\beta}} = \frac{\mathbf{1}}{\mathbf{m}} \sum_{\mathbf{i=1}}^{\mathbf{m}} \mathbf{x_i} \qquad \textbf{(3)}$$

In Equation (3), m refers to the number of batches of the brain images. Then, the data distribution variance within each batch $\delta_{\beta}^{2}$is calculated as Equation (4):

$$\boldsymbol{\delta_{\beta}^{2}} = \frac{\mathbf{1}}{\mathbf{m}} \sum_{\mathbf{i=1}}^{\mathbf{m}} \left(\mathbf{x_i} - \boldsymbol{\mu_{\beta}}\right)^{\mathbf{2}} \qquad \textbf{(4)}$$

Next, data in the current batch are normalized as Equation (5):

$$\hat{\mathbf{x}}_{\mathbf{i}} = \frac{\mathbf{x_i} - \boldsymbol{\mu_{\beta}}}{\sqrt{\boldsymbol{\delta_{\beta}^{2}} + \boldsymbol{\varepsilon}}} \qquad \textbf{(5)}$$

BN can keep the feature with a mean value of 0 and a fluctuation of 1, which is steady with the info information distribution. At last, BN likewise adds a stage, "scale and shift," as described in Equation (6)

$$\mathbf{y_i} = \boldsymbol{\gamma}\hat{\mathbf{x}}_\mathbf{i} + \boldsymbol{\beta} = \mathbf{BN}_{\boldsymbol{\gamma\beta}}(\mathbf{x_i}) \qquad \textbf{(6)}$$

Equation (6) seems to be somewhat contrary to the previous operation; however, it can restore the original input. Besides, parameters γ, β

In this way, the entire model may or may not change the input distribution of the current layer in the end. The overall effect is to maintain the consistency of the feature distribution to stabilize the model during training and learning. Meanwhile, BN also helps accelerating the convergence time during model training, prevents gradient dispersion or gradient explosion, and improves training accuracy.

4. Experiment Results

This results used the Improved fuzzy clustering model (IFCM)to process MR dataset and the segmentation method described in Figure 1 and the prediction method as shown in Figure 2.

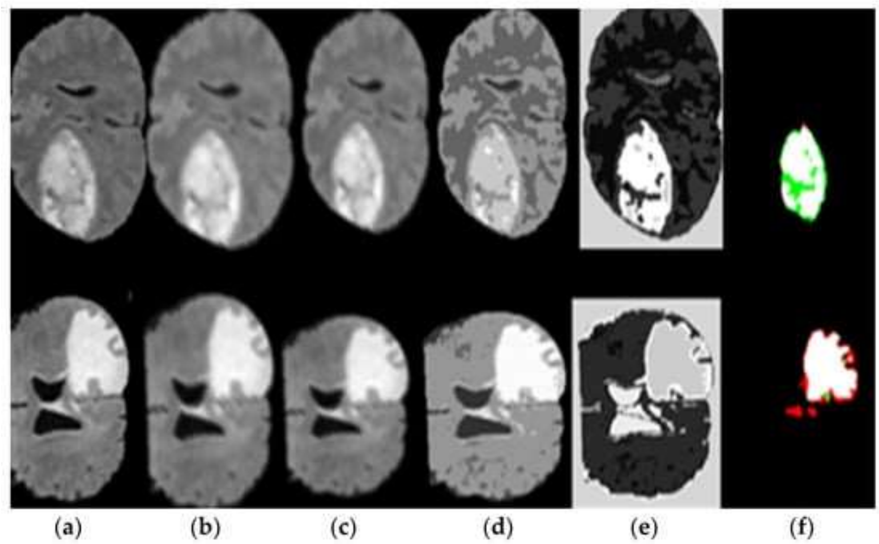

Figure 1: (a) Original image, (b) image sharpening, (c) high pass filter, (d) seed growing, (e) applied thresholding, and (f) segmented tumor alone.

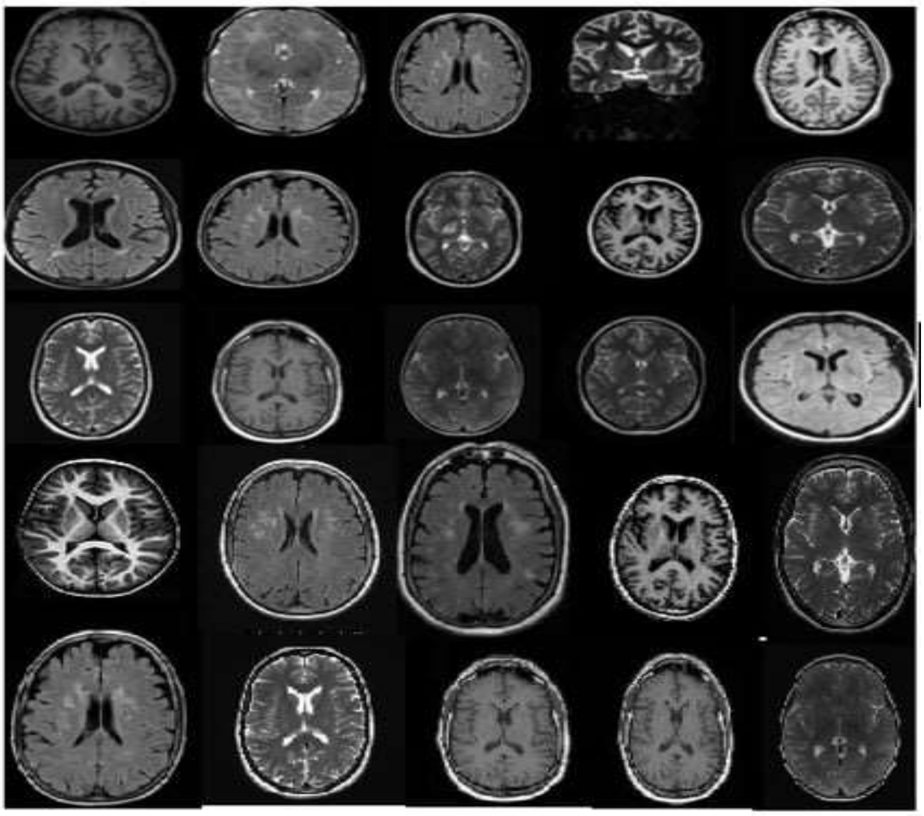

Figure 2.Samples showing the results of MR brain normal images using the improved fuzzy clustering model (IFCM).

5. Conclusion

Brain cancer images have complicated edge structures and are structures to artifacts and offset fields, affecting image segmentation. The feature extraction and correct diagnosis of brain tumors in multi-sequence X-ray images are particularly fundamental. Besides, a brain image processing and brain disease diagnosis prediction model is proposed based on improved fuzzy clustering model (IFCM). Reproduction experiments demonstrate that the proposed algorithm can give high accuracy to feature extraction and recognition, superb noise reduction effect, and the ideal image segmentation recognition effect.

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