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INTEGRATION OF DIFFERENT KERNELS FOR NEURO FUZZY BASED CONCEPT USING FOR MRI MEDICAL IMAGE SEGMENTATION

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Abstract: One of the most essential technologies for computed tomography is medical image segmentation. As a result, image segmentation is critical in image-guided surgery, both in terms of benefits and drawbacks. Traditional machine learning methods have aided in the segmentation of medical images, but they suffer from limitations such as low classification accuracy and robustness. Medical image segmentation problems are solved anew using deep learning theory because of its good generalizability and ability to extract features. To solve these challenges, we adapt a normal neural network to medical imaging properties by adding cross-layer connections to a standard CNN. In addition, a better version of the CNN is being developed. Medical images can be segmented using data from two scales at the same time by optimising a CNN model. A new approach for medical picture segmentation is proposed that uses an optimised CNN and an adjustable dropout depth computation. The kernel approach was created by support vector machines (SVMs), and it has since received a lot of attention. We describe a spatially contextualised kernel-based approach for clustering image data. This approach improves the objective function in the traditional fuzzy c-means algorithm by utilising a kernel-induced distance metric and a spatial penalty term that accounts for the influence of the surrounding pixels on the centre pixel. The study reported in this article attempts to look at medical image segmentation.

Index Terms: Kernel method; CNN; multi-hyperbolic tangent function; Segmentation; fuzzy; multi-modality fusion.

1. INTRODUCTION

Neuro-fuzzy systems have been derived from fuzzy systems that are trained with the help of a neural network-inspired learning algorithm. The fuzzy system is only modified locally by (heuristical) learning procedures, which operate on local information. It's possible to think of neuro-fuzzy systems as feed forward neural networks with three layers. The input variables are represented by the first layer, the fuzzy rules by the second layer, and the output variables by the third layer. (Fuzzy) connectivity weights represent fuzzy terms. A fuzzy system of this type does not need to be represented in order to be learned from. The model flow is used to depict the data flow of processing and learning, which might be beneficial. High-performance fuzzy systems are difficult to develop. In addition to the search of membership functions and appropriate rules, which is often error-prone, there are several other challenges [1]. Thus, fuzzy systems were also treated with the learning algorithms. A fuzzy system could also be automated by using neural networks [2]. In addition to their use in process control applications, neural networks can also be used to analyze data, classify data, detect imperfections, and support decision-making. To increase their advantages and to eliminate their shortcomings, neural networks and fuzzy systems can be combined. Neural network learning techniques can be used to accelerate the creation of fuzzy systems, lower their costs, and increase their performance [3]. The Figures 1 and 2 demonstrate two possible fuzzy neural network models. A multilayer neural network is triggered by linguistic statements by a fuzzy interface block (Figure 1). Taking into account a multi-layered neural network representation, fuzzy inference is determined in the Figure 2.

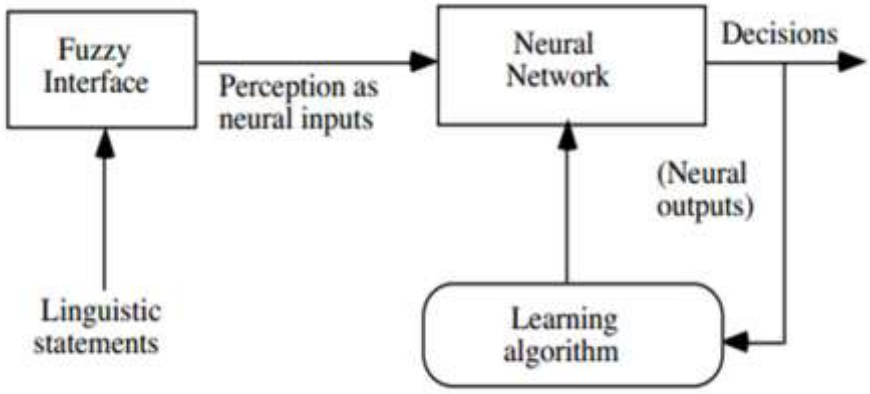


Figure 1. Neuron model based on fuzzy logic

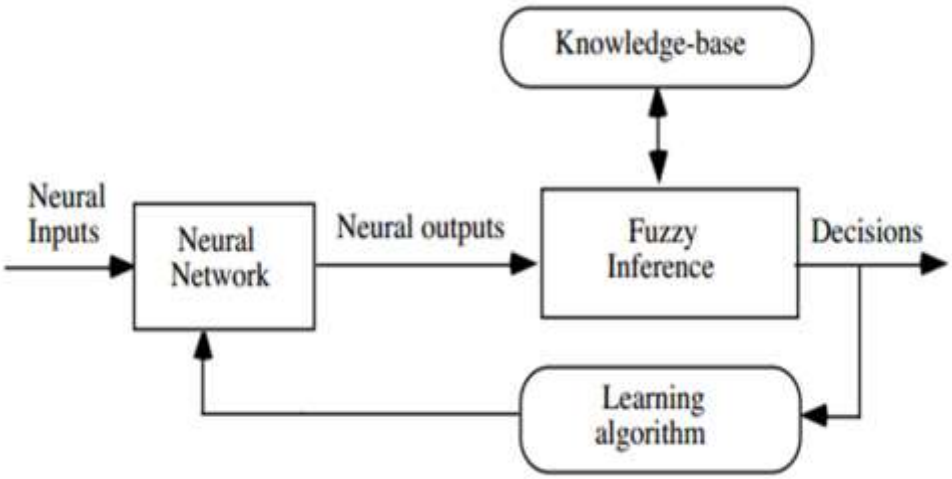


Figure 2. Fuzzy Neuron model

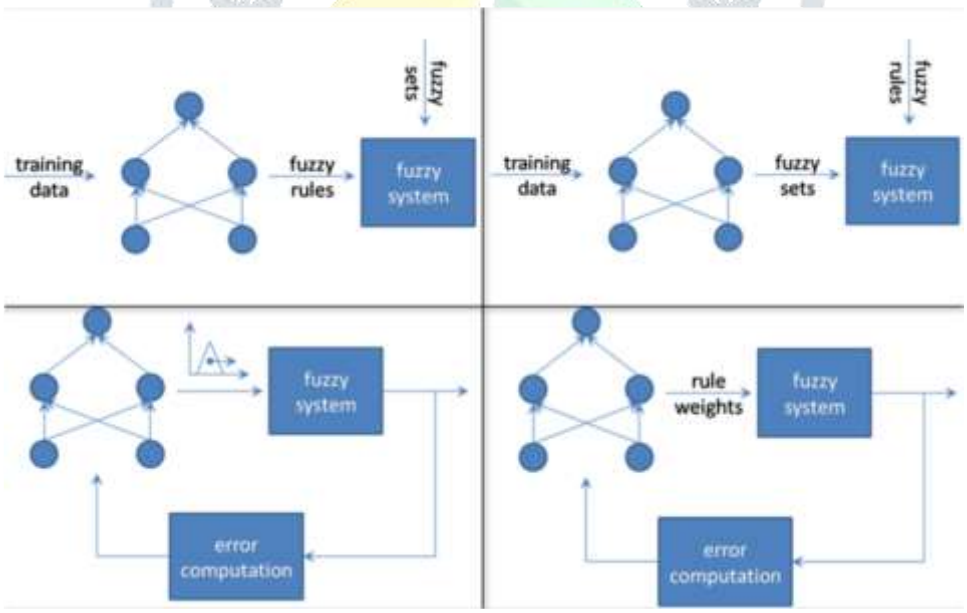
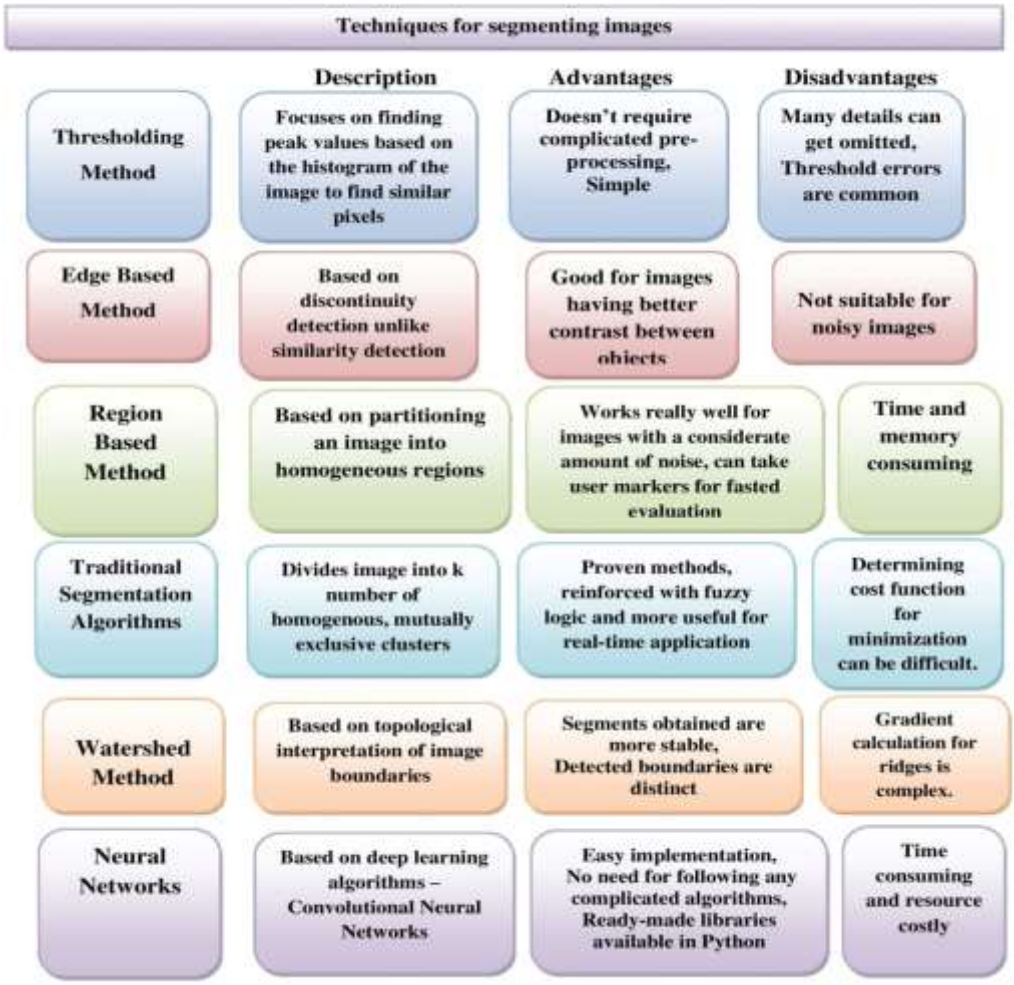


Figure 3. Cooperative fuzzy neural networks of four types.

Image assisted radiotherapy, image assisted surgery, image approach to solving therapy, and advanced imaging navigation are all quite popular right now. It encourages medical imaging technology research and development [4-5]. Compared to traditional surgical procedures, image-guided surgery is much more accurate and efficient, and can reduce surgical risks. Image segmentation technology is essential for guiding surgery with images. In image-guided surgery, the benefits and drawbacks of segmentation are critical. [6-8]. Medical image analysis is a growing field, where segmenting medical images is a complicated and critical step. By using this type of diagram, the area of anatomical interest or a certain tissue can be depicted with the greatest degree of accuracy. Various methods exist for segmenting medical images. Machine learning and deep learning are the two main categories of medical image segmentation methods [9-12]. Artificial intelligence applications have focused much attention on deep learning [13-14] in

recent years. Its precision has substantially improved a range of applications. The aforesaid issues can be handled. An alternative deep learning-based method for medical image segmentation emerged in this technical background.

Medical image acquisition systems have extensively studied multi-modal segmentation. Image fusion can be achieved using many different strategies, including probability theory, fuzzy concepts, believe functions, and machine learning. It is difficult to model certain data modalities using shallow models for the methods based on probabilistic theory and machine learning because they have different statistical properties. Fuzzy measurements estimate the degree of membership associated to a judgement for each source in methods based on the fuzzy principle. When fuzzy operators are applied to fuzzy sets, several sources are merged together. The DempsterShafer rule is used to fuse all source models based on the belief function theory, then each source is modeled by an evidentiary mass. The decision should not be taken until the evidentiary mass, the fuzzy measure, and the fuzzy conjunction function have been calculated in order to apply the belief function theory and the fuzzy set theory. The mapping can be directly encoded by a deep learning-based network. As a result, utilizing deep learning to produce better fusions has a huge amount of potential.



2. METHODS

2.1 K-Means Algorithm

In general, K-Means algorithms are quite fast. The system is easy to understand and robust. Clustering is one of the most well known problems, K-means solves that problem effectively and it is a unsupervised learning algorithm. Using a certain number of clusters that are fixed a priori, a given data set is categorized as easily as possible. There are k centroids for each cluster, which is the concept. Because the results from different locations are different, these centroids must be placed in a clever manner. In other words, placing them as far away from one another as possible is the better option. The following step entails choosing a centroid for each point in a given data set. The first step is complete when no pending points exist, and an early grouping is done. As a result of the previous step, we need to recalculate k new centroids as barycenters of the clusters. After acquiring these k new centroids, a fresh binding must be conducted to bind the identical points to the nearest new centroid. Thus we have generated a loop. This loop would cause the k centroids to move around in their location until no more changes are made. To put it differently, centroids stop moving. This algorithm's main goal is to minimize a squared error function. The objective function is given by.

$$F = \sum_{i=1}^{k} \sum_{j=1}^{m} \left\| x_j^{\,i} - C_i \right\|^2$$

2.2 Clustering Algorithm using Fuzzy C Means (FCM)

Among the most classical and traditional image segmentation algorithms is fuzzy c-means (FCM). An objective function is minimized by using an FCM algorithm. A dataset is partitioned into c clusters according to the objective function. A weighted squared error objective function is minimized by employing an iterative clustering algorithm to determine an optimal cell partition.

The fuzzy c-means (FCM) clusters data by allowing one piece of information to are considered. Pattern recognition usually entails using this method. The following objective function can be used to minimize the FCM algorithm.

$$F_m = \sum_{j=1}^{k}\sum_{i=1}^{m} u_{ij}^{n} \left\| x_j - c_i \right\|^2$$

In a cluster, n represents the real number of members, u_{ij} represents the degree of membership, and c_i indicates the cluster's center in d-dimensions.

$$U_{ij} = \frac{1}{\sum_{l=1}^{c}\left(\frac{\left\| x_j - c_i \right\|}{\left\| x_j - c_l \right\|}\right)^{\frac{2}{n-1}}}$$

$$C_i = \frac{\sum_{j=1}^{k} U_{ij}^{n} x_j}{\sum_{i=1}^{k} U_{ij}^{n}}$$

For overlapped data sets, FCM provides the best results. In comparison with K-means, it is more accurate. The k-means algorithm requires that data points belong to only one cluster centre. Data points are allocated membership to each cluster centre as a result, and they can belong to many cluster centres. The number of clusters must be specified a priori.

2.3 Clustering Algorithm using Kernel Fuzzy C Means (KFCM-CA)

Kernel information is added to the classic fuzzy c-means technique with the KFCM-CA algorithm. The KFCM-CA algorithm also addresses the problem that it is unable to account for small differences between clusters in FCM algorithms. Kernel methods map the input data space into the input data space nonlinearly, resulting in a high-dimensional feature space. As the name implies, kernel-based methods operate by performing a non-linear mapping from the originally d-dimensional feature space to a higher dimensional space (kernel space). There is no limit to the size of kernel space. Taking the problem to higher dimensions may allow a linear classifier to be applied in the kernel space, although the original problem in the feature space may be very non-linear and difficult to separate using linear methods. This method functions by taking advantage of the fact that Mercer kernels can be used to represent dot products in the kernel space. The distance in the kernel space does not need to be determined explicitly because Mercer kernel functions can replace the distance computation.

As an alternative to the original squared-norm distance metric, the algorithm uses a kernel-induced distance metric. With this kernel version, we may modify the FCM algorithm's objective function as follows

$$F_n = \sum_{i=1}^{c}\sum_{j=1}^{N} u_{ij}^{n} \left\| f(x_j) - f(y_i) \right\|^2$$

Where, $\left\| f(x_j) - f(y_i) \right\|^2 = Z(x_j, x_j) + Z(y_i, y_i) - 2Z(x_j, y_i)$

So, $F_n = 2\sum_{i=1}^{c}\sum_{j=1}^{N} u_{ij}^{n}\left[1 - Z(x_j, y_i)\right]$

Where, $u_{ij} = \frac{\left[1 - Z(x_j, y_i)\right]^{\frac{-1}{n-1}}}{\sum_{i=1}^{c}\left[1 - Z(x_j, y_i)\right]^{\frac{-1}{n-1}}}$ and

$$y_i = \frac{\sum_{j=1}^{N} u_{ij}{}^{n} Z(x_j, y_i) x_j}{\sum_{j=1}^{N} u_{ij}{}^{n} Z(x_j, y_i)}$$

2.4 CNNs modelling optimization

The optimised CNN model architecture includes a fully connected layer, a convolutional layer pooling layer, an interleaved convolutional layer, and an output layer. In Figure 4, we see how layers of convolution are combined with layers of pooling in a cross-layer connection to produce a fully connected layer.

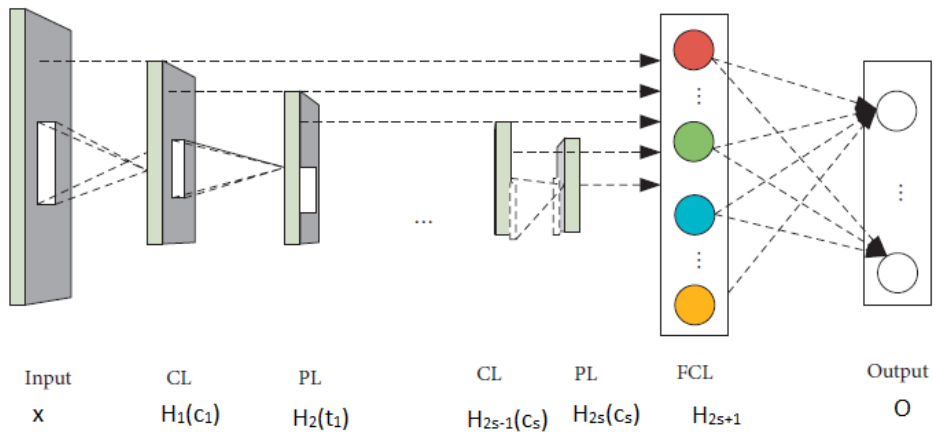


Figure 4. Splicing a CNN.

Consider there are 3 spatial dimensions to the input X are H, W, and n (H*W*n); channel dimension is n; color images are represented when n=2 , and n = 1 representing grayscale images. F denotes the activation function. Following are the calculations for the convolutional layer:

$$H_{2m-1,i}^{1} = C_{m,i}^{1} = F\left(u_{2m-1,j}^{1}\right) = F\left[\sum_{j} H_{2m-1,j}^{1} * W_{ji}^{2m-1} + B_{i}^{2m-1}\right]$$

The step size of all feature faces in a pooled layer is fixed. In this case, pooling [*] can be average or maximum. We can define the pooling function as follows:

$$H_{2m,i}^{1} = t_{m,i}^{1} = pooling\left(H_{2m-1,i}^{l}\right)$$

Layers are connected through a cross-layer connection when two or more convolutional layers are activated along with a pooled layer. Several fully connected layers can constitute a multiscale feature discriminate vector. It can be represented as follows:

$$H_{2s+1}^{1} = \left[s_1 h_1^{1}, s_2 h_2^{1}, \ldots\ldots, s_{2s} H_{2s}^{1}\right],$$ here binary string S={s_1, s_2, ...s_{2s-1}}

2.5 Designs based on adaptive distribution functions

Adaptive distribution functions are employed in this study to mask the layer's position as an independent variable and the layer's activation probability as a dependent variable. Each hidden layer is given a probability of activation, which is set by its position. The adaptive distribution function lowers monotonically as the hidden layer position increases, according to this investigation. [15-16] . According to Hinton's dropout model, neurons in each layer should have an activation probability of about 0.5. The goal is to maintain enough active neurons. Furthermore, the depth calculation model is discarded enough neurons to make it suitable for generalization. As a final measure, the dropout rate of each layer should lie anywhere between 0 and 1. In this paper, we propose the following adaptive distribution function:

$$\rho = f(x) = \begin{bmatrix} 1 - \dfrac{1}{\tau\sqrt{2\Pi}} \displaystyle\int_{-\infty}^{x} e^{\frac{-(1-m/2)^2}{2\tau^2}} dx \\ 1 - \dfrac{1}{\tau\sqrt{2\Pi}} \displaystyle\int_{-\infty}^{x} e^{\frac{-[x-(1+m/2)]^2}{2\tau^2}} dx \end{bmatrix}$$

With x indicating the hidden layer's location, m indicating the depth calculation model's number of layers, and r indicating the dropout rate range control parameter.

2.6 An efficient CNN approach for estimating dropout depths – Image segmentation

Based on sections 2.4 and 2.5 of the paper, this section proposes an adaptive drop-out depth calculation method for CNNs used to segment medical images. By adding cross-layer connections into a normal CNN, an optimized CNN model is generated. This solution will allow deep learning models to be flexible with their network structure. Similarly, this study proposes an adaptive dropout model that will increase the generalizability of the dropout strategy while reducing deep learning complexity. Based on the foregoing study, we developed a medical image segmentation technique that employs a CNN with adaptive drop out depth calculation. This algorithm is depicted in Figure 5 as a basic idea. In summary, it consists of the following steps:

1.The first step is to denoise, add, and expand the data in the medical images.

2. In this paper, we propose a new optimized CNN model that extends traditional CNNs with cross-layer connections and thus significantly improves network structure of deep learning models. By using two scale features simultaneously in an optimized CNN model, it is possible to better segment medical images.

3. The activation probability of each layer of neurons is set up using an adaptive distribution function based on the location of each hidden layer, improving the generalizability of the dropout model even further. Thus, the general dropout method of deep learning is

no longer applicable, reducing generalizability. The deep learning model can be made more generalizable and the over fitting risk reduced.

4. In steps (1) – (3), the goal of medical image segmentation is met by integrating the method of step (3) with the method of step (2). This leads to a segmentation algorithm that relies on an optimization of CNNs with adaptive dropout depth calculations. Analyzing related examples, comparing and analyzing with mainstream methods of segmenting medical images is the objective of this algorithm.

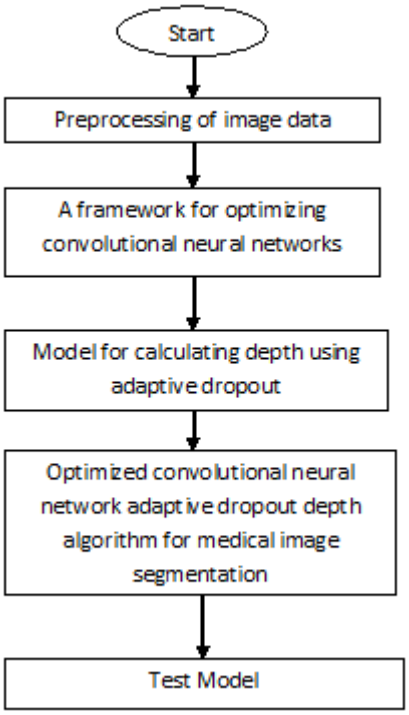


Figure 5. Algorithm of segmenting medical images based on optimized CNNs with adaptive dropout depths.

2.7 A Model of Weighed Level Sets

Because of noise and bias fields, many existing algorithms are unable to correctly segment brain MRI images. The problem of local multiple-information is addressed by combining a weighted level set model with local multiple-information. Using kernel metrics and fuzzy spatial membership limits, the approach allows for accurate segmentation of brain MRI images. The neighbourhood information of the central pixel yi, which was most successful on pictures of low-contrast brain MRI, where white matter and grey matter are intermingled and the line between them is indistinct, was used to improve image quality in this study. Local variation, spatial distance, and gray-level difference are all employed simultaneously for the weighted neighbourhood information, which will be explored separately in this part. Variation occurs in the local window of yi based on the pixel intensity mean and variance. Pixels can be related to each other intuitively by variance, which is defined as deviation from the mean. The set of neighbor pixels yj surrounding the center pixel yi is represented by the coefficients Cij, where Cij represents the local variation coefficient:

$$C_{ij} = \frac{Variance\left[y_j\right]}{\left[\overline{y_j}\right]^2}$$

Due to its computational simplicity, Euclidean distance continues to be used in some traditional studies. If noise, inhomogeneity in intensity, and other effects destroy the images, Euclidean distance will be difficult or impossible to measure accurately. Hence, we construct a nonlinear distance metric that improves Euclidean distance by using kernel metrics. The fuzzy spatial C-means [31] and support vector clustering [32] have been developed utilizing this technique. An efficient distance measure is the Gaussian kernel function, which is defined as:

$$D_{ij}^{\ 2} = e^{\left[\frac{-\left\|y_j - y_i\right\|^2}{\sigma}\right]}$$

3. MULTIMODAL SEGMENTATION NETWORKS

The development of various semi-automated and automated methods, such as CNN [19] and FCN [17] as well as U-Net [18], has been explored for multi-modal medical image segmentation over the years.

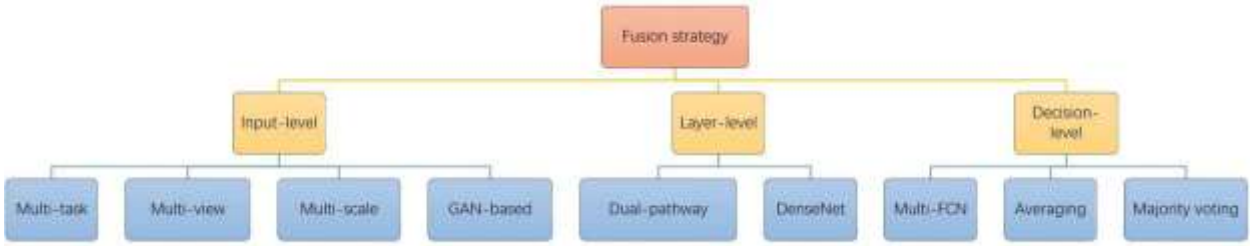


Figure 6: Classification of the fusion strategy

3.1 Input-level fusion network

Fusion of multi-modality images at the input level involves fusing images channel by channel to learn a merged feature representation, and then training the segmentation network using the merged representation. A majority of existing multimodal medical image segmentation networks apply the input-level fusion technique to integrate these images directly into the original input space [20-24]. An input-level fusion segmentation network is shown in figure 7. Using CT and MRI as inputs, CNN as segmentation network, and brain tumor segmentation to perform the segmentation task, we use CT and MRI to segment brain tumors. A multilevel fusion strategy can fully utilize the rich feature information in all layers, from the first layer to the last layer, in order to exploit the rich feature information from different modalities. It is possible to maximize the preservation and learning of original image information using the input-level fusion strategy. Sequentially segmenting images with sequential segmentation networks generates many different strategies, such as multitasking, multi-viewing, multi-scale, and GAN-based segmentation networks, for fully exploiting the features found in multi-modal images.

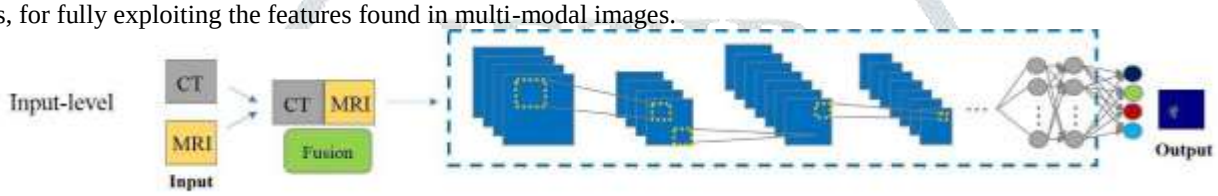


Figure 7: Network architecture of the input-level fusion

3.2. Layer-level fusion

To train individual segmentation networks using the layer-level fusion strategy, only one or two modal images are used as inputs. Following that, the layers of the network will fuse these learned individual feature representations. A final segmentation result will be obtained by feeding the fused results into the decision layer. Multi-modal images can be effectively integrated and fully leveraged by the layer-level fusion network [26-28]. Layer-level fusion segmentation works are shown in Figure 8.

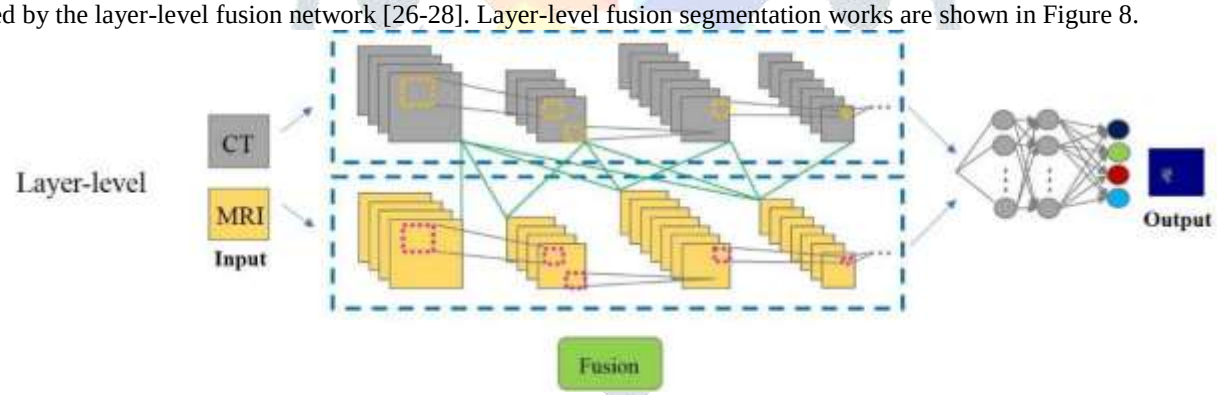


Figure 8: Network architecture of the layer-level fusion

3.3. Decision-level fusion

In a single segmentation network composed of decision-level fusion segmentation, each modality image contains one input. By combining the individual networks, the unique features of each can be more efficiently exploited. Finally, the segmentation result will be generated by integrating the resulting outputs of the individual networks. Since multimodal images usually contain little complementary information due to different acquisition techniques, they tend to have fewer direct complementarities. In decision-level fusion segmentation, information from different sources is independently learned in different modes. Layer-level fusion segmentation work is illustrated in Figure 9 as a generic network architecture.

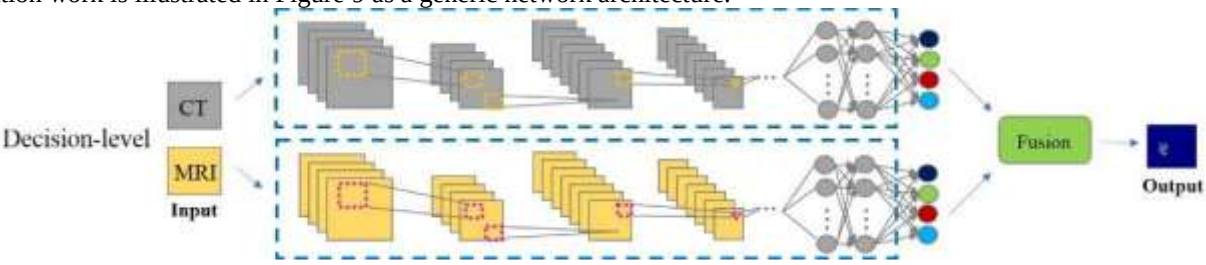


Figure 9: Network architecture of the decision-level fusion

4. RESULTS & DISCUSSION

WLSM used to segment realistic and synthetic images of MRI and compares them to state-of-the-art models. In the first step, it enhances the quality of MRI images by using the weighted neighborhood information within WLSM. This will improve the segmentation accuracy (SA) of MRI images with varying degrees of noise. MRI images with inhomogeneous intensities are corrected using this method, and the bias field is estimated as well. Finally, the WLSM segmentation method is tested on sagittal, coronal, and axial slices of synthetic and actual MRI images to demonstrate its performance. An MRI simulator produces simulated brain MR images that are close to actual brain MRI images. This is known as BrainWeb, a simulated brain database (SBD). The Montreal Neurology Institute developed it as part of its brain imaging center. A three-dimensional matrix is used to represent the brain MR images in SBD. The original images in the first column were ruined by noise, as can be seen in the somewhat expanded regions denoted by green rectangles, notably in areas where WM and GM are intertwined. By comparison, the improved images in the second column, which use weighted neighborhood information, are more noise free than original images and allow clear demarcation of the boundaries between tissues. For purposes of updating the central pixel, WLSM uses local variation, spatial distances and gray-level information obtained from the neighbors of the central pixel. In a given tissue, pixels that are adjacent in weight will have a larger weight, and vice versa. Pixels in the weak borders can subsequently be classified into the respective tissues based on their weighted neighbour information.

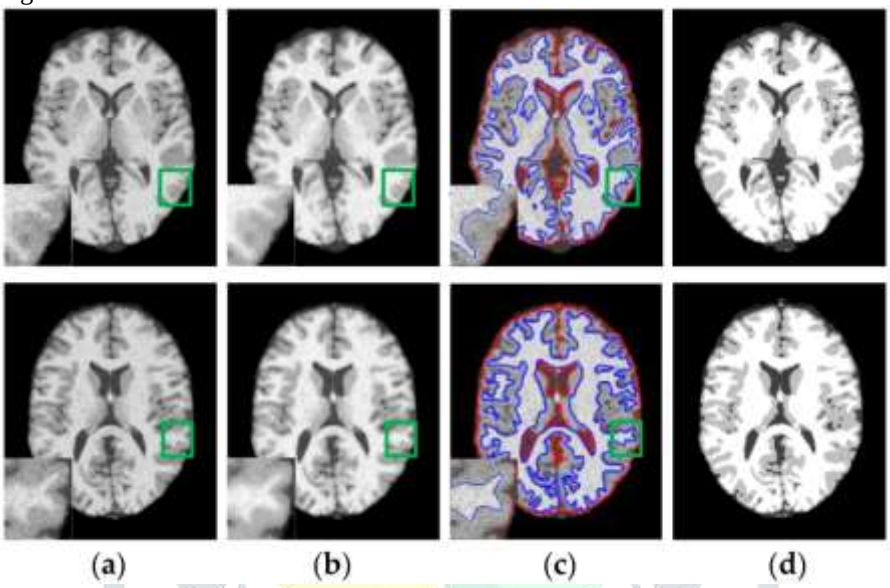


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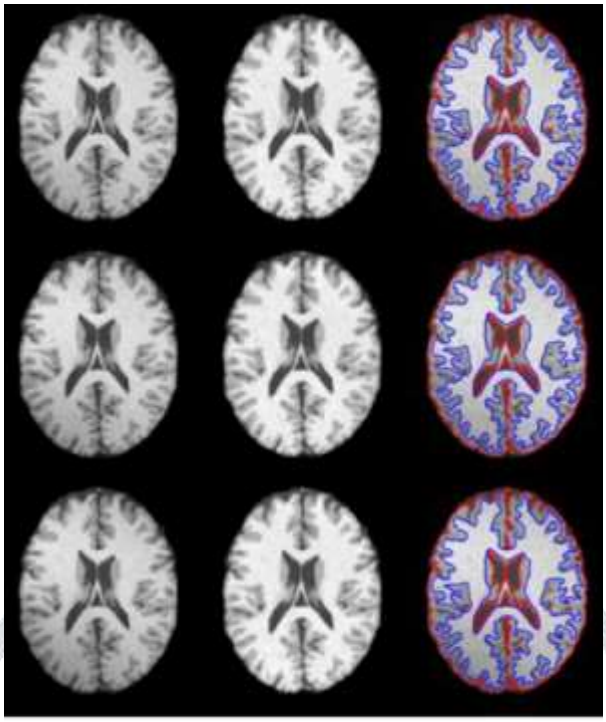
Figure 10. Images of the brain segmented by WLSM; a)Original Image b) improved image c) segmentation

Because both noise and intensity inhomogeneity frequently damage MRI images, the model's ability to adjust inhomogeneous intensity and estimate bias field is crucial. To demonstrate WLSM's performance, the experiment of this subsection uses MRI images of the brain with a noise of 3% and different degrees of intensity inhomogeneity to segment them. Figure 11 shows pictures with 3% noise as well as 60%, 80%, and 100% intensity inhomogeneity. As illustrated in the corrected and segmented images in the second column, Without being impacted by noise or intensity inhomogeneity, WLSM can be used to correct inhomogeneous intensity and segment images at the same time. The segmentation results in the third column are the same whether the inhomogeneous intensity is lower or higher, WLSM's ability to simultaneously correct inhomogeneous intensity and segment pictures without affecting noise and intensity inhomogeneity is demonstrated.



(a) (b) (c)

Figure 11. a) Original image b) Corrected image c) Segmentation

5. CONCLUSION

In this research, noise-affected MR images were segmented using a novel method. Based on the kernel method, the algorithm is simple to understand. In this algorithm, the distance metric is introduced into the objective function as a kernel-induced modification of conventional fuzzy c-means. In terms of spatial penalty, neighboring pixels have an influence on the central pixel. To construct a better medical picture segmentation method based on deep learning, it is first proposed to analyse the network topology of the deep learning model and add cross-layer connections to the standard CNN. This model is optimized using CNNs. CNNs can segment images using two scale features simultaneously. On the basis of this, this research paper proposed an adaptive dropout depth-based CNN algorithm that processes medical images for segmentation. Fusion strategy plays a crucial role in the segmentation of multi-modal medical images in order to achieve a high level of accuracy. In conventional image fusion, source images and target images are directly mapped to each other. To segment brain MRI images damaged by noise and intensity inhomogeneity, a weighted level set model based on local kernel metrics and spatial limitations is proposed. WLSM has superiority over state-of-the-art models in both synthetic and real MRI images, according to the visual experiment including both real and synthetic images.

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