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Segmentation of MRI Image Using Patch-wise Approach

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Abstract: Multi-modal imaging integration is necessary for developing robust models for diseases and improving the statistical potency of already-developed imaging biomarkers. In computer vision, dense connections are frequently employed to enhance gradient flow and provide inherent deep supervision throughout training. In particular, DenseNet, which creates feed-forward direct linkages between every layer, has demonstrated remarkable performance in tasks related to the classification of natural images. The paper introduces a methodology Patch-wise approach to perform the segmentation of MRI images into distinct regions, namely Gray matter (GM), White matter (WM), and Cerebrospinal fluid CSF). The findings of our tests carried out with the help of the suggested system, show that the average Dice Similarity Coefficients for CSF: 0.965, GM: 0.935, and WM: 0.918 are notably high.

Keywords: *MRI, Convolutional neural network, Multi-modal, Patch-wise*

1 Introduction:

Image segmentation refers to a technique for dividing an image into separate objects or regions to extract valuable information [1] [2] [3] [4] [5] [8]. It is crucial in applications like medical imaging, autonomous driving, and object recognition. CNNs, which automatically learn hierarchical features, have shown success in accurately segmenting images [3] [7]. They not only recognize elementary features like edges and textures but also comprehend advanced semantic information. This capability enables them to understand context and interconnections among different regions. This enables CNNs to accurately delineate boundaries and identify objects within an image [7] [9]. Their hierarchical nature allows them to refine their understanding of the image, starting with basic low-level features and gradually building up to more complex high-level representations. As a result, CNNs are invaluable tools in various fields where image analysis and understanding are critical [10] [11].

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2 Related works

MRI segmentation shows a decisive role in medical imaging, enabling accurate identification and delineation of anatomical structures for diagnosis and treatment planning. Over the past few years, patch-wise segmentation techniques have gained increased popularity as a result of their ability to effectively handle the challenges posed by MRI images, such as noise, intensity inhomogeneity, and anatomical variability. Here is an overview of the primary discoveries and emerging patterns in this domain:

Moeskops P, et al. [12], to achieve precise segmentation details and spatial consistency, the approach makes use of a variety of patch sizes and convolution kernel sizes. It applies to five distinct data sets and only needs one anatomical MR image. The approach successfully segments all five sets accurately, proving its adaptability to variations in acquisition methodology and age.

Zhang, et al. [13], according to the research, isointense stage brain tissues can be segmented using deep-CNNs. To generate a hierarchy of complicated features, the approach employs trainable filters and local neighbourhood pooling processes. The model produces the segmentation maps utilizing the multimodality data from the inputs of the T1, T2, and fractional anisotropy images. Achieved results better than existing approaches for segmenting baby brain tissue and that merging multi-modality images increases performance.

A. De Bre´bisson, et al. [14], the sophisticated artificial neural network was employed to segment human brain MRI into distinct anatomical sections. This was achieved using 3D and orthogonal 2D intensity patches, along with global spatial consistency, all without requiring non-linear registration of the images.

Luna, et al. [15], a 3D CNN based on patch-wise processing is introduced for MRI segmentation. The network is made up of decoding layers for reconstructing segmentation labels and encoding layers for obtaining useful features. Transition layers highlight the significance of feature maps, batch normalization guarantees the generalizability of the model, and a novel loss function normalizes categorical cross entropy to enable precise segmentation of misclassified areas.

Mlynarski et al. [16], In order to resolve missing MR sequences during training, the model mixes 3D contextual information at a short range and 2D contextual information over a longer range of contexts and suggests a network design using subnetworks tailored to specific modalities. The outputs of many segmentation models are combined using a hierarchical decision-making procedure.

Andrew B, et al. [17], to construct segmentations many deep neural networks are trained in a tree structure using a 3D patch U-Net. To anticipate both enhancing and non-enhancing tumor, several models are fed the output segmentation from training, which is programmed to forecast the whole tumor region, including edema.

Lee et al. [18], this study introduces a U-Net architecture designed for patch-wise processing. In comparison to traditional U-net techniques, this method, which separates slices into non-overlapping patches, enhances local information retention.

Ullah et al. [19], the segmentation of infancy brain tumors utilizing big data analysis and patch-based CNNs (PBCNNs) is described in this work. The procedure preprocesses the data using techniques including profiling, cleaning, transformation, and enrichment. The suggested CNN model evaluates various parts of the image at various resolutions using a global and local layer design based on patches.

Wu, G. et al. [20], research offers a generative probability model. It reduces the likelihood of adding erroneous atlas patches by selecting patches that closely resemble the target patch. Labelling unanimity is achieved by examining dependencies between atlas patches. The Expectation Maximization framework is used to adjust patch requirements based on recent labelling discoveries.

Kao, P. et al. [21], this study propose a novel method that blends patch-based neural networks and location data. The method combines subject information with an existing MNI space brain parcellation atlas. To categorize various kinds of brain lesions, 3D U-Net and DeepMedic, both patch-based networks, are being developed. XGBoost fusion is used in the two-level ensemble technique that has been developed to reduce uncertainty and optimize the advantages of various neural network models.

Wang, et al. [22], the use of atlas-based techniques raises the possibility that test subjects in areas with substantial inter-subject variability may not be well represented. To solve this problem, a brand-new patch-driven level set approach is suggested. Using sparse representation techniques, the method creates a personalized atlas derived from a set of images manually segmented for each individual subject. By taking into account the constancy of a patch's location in relation to its neighbours' patches. The process uses sparse representation techniques to create manually separated image collections into a subject-specific atlas. Spatial consistency is ensured by taking into account how a patch compares to the patches around it.

Yamanakkanavar, et al. [23], in this study "M-Net operating in a patch-wise manner" is suggested for automatically segmenting brain MR images. To provide appropriate ground-truth patches to an M-net model, a method separates slices into non-overlapping patches. The extraction of semantic features from scans is done using dilated convolutional kernels. The disadvantages of traditional methods are overcome by the suggested method, which also offers better retention of fine details.

Yogananda, et al. [24], as part of the deep learning pipeline, "triple-network structure" was developed to segment the brain and strip the skull. A 32x32x32 patch-based strategy was used to create three 3D Dense-Unets that can break down complex tasks into binary segmentation issues. Seven dense, four-layer blocks made up the networks, which were interconnected.

Table 1. Summary of works on Patch-wise segmentation

References	Year	Architectures
Wang, et al. [22]	2014	Patch-driven level set
Wu, G. et al. [20]	2014	Patch-based labeling
Zhang W, et al. [13]	2015	Patch-Size Deep-CNN
A. De Bre´bisson, et al. [14]	2015	2D and 3D intensity patch with SegNet
Moeskops P, et al. [12]	2016	Multiple Patch size CNN
Andrew B, et al. [17]	2017	3D patch U-Net
Luna, et al. [15]	2019	3D-CNN Patch-based
Mlynarski et al. [16]	2019	2D, 3D patch
Yogananda, et al. [24]	2019	Patch-based 3D Dense-UNet
Kao, P. et al. [21]	2020	Patch-based CNN
Lee et al. [18]	2022	Non-overlapping patch-wise U-net
Ullah et al. [19]	2023	Patch-based-CNN

3 Methods and Materials

3.1 DenseNet CNN

DenseNet consists of a densely connected system where every layer is linked to all the other layers. A skip connection or identity mapping is used to do this. The output of one layer is directly added to the output of all subsequent layers. Figure 1 shows DenseNet framework.

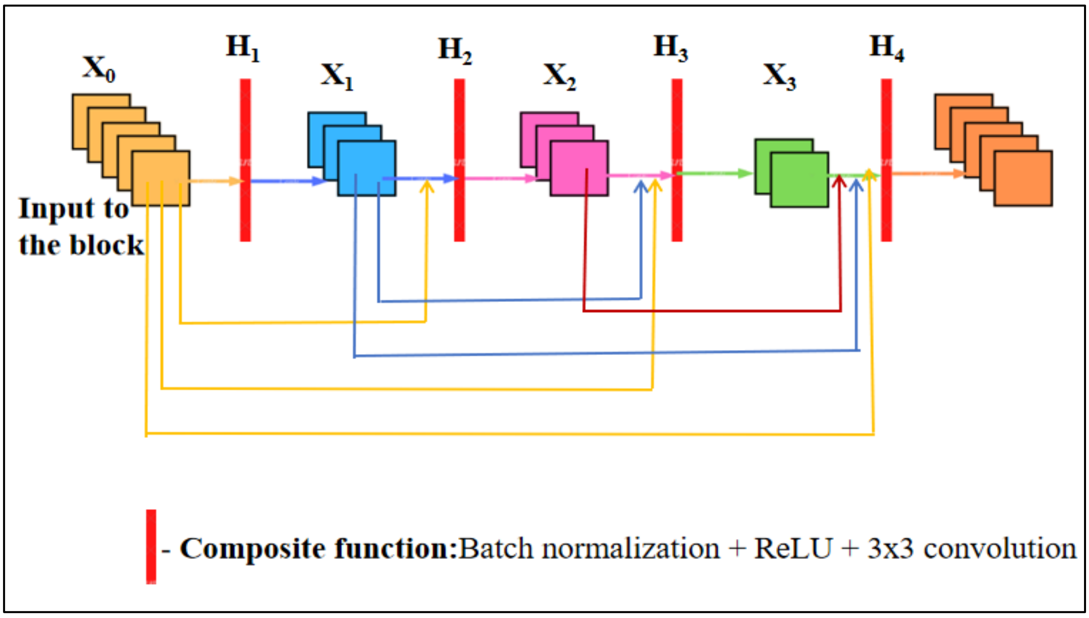

Fig 1: DenseNet framework

3.2 Patch-wise Approach

DenseNets are susceptible to overfitting, especially when dealing with small datasets. The high capacity of the model, combined with the dense connections, can result in models that memorize training data rather than generalize well to unseen data. A patch-wise DenseNet approach can help mitigate overfitting.

In the proposed approach the entire input image, is partitioned into number of patches. The same patch-wise division process is applied to the ground truth segmentation maps, ensuring alignment between the input data and the corresponding target labels. This consistency in patch sizes and positions is vital for accurate training and evaluation of segmentation algorithms, as it maintains the spatial correspondence between the input image patches and their corresponding ground truth annotations. Please refer to Figure 2 for an illustration of our proposed Patch-wise DenseNet. During the testing phase, the complete input image is similarly divided into patches. These patches are subsequently inputted into the trained model for the purpose of segmenting the MRI image.

3.3 Dataset

In our research, we utilized iSeg 2017 dataset [25], which is readily available on the iSeg 2017 website. This dataset is specifically designed for brain image segmentation tasks. The training dataset for iSeg 2017 comprises a group of T1 and T2 magnetic resonance images that were acquired from 10 baby individuals. The testing collection also includes T1 and T2 MRI's from 13 newborn individuals.

3.4 Proposed Methodology

Segmenting multimodal MRI images poses several challenges due to variances in intensity and contrast across various modalities. The varying appearance of structures in different modalities makes it difficult to accurately delineate and classify regions of interest. To address these challenges, a patch-wise approach can be employed, which involves dividing the image into smaller patches and analyzing them individually. Therefore method for segmenting multimodal MRI images based on patch-wise is presented in this paper. In the training phase, we begin by using multimodal whole images as our input. The complete input image divided into patches. The ground truth segmentation maps are divided using the same procedure. We then proceed to extract features from these patches. These feature-rich patches are then utilized to train the DenseNet model, ultimately yielding a Trained Patch-wise model. In the testing phase, we take the whole image and divide it into patches next the features are extracted from these divided patches then they are passed to Trained Patch-wise Model and as a final result we get Classification Labels (CSF, GM, and WM). Figure 2 shows Proposed Patch-wise Approach below.

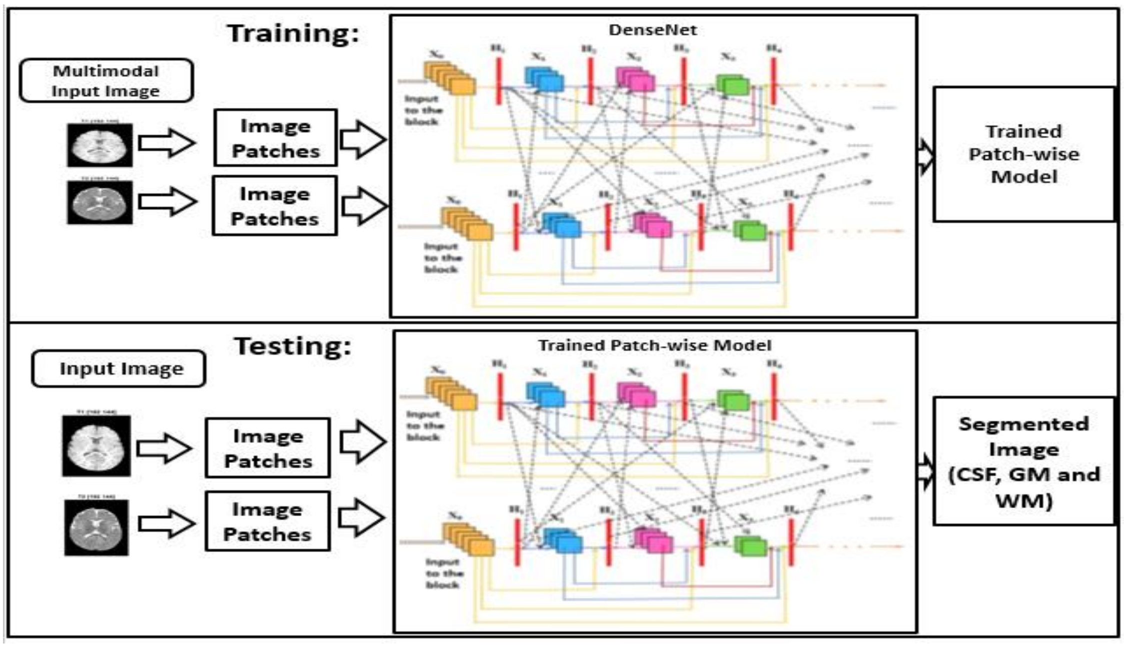

Fig 2: Proposed Patch-wise Approach

4 Results and Discussion

In Proposed system experiments are conducted using the iSeg-2017 dataset, which is freely available on iSeg-2017 website. The dataset contains a total of 23 subjects of infant brains. Of them, 10 subjects are utilized for testing and the remaining 13 are used for training. Each subject contains 256 slices of T1 and T2 MRI images. Each input image is divided into patches to facilitate the processing of the image data. Specifically, the entire input image is partitioned into patches same division process is applied to the ground truth segmentation maps, ensuring alignment between the input data and the corresponding target labels.

4.1 Evaluation Metrics

The suggested system's performance analysis makes use of a number of assessment indicators, these metrics collectively evaluate the efficacy of the suggested approach. Table 2 shows evaluation metrics.

Table 2. Evaluation Metrics

Metrics Details
$\boldsymbol{Dice\ Similarity\ Coefficient(A_r,\ A_p) = \frac{2\lvert A_r \cap A_p\rvert}{\lvert A_r\rvert + \lvert A_p\rvert}}$
$\boldsymbol{Modified\ Hausdorff\ distance(A_r, A_p) = max\left[\max_{b\in A_r} d(b, A_p), \max_{b\in A_p} d(b, A_r)\right]}$
$\boldsymbol{Average\ surface\ distance(A_r,\ A_p) = \frac{1}{\lvert A_r\rvert}\sum_{a\in A_r} d(a,\ X_p)}$
$\boldsymbol{Jaccard\ Index(A, B) = \frac{\lvert A\cap B\rvert}{\lvert A\cup B\rvert}}$

4.2 Performance Evaluation

In our experiments, we conducted an investigation on proposed Patch-wise with the help of above evaluation metrics. Table 3 shows the performance evaluation.

Table 3. Performance evaluation

	CSF	GM	WM
DSC	0.965	0.935	0.918
MHD	8.906	8.916	8.915
ASD	0.054	0.120	0.190
JCD	0.932	0.879	0.918

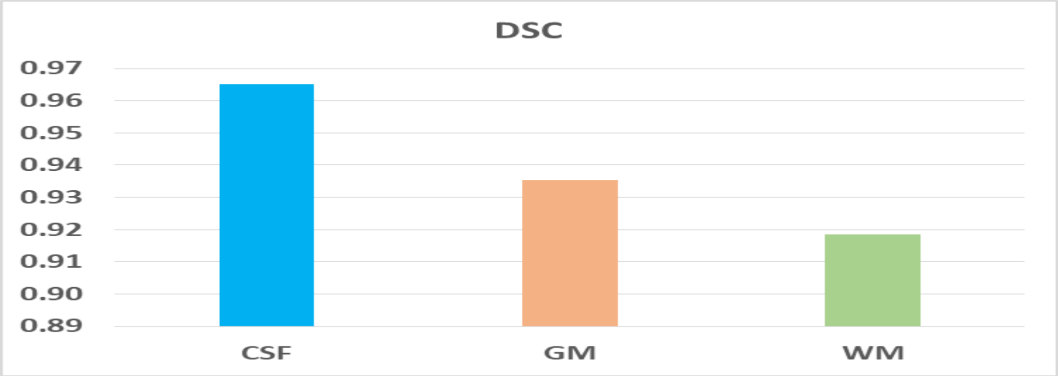

Fig 3: DSC metric values

Fig 3 displays the Dice similarity coefficient (DSC) metric values attained.

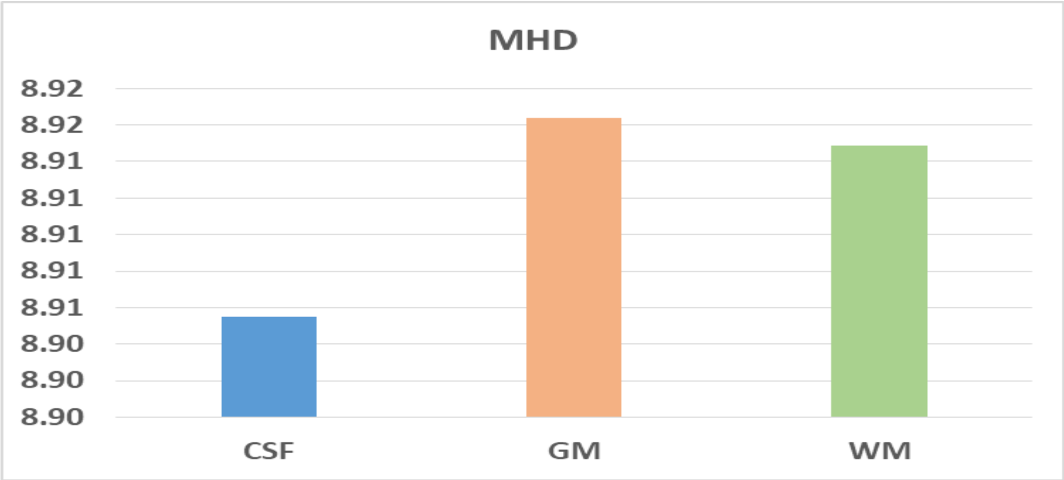

Fig 4: MHD metric values

Figure 4 illustrates the MHD metric values achieved for proposed system.

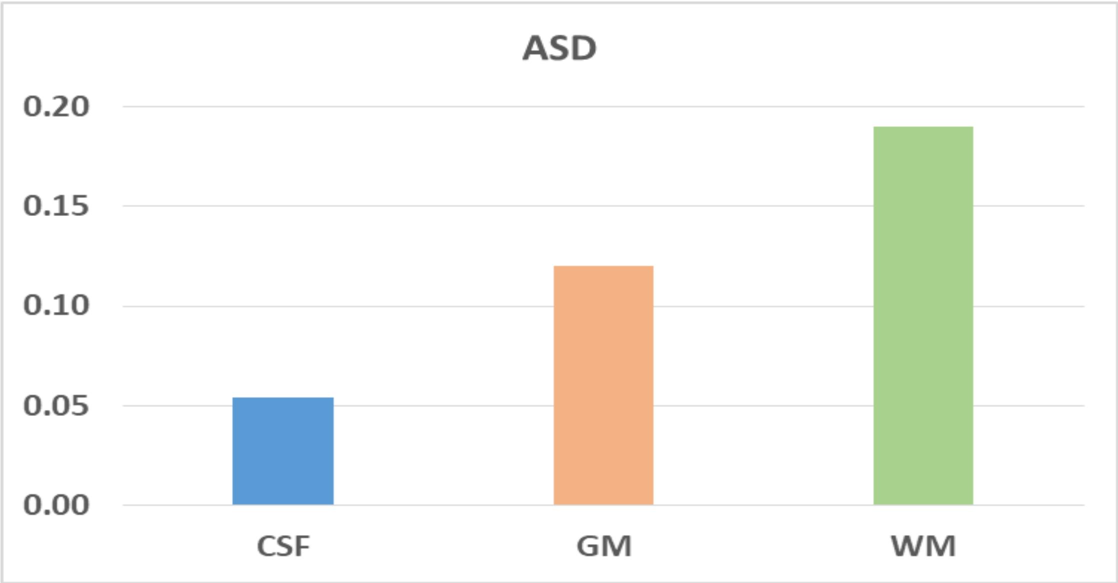

Fig 5: ASD metric values

Above is Figure 5 demonstrates the ASD which calculates the average variation between the surface of the segmented item and the reference.

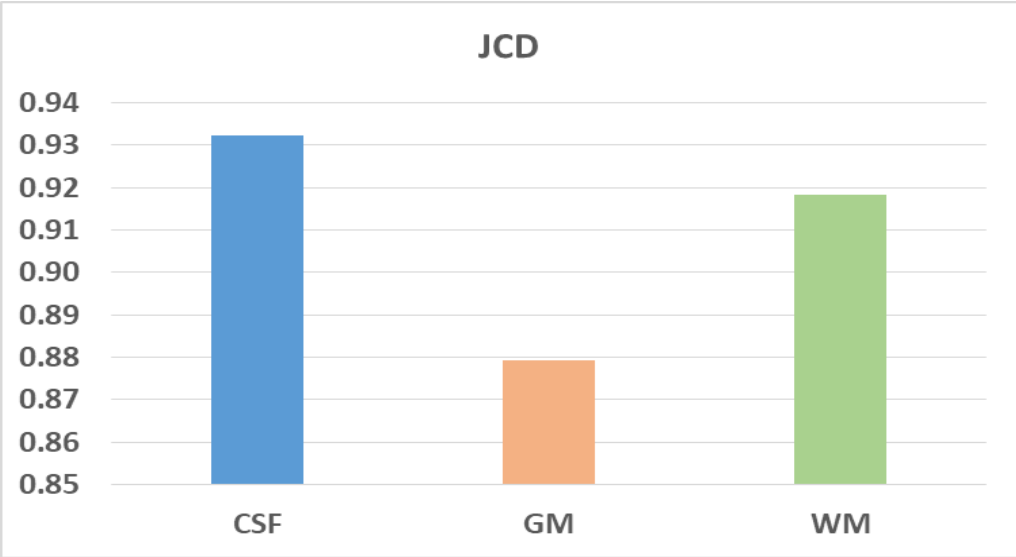

Fig 6: JCD metric values

Figure 6 indicates the performance of JCD, which gives the similarity and intersection of two sets.

Table 4. Comparison with other patch-wise methods obtained on the different datasets

Methods	DSC			Avg.
	CSF	GM	WM	
2D and 3D intensity patch with SegNet [14]	-	-	-	0.725
Patch-Size Deep CNN [13]	-	-	-	0.851
Patch-based 3D CNN [15]	0.837	0.860	0.882	0.859
Patch-based 3D Dense-UNet (Full-resolution data) [24]	0.83	0.9103	0.93	0.891
Patch-based 3D Dense-UNet (Down-sampled data) [24]	0.845	0.92	0.94	0.901
Patch-driven level set [22]	0.919	0.901	-	0.910
Non-overlapping patch-wise U-net [18]	-	-	-	0.930
Patch-wise [Proposed]	**0.965**	**0.935**	**0.918**	**0.940**

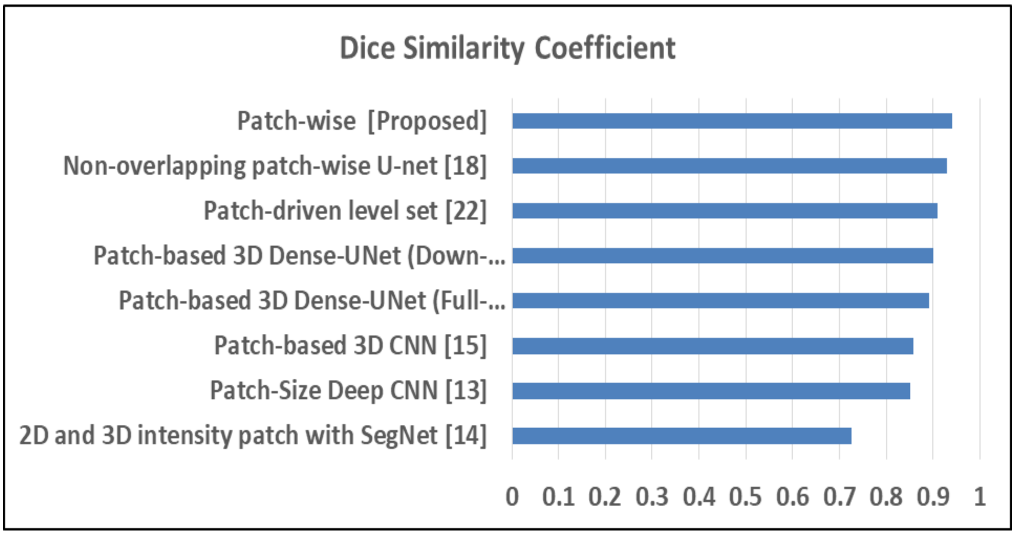

Fig 7: Comparative analysis of Avg. DSC metric with Other Methods

Table 4 illustrates a DSC comparison with other patch-wise methods obtained on the different datasets, in this comparative study we considered related works based on a patch-wise approach. Comparative analysis of the average DSC has been done by taking the average of all three matters (CSF, GM, and WM) dice values. Zhang, et al. [13], approach employs trainable filters and local neighbourhood pooling processes. De Bre´bisson, [14], network assigns MR image voxels to their corresponding anatomical regions, capturing local spatial context with orthogonal 2D intensity patches and 3D patches, and enforcing global spatial consistency using massive, compressed 2D orthogonal patches and regional centroids distances, [13] and [14] achieved 0.725 and 0.851 dice score respectively. Yogananda, [24] "triple-network structure" was developed to segment the brain and strip the skull and scored dice 0.891 for full resolution and 0.901 for down-sampled data which is better compared to [13] and [14] methods. Patch-driven level set [22] used sparse representation techniques (DSC-0.910) and Non-overlapping patch-wise U-net [18] separates slices into non-overlapping patches for segmentation, this approach DSC is 0.930 showing improved results. In our proposed method, achieved an average dice value of 0.940, which shows an outperformance result with other state-of-the-art models in Table 4 and Figure 8.

5 Conclusion and Future Scope

The MRI image segmentation based on the patch-wise method has shown promising results in accurately segmenting brain structures. This approach has the potential to be further developed and optimized for clinical applications, such as tumor segmentation and treatment planning. Future research could focus on refining the network architecture, exploring different patch sizes and investigating the performance on larger datasets. Additionally, the integration of other imaging modalities could be explored to improve the results of the segmentation process in terms of precision and accuracy.

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