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Brain tumor segmentation with deep learning strategy and wavelet functions

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INTRODUCTION & AIM

- This study proposes a deep learning-based framework for brain tumor segmentation utilizing a modified U-Net architecture integrated with wavelet transforms and dense residual connections to enhance feature propagation, mitigate vanishing gradient issues, and improve segmentation performance.
- The proposed network architecture employs an encoder–decoder mechanism, where the encoder progressively extracts high-level semantic features from MRI scans, while the decoder reconstructs spatial information to achieve precise tumor localization and segmentation.
- The effectiveness of the proposed approach is evaluated on the MICCAI BraTS 2020 dataset comprising labeled 2D brain MRI scans, with comparative analysis conducted using Haar and Daubechies wavelet families to assess segmentation accuracy and computational efficiency.

METHOD

- Magnetic Resonance Imaging (MRI) is a leading imaging technology used for detecting, localizing, and characterizing brain tumors due to its non-invasive nature and high soft-tissue contrast. Standard MRIs create a series of 2D slice images of the brain.
- The mathematical model of the procedure is given by the equation below:

Given an input image f consider an initial valued problem

$$\frac{\partial u}{\partial t} - P(x,t) * u - d(t) + ln\frac{u}{1-u} + \partial R_{\sum}(u) \quad (1)$$

$$u(x,0) = M(f) \quad x \in \omega \quad (2)$$

where $\partial R_{\sum}$ denotes the sub-differential of $R_{\sum}$. $P(x,t), d(t)$ are the variables that govern the changes in u, $*$ indicates the convolution, and $M(f)$ is an operation to generate the initial condition from f. By solving the equation for any input image f we suppose that $u(x,0)$ will eventually reach $u(x,T)$ which is close to the binary function.
[Xue-Cheng Tai1 2025]
For a given data set $\{f_i, p_i\}_{i=1}^{N}$.

Denoting $\phi_1 = X(x,t), d(t)$ as the set variables and a mapping $M_1 : f \to u(x,T)$ as a mapping from f to the solution of equation (1) at time $T : M_1(f, \Phi_1) = u(x,T)$, we optimize Φ_1 by solving

$$\min_{\Phi_1} \sum L(M_1(f_i, \Phi_1), p_i) \quad (3)$$

where $L(.,.)$ is the loss function that measures the difference between its arguments. The common loss function includes logistics loss and lighting loss. The proposed approach uses the wavelet function as an activation function with the UNet algorithm. The next section explains the detailed proposed method along with the morlet wavelet utilized and its properties, which explains the underlying reason for the specific choice of wavelet family.

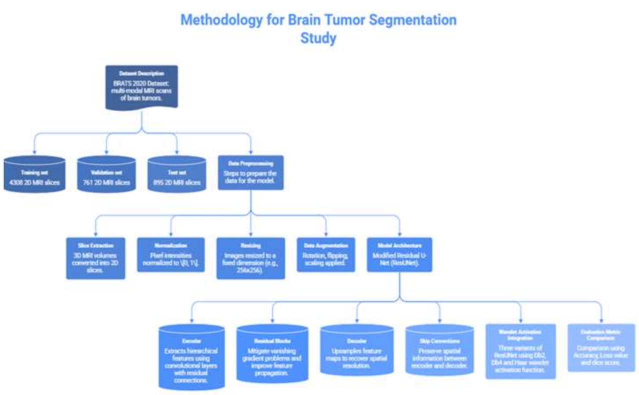


Figure 1. Flow of algorithm

RESULTS

Model	Accuracy				
	Maximum Training Accuracy	Average training Accuracy	Maximum Validation Accuracy	Average Validation Accuracy	Test Accuracy
ResUnet_db2	0.99	0.99	0.99	0.88	0.98
ResUnet_db4	0.99	0.98	0.99	0.92	0.98
ResUnet_Haar	0.97	0.96	0.97	0.96	0.97

Table 1
Comparison of the wavelet families with respect to training accuracy, validation accuracy and test accuracy

Model	Loss				
	Minimum Training Loss	Average Training Loss	Minimum validation Loss	Average Validation Loss	Test Loss
ResUnet_db2	0.38	0.46	0.37	0.79	0.38
ResUnet_db4	0.39	0.48	0.42	0.72	0.42
ResUnet_Haar	0.76	0.85	0.76	0.88	0.75

Table 2
Comparison of the wavelet families with respect to training loss, validation loss and test loss

The Accuracy is calculated using binary classification formula and Loss is computed using mean square error

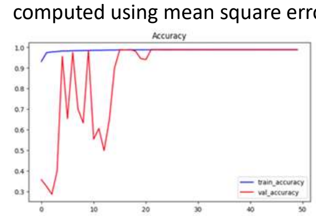
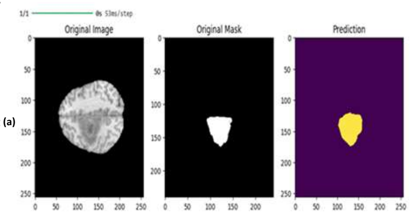


Figure 2.
Accuracy of ResNet_db2

Fig (a)



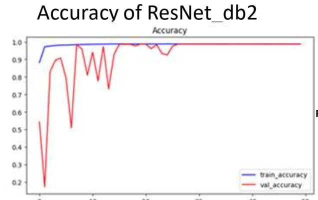
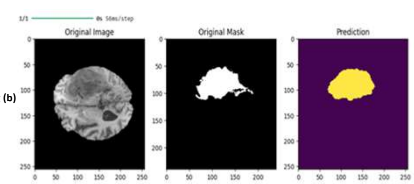


Figure 3.
Accuracy of ResNet_db4

Fig (b)



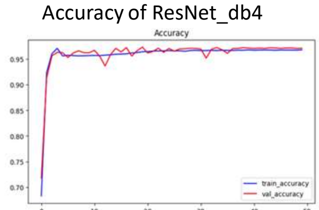


Figure 4
Accuracy of ResNet_Haar

Fig (c)

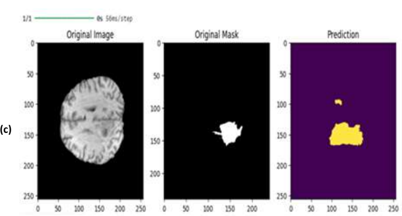


Figure 5. a) Predicted mask of ResNet_db2, b) Predicted mask of ResNet_db4, c)Predicted mask of ResNet_Haar

CONCLUSION

- The brain tumor segmentation study was performed on BRAT2020 dataset, with 4308 2D images validation was performed over 761 images and the test data was 895 images.
- The hybrid algorithm depicted improved results with different activation functions such as wavelet families namely Haar, db2 and db4.

REFERENCES

[Xue-Cheng Tai1 2025] Xue-Cheng Tai1, Hao Liu, Raymond H. Chan and Lingfeng Li, A MATHEMATICAL EXPLANATION OF UNET, Mathematical Foundations of Computing Vol. 8, No. 5, October 2025, pp. 874-889,doi:10.3934/mfc.2024040.