

U-Net Supported Segmentation of Ischemic-Stroke-Lesion from Brain MRI Slices

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Abstract— The brain abnormality is one of the major sicknesses in human's health and the untreated brain defect will cause major illness. Ischemic stroke is one of the major medical emergencies and the timely diagnosis and treatment will save the patient from serious sickness. The proposed research employs the U-Net scheme to extort the Ischemic-Stoke-Lesion (ISL) from the brain MRI slices of ISLES2015 database. In this work, a pre-trained U-Net encoder-decoder system is employed to extort the ISL fragment from the chosen test image. After the extraction, a relative assessment is performed with the ground-truth available along with consequent test image. In this work, 20 patients' images (20 patient x 25 slices = 500 images) are adopted for the assessment and the general result achieved with the executed methodology helped to achieve a better value of Jaccard (>90%), Dice (>95%) and Accuracy (>98%) on the considered image dataset.

Keywords—Ischemic-stoke, Brain MRI, U-Net, decoder-encoder, assessment.

I. INTRODUCTION

In human physiology, the brain plays a major role that monitors and controls every other part of the body. The abnormality in the brain will severely affect the sensory signal processing and the decision-making process. Ischemic-stroke is one of the common brain abnormalities in humans, largely occurs due to the lack of blood flow to the brain parts and timely recognition and treatment is very essential to help the patient to recover from the abnormality [1-3]. According to the level, the stroke impact varies from mild to severe and the unrecognised and untreated stroke may lead to temporary/permanent disability. In some cases, the untreated ischemic-stroke will lead to death [4,5].

Due to its importance, in the literature, a considerable amount of works are planned to examine the ischemic-stroke in humans using bio-signals [6] and bio-images [7,8]. The image supported diagnosis will help to get better information regarding the severity of the infection and its location compared to the bio-signal supported methods.

The image assisted detection of ischemic-stroke normally involves the examination of brain CT or MRI slices and due to its better visibility and multi-modality nature, brain MRI slices are widely adopted by the researchers compared to brain CT. The earlier works on Ischemic-Stoke-Lesion (ISL) assessment using the brain MRI slices can be found in [9-15].

The commonly adopted ISL assessment from the brain MRI involves in; (i) Collection of the clinical level brain MRI image, (ii) Pre-processing the image to get the appropriate dimension of MRI slice for the assessment, (iii) Implementing the appropriate imaging approach to extort and assess the ISL fragment and (iv) Validation and confirmation of the proposed scheme to confirm its accuracy.

The previous studies on the ISL assessment has implemented a variety of image processing methodologies on the clinically collected images and benchmark brain MRI slices. The clinical grade images are preserved by the researchers for their own use and most of these images are protected by copyright and not freely available for research purposes. Hence, the brain MRI slices collected from the benchmark database is extensively considered by most researchers to test and validate the developed scheme.

The ISLES2015 [11] is one of the commonly adopted brain MRI databases for the ISL related study and the earlier works implemented using this database can be found in the literature [7-12]. This dataset consists of the carefully recorded clinical-grade brain MRI with diverse modalities, such as Flair, T2, diffusion-weight (DW), and every MRI slice is associated with the essential Ground-Truth (GT) offered by two expert members. The visibility of the ISL is good in the Flair modality MRI slice compared to other approaches and hence, the Flair modality slices are one of the favourite choices of the researchers to test and validate their decrease detection system [8-10].

Recently, the Convolutional-Neural-Network (CNN) based Artificial-Intelligence (AI) practice helped to construct a number of the automated disease detection systems and the results of the earlier approaches also confirmed the merit of the CNN schemes compared to the tradition as well as other disease detection approaches. The merit of the CNN is its improved accuracy compared to other methods and its adaptability on the greyscale as well as RGB scaled images. Further, most of the CNN schemes are available as the pre-trained architecture and the existing structure can be easily implementable on any database with effortless training [16,17].

The proposed research aims to implement a U-Net scheme to extort the ISL area from the trial images with enhanced segmentation accuracy. The earlier work related to the U-Net scheme can be accessed from [18-20]. The pre-trained U-Net is allowed to extract the ISL fragment from the chosen brain MRI slice and after the extraction of the ISL, a

comparative measurement among the ISL section and the related GT is performed and the necessary Image-Quality-Measures (IQM) are computed. Based on the attained values of the IQM, the worth of the planned scheme is validated.

The other sections of this work is organised as below; Section 2 discuss the Context, Section 3 demonstrates the methodology, Section 4 and 5 give the experimental outcome of this research and the conclusion of the proposed work, respectively.

II. CONTEXT

The earlier works are executed to examine the brain abnormality using Flair modality MRI slices. The earlier works implemented using the ISLES2015 database can be found in [7-12] and in most of the works, segmentation of ISL using a chosen semi-automated/automated image processing approach is implemented.

A number of procedures are proposed and applied to inspect the ISLES2015 datasets and the implemented approaches vary from; traditional methods to the recently developed deep-learning approaches. The ultimate aim of every method is to extort the ISL fragment from the MRI slice of chosen modality; which offers a better result.

In the literature, the MRI modalities, such as Flair, T1, and DW are separately evaluated with; (i) direct semi-automated and automated segmentation techniques, (ii) Combination of the multi-thresholding-based enhancement, and chosen segmentation method, and (iii) Deep-learning assisted segmentation and classification techniques. Every method will have its own merit and the chief aim in each scheme is to extract the ISL with the enhanced image performance measure values.

The traditional assessment and the combined thresholding and segmentation outcome can be found in the earlier literature [7,8]. The earlier works also confirmed that; most of the existing methods are semi-automated procedures and may require partial or full human supporters to execute the evaluation. In this work, an attempt is made to implement the U-Net based segmentation approach to extort the infected segment of the brain MRI with improved accuracy. The main advantage of this approach compared to the existing approach is its availability and its implementation issue. The U-Net considered in this work is a pre-trained system and the implementation and validation of the pre-trained scheme is quite simple compared with the customary methods.

III. METHODOLOGY

This section shows the methodology adopted in this research work. After collecting the essential test image from the ISLES2015 database, every image is resized to the dimension of 256x256x3 pixels. Initially, this work considered the pre-trained U-Net model to extract the ISL segment from the considered test images. The total number of test images considered is only 500 images and hence image augmentation (horizontal/vertical flip, $\pm 30^\circ$ rotation and $\pm 60^\circ$ rotation) is implemented to increase the number of test images to train the U-Net system for the ISLES2015 images. When the U-Net is perfectly trained, then the performance of the U-Net is validated for all the 500 test images. The role of the U-Net is to extract the ISL section

from the test image with better accuracy. After getting the ISL fragment, a relative assessment with the GT is performed and the essential performance measures are then computed. Based on these values, the significance of the U-Net segmentation is validated. Figure 1 depicts the various sections existing in the proposed approach.

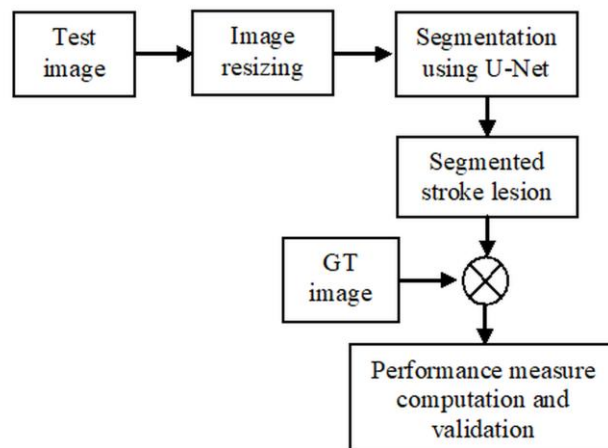


Fig.1. Proposed ISL examination scheme

A. Image database

The development of an appropriate image examination system is essential for the efficient assessment of the brain abnormality. The proposed work considered the test images from the Ischemic-Stroke-Lesion-Segmentation Challenge 2015 (ISLES2015) [11]. This dataset consists of the clinical-grade, skull-stripped 3D brain MRI of Flair, T2, and DW modality associated along with the necessary GT. Assessment of 3D brain MRI is quite complex and requires a complex computation; hence a 3D to 2D alteration is realized using the ITK-Snap tool [21,22] and the transformed images are then considered for the evaluation.

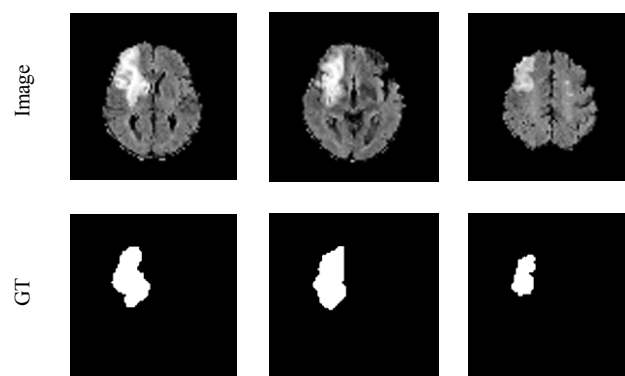


Fig.2. Sample test images of ISLES2015

All the extracted images are available with a dimension of 77x77x3 pixels and every test image is resized to 256x256x3 pixels. In this research, 20 patients' images are considered for the assessment, and from every patient, 25 slices are extracted and included in the test image database. All the 500 images (20 patients' x 25 slices) are separately processed using the U-Net scheme implemented in this study. The sample trial images and the GT is depicted in Figure 2. Other essential information and the earlier works on this dataset can be found in [12-14].

B. U-Net Scheme

In the proposed work the well-known pre-trained U-Net scheme (VGG-U-Net) shown in Figure 3 is considered to segment the ISL region from the test images.

This scheme consists of two sections namely the encoder and the decoder using as presented in the figure. The encoder section is implemented by considering the VGG11 scheme with the essential convolutional (Conv) and MaxPool layers as presented in the figure and the decoder section is associated with the Up-Conv section which will reconstruct the images from the extracted features of the encoder unit. The final layer of the decoder section consists of the SoftMax layer, which will help to implement a binary classification to separate the ISL section from the background. The proposed scheme helps to get a binary image, which is then compared against the related ground truth for validation. Other essential information regarding the U-Net (VGG-U-Net) can be found in the literature [18-20].

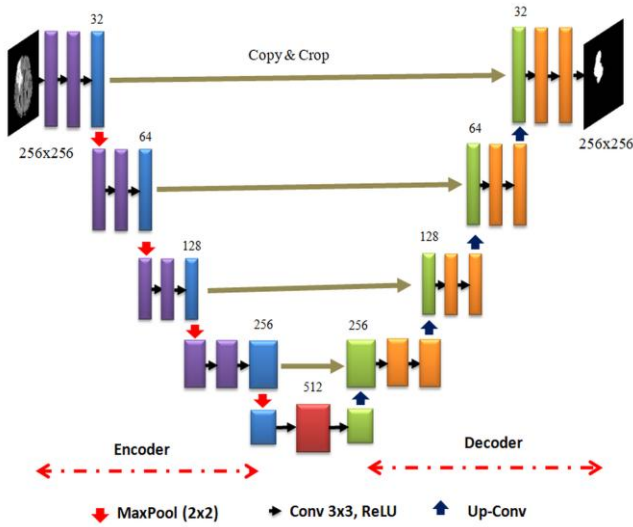


Fig.3. Structure of the VGG-U-Net (U-Net) scheme considered in this research

C. Validation

The success of every disease detection system depends on its performance on the considered benchmark image database. When better performance is achieved with the system on the benchmark datasets, then it can be assumed that the developed scheme also will provide a better result when the real clinical images are evaluated.

The essential Performance-Measures (PM) such as True-Positive (TP), False-Positive (FP), False-Negative (FN), and True-Negative (TN) are initially computed during the comparison between the segmented ISL and the GT. From these initial measures, other values, such as Jaccard, Dice, Accuracy (ACC), Precision (PRE), Sensitivity (SEN), Specificity (SPE), and Negative-Predictive-Value (NPV) are also attained, and based on these values; the performance of the proposed segmentation approach is validated [7-10].

IV. EXPERIMENTAL RESULT AND DISCUSSION

This part of research reveals the attained experimental results and its discussions. All the experimental work is executed using a workstation; Intel i5 2.5GHz processor with 16GB RAM and 2GB VRAM set with MATLAB®.

Initially, the considered U-Net scheme is trained using the image database (original and augmented images) and after the complete training process; every test image (500 images) is separately tested and the attained result is compared with its GT image. The comparison among segmented ISL and GT will help to get the necessary PMs and based on its value, the merit of U-Net on the ISLES2015 dataset is confirmed.

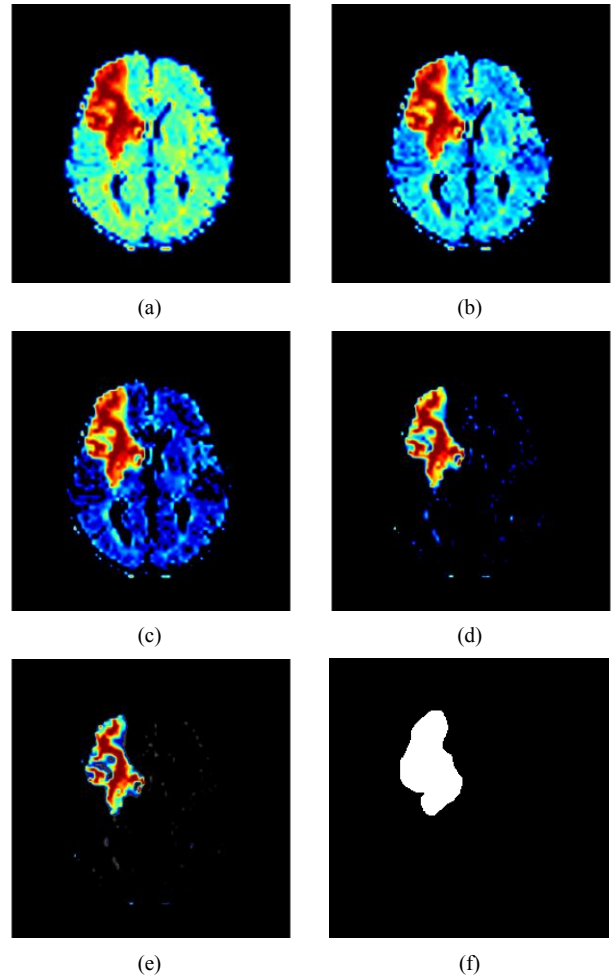


Fig.4. Segmentation outcome attained with U-Net for a sample test image.

(a) – (c) Images extracted from various layers of the encoder section, (d) and (e) reconstructed image by the decoder unit, (f) Segmented ISL by the SoftMax

The pre-trained U-Net scheme is successfully executed to extort the essential ISL fragment from the chosen test images and the result attained for a sample test image can be found in Figure 4. In this figure, both the encoder as well as the decoder outcomes is depicted. Even though the brain MRI slices look like the greyscale images, actually, these images are in the form of RGB and this information is clearly discussed in [7,8]. When the initial image is fed to the encoder part, the essential convolution, as well as the MaxPool operation, is performed to extort the indispensable features from the image. Normally, the encoder section is the pre-trained VGG11 architecture without the fully connected layer. The outcome of the encoder section is in the form of image features. During the encoding operation, every down-convolution layer output is passed towards the up-

convolution layer in which the pixel level segregation image reconstruction is taking place.

The total number of up-convolution operation in the decoder is similar to the encoder unit and this supports the reconstruction of the features into images with varied pixel groups. The final part of this section has a SoftMax classifier unit, which helps to segregate the existing images into the ISL section (binary1) and the background (binary 0). In this figure, Fig. 4(a) to (c) depicts the results of the encoder section, Fig 4(d), (e) are the results of the decoder sections and Fig 4(f) is the outcome by the SoftMax classifier. Normally, in the medical image segmentation task, Fig 4(f) will be the binary image with the ISL and background and finally, this binary picture is evaluated and confirmed against the GT image.

The comparison of the ISL and the GT will help to get the essential PM values and according to these measures, the merit of U-Net approach is confirmed. In this work, the results attained in the sample test images (depicted in Fig 2) is presented and IM1 to IM3 respectively denotes the Image 1 to Image 3 of brain MRI slices existing in Fig 2. From Table I and Table II values, it can be noted that the U-Net segmentation helps to realize superior values of PMs for every image with healthier values of Jaccard, Dice, and ACC. A similar procedure is repeated for all other images of the considered ISLES2015 database and the average of performance measure is accounted to verify the performance of the proposed CNN supported segmentation.

TABLE I. ESSENTIAL PERFORMANCE MEASURE COMPUTED BETWEEN SEGMENTED SECTION AND GT

Image	TP	FP	TN	FN	Jaccard (%)	Dice (%)
IM1	3254	107	62033	142	92.89	96.31
IM2	3092	163	62196	85	92.57	96.14
IM3	1485	114	63829	108	86.99	93.04

TABLE II. IMAGE PERFORMANCE MEASURES OF SAMPLE TEST IMAGES

Image	ACC (%)	PRE (%)	SEN (%)	SPE (%)	NPV (%)
IM1	99.62	96.82	95.82	99.83	99.77
IM2	99.62	94.99	97.32	99.74	99.86
IM3	99.66	92.87	93.22	99.82	99.83

The overall outcome (average of all 500 images PMs) of the proposed scheme is confirmed alongside the available results in the literature as represented in Table III. This information confirms that the results attained with the proposed scheme are better and it works well on the brain MRI slices of the Flair modality. Further, the other existing methods are requiring a combined traditional thresholding and segmentation methods and most of the existing methods are also are of semi-automated approaches. The U-Net scheme supported method is an automated approach and extracts the ISL fragment with improved PM values compared to the existing works.

This scheme is experienced and authenticated by means of the Flair modality MRI and in the future, the performance of U-Net segmentation can be tested with other brain MRI

modalities. Further, the merit of U-Net can be compared and confirmed against other pre-trained CNN segmentation methods available in the literature.

TABLE III EVALUATION OF PROPOSED APPROACH WITH EXISTING METHODS

Method		Jaccard (%)	Dice (%)	ACC (%)
Rajinikanth and Satapathy [7]		78.60	88.54	91.17
Rajinikanth et al. [8]		90.34	94.92	-
Lin et al. [9]	Otsu	88.48	90.48	95.94
	Kapur	90.36	92.21	96.12
Rajinikanth et al. [10]	Watershed	90.34	94.92	98.49
	Active Contour	88.05	93.63	97.31
	Markov random field	86.12	92.46	97.76
Proposed U-Net segmentation		90.74	95.18	98.68

V. CONCLUSION

Assessment of a chosen brain MRI slice is one of the commonly adopted real-time investigation approaches. Evaluation of the ISL section with an appropriate image processing scheme is very essential during the brain abnormality assessment. The extracted ISL will help to locate the brain section where the problem existing and the severity of the problem. This work implemented a pre-trained U-Net scheme to extort the ISL with superior accuracy. The outcome of the extracted section is then compared with the GT image and the disease detection performance of proposed scheme is confirmed based on the computed values of the PMs. In this work, 500 numbers of brain MRI slices of ISLES2015 is examined and the average values of the PMs confirmed that the proposed scheme offers better result compared to the results of other existing methods.

REFERENCES

- [1] M. A. Khan, I. Ashraf, M. Alhaisoni et al., "Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists," *Diagnostics*, vol. 10, no. 8, pp.565, 2020. <https://doi.org/10.3390/diagnostics10080565>.
- [2] Q. Ke, J. Zhang, W. Wei, R. Damaševičius, and M. Woźniak, "Adaptive independent subspace analysis of brain magnetic resonance imaging data," *IEEE Access*, vol. 7, pp.12252-12261, 2019. DOI: 10.1109/ACCESS.2019.2893496.
- [3] S.L. Fernandes, U. J. Tanik, V. Rajinikanth, and K. A. Karthik, "A reliable framework for accurate brain image examination and treatment planning based on early diagnosis support for clinicians," *Neural Computing and Applications*, vol. 32, no. 20, pp. 15897-15908, 2020. <https://doi.org/10.1007/s00521-019-04369-5>.
- [4] S. Kadry, V. Rajinikanth, N.S.M. Raja, D. J. Hemanth, N. M. S. Hannon, and A. N. J. Raj. "Evaluation of brain tumor using brain MRI with modified-moth-flame algorithm and Kapur's thresholding: a study," *Evolutionary Intelligence*, pp. 1-11, 2021. <https://doi.org/10.1007/s12065-020-00539-w>.
- [5] K. Revanth, N.S.M. Raja, and V. Rajinikanth, "Computational investigation of stroke lesion segmentation from Flair/DW modality MRI," In 2018 Fourth International Conference on Biosignals, Images and Instrumentation (ICBSII), pp. 206-212. IEEE, 2018. DOI: 10.1109/ICBSII.2018.8524617.
- [6] N. Krishna, M. K. Sekaran, A. V. N. Vamsi et al., "An efficient mixture model approach in brain-machine interface systems for extracting the psychological status of mentally impaired persons using EEG signals," *IEEE Access*, vol. 7, pp. 77905-77914, 2019. DOI: 10.1109/ACCESS.2019.2922047.

- [7] V. Rajinikanth, and S. C. Satapathy, "Segmentation of ischemic stroke lesion in brain MRI based on social group optimization and Fuzzy-Tsallis entropy," *Arabian Journal for Science and Engineering*, vol. 43, no. 8, pp. 4365-4378, 2018. <https://doi.org/10.1007/s13369-017-3053-6>.
- [8] V. Rajinikanth, K. P. Thanaraj, S. C. Satapathy, S. L. Fernandes, and N. Dey, "Shannon's entropy and watershed algorithm based technique to inspect ischemic stroke wound," *Smart intelligent computing and applications*, vol.105, pp. 23-31. 2019. https://doi.org/10.1007/978-981-13-1927-3_3.
- [9] D. Lin, V. Rajinikanth, and H. Lin, "Hybrid Image Processing-Based Examination of 2D Brain MRI Slices to Detect Brain Tumor/Stroke Section: A Study," In *Signal and Image Processing Techniques for the Development of Intelligent Healthcare Systems*, pp. 29-49. Springer, Singapore, 2021. https://doi.org/10.1007/978-981-15-6141-2_2.
- [10] V. Rajinikanth, S. C. Satapathy, N. Dey, and H. Lin, "Evaluation of ischemic stroke region from CT/MR images using hybrid image processing techniques," In *Intelligent multidimensional data and image processing*, pp. 194-219. IGI Global, 2018. DOI: 10.4018/978-1-5225-5246-8.ch007.
- [11] O. Maier, B.H. Menze, J. V. D. Gablentz et al., "ISLES 2015-A public evaluation benchmark for ischemic stroke lesion segmentation from multispectral MRI," *Medical image analysis*, vol 35, pp.250-269, 2017. <https://doi.org/10.1016/j.media.2016.07.009>.
- [12] O. Maier, M. Wilms, and H. Handels, "Image features for brain lesion segmentation using random forests," In *BrainLes 2015*, pp. 119-130. Springer, Cham, 2015. https://doi.org/10.1007/978-3-319-30858-6_11.
- [13] A. Carass, S. Roy, A. Gherman et al., "Evaluating white matter lesion segmentations with refined Sørensen-Dice analysis." *Scientific reports*, vol. 10, no. 1, pp.1-19, 2020. <https://doi.org/10.1038/s41598-020-64803-w>.
- [14] S. Winzeck, A. Hakim, R. McKinley et al., "ISLES 2016 and 2017-benchmarking ischemic stroke lesion outcome prediction based on multispectral MRI," *Frontiers in neurology*, vol. 9, pp.679, 2018. DOI: 10.3389/fneur.2018.00679.
- [15] O. Maier and H. Handels, "Predicting stroke lesion and clinical outcome with random forests," In *International Workshop on Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*, *Lecture Notes in Computer Science*, vol. 10154, pp. 219-230. 2016. https://doi.org/10.1007/978-3-319-55524-9_21.
- [16] N. Dey, Yu-Dong Zhang, V. Rajinikanth, R. Pugalenthi, and N.S.M. Raja, "Customized VGG19 architecture for pneumonia detection in chest X-rays," *Pattern Recognition Letters*, vol.143, pp.67-74, 2021. <https://doi.org/10.1016/j.patrec.2020.12.010>.
- [17] V. Rajinikanth, A.N.J. Raj, K.P. Thanaraj, and G.R. Nai, "A customized VGG19 network with concatenation of deep and handcrafted features for brain tumor detection," *Applied Sciences* 10, no. 10, pp.3429, 2020. <https://doi.org/10.3390/app10103429>.
- [18] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," *Lecture Notes in Computer Science*, vol. 9351, pp. 234-241, 2015. https://doi.org/10.1007/978-3-319-24574-4_28.
- [19] V. Iglovikov and A. Shvets, "Ternausnet: U-net with vgg11 encoder pre-trained on imagenet for image segmentation," *arXiv preprint arXiv:1801.05746*, 2018.
- [20] T. Falk, D. Mai, R. Bensch et al., "U-Net: deep learning for cell counting, detection, and morphometry," *Nature methods*, vol. 16, no. 1, pp.67-70, 2019. <https://doi.org/10.1038/s41592-018-0261-2>.
- [21] P.A. Yushkevich, J. Piven, H. C. Hazlett, R. G. Smith, S. Ho, J. C. Gee, and G. Gerig, "User-guided 3D active contour segmentation of anatomical structures: Significantly improved efficiency and reliability," *Neuroimage*, vol.31, no.3, pp. 1116-1128, 2006. <https://doi.org/10.1016/j.neuroimage.2006.01.015>.
- [22] <http://www.itksnap.org/pmwiki/pmwiki.php?n=Main.Publications>