

U-Net:(Semantic Segmentation)

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1. Abstract:-It is widely acknowledged that the effective training of deep neural networks typically demands a substantial volume of annotated training data. In this paper, we introduce an innovative network architecture and training strategy that places significant emphasis on the implementation of data augmentation to maximize the utility of the available annotated samples. Our research primarily revolves around the U-Net architecture, meticulously designed for Semantic Segmentation. This architecture incorporates a contracting path, enabling comprehensive context extraction, and a symmetric expanding path, which in turn facilitates precise localization. The continual advancements in medical imaging technologies have ushered in a new era of precise and efficient diagnosis for various health conditions, with a particular emphasis on early tumor detection.

This research paper presents a pioneering approach to tumor detection in medical images, leveraging the powerful techniques of semantic segmentation. Notably, we highlight our utilization of Python programming for constructing the U-Net architecture using a minimal image dataset, which surprisingly yielded performance superior to prior state-of-the-art methods, as demonstrated in the challenging context of the ISBI competition. This competition pertains to the segmentation of neuronal structures within electron microscopic stacks.

The adoption of the proposed architectures for segmentation tasks brings several significant advantages to the forefront. Firstly, the incorporation of residual units demonstrates its efficacy in the training of deep architectures, contributing to improved model performance. Secondly, the feature accumulation facilitated by recurrent residual convolutional layers ensures an enriched feature representation tailored explicitly for segmentation tasks.

Empirical results underscore the notable superiority of these segmentation architectures when compared to their counterparts. Notably, this comparison includes a variant of a fully connected convolutional neural network known as SegNet, alongside the U-Net and the residual U-Net models. This research thus contributes valuable insights and innovations to the domain of deep learning-based medical image analysis, with

potential far-reaching implications in improving diagnosis and treatment planning..

INTRODUCTION:-

Nowadays deep learning provides the performance for image classification, i.e Segmentation, detection and tracking, and many more. The convolution network has already existed for a long time, their success was not as much due to the size of the available training sets. The application of deep learning technology in medical imaging has attracted extensive attention. Since 2012, several deep convolution neural network models have been proposed such as AlexNet, VGG, GoogleNet, and Residual Net but the proposed U-Net model is tested on superior benchmark datasets, it is used as blood vessel segmentation in retinal images, skin cancer segmentation, and lung lesion segmentation.

U-Net is a fully Convolutional Network applied for biomedical image segmentation, which is composed of the encoder, and the decoder. The widely used U-Net meets the requirement of medical image segmentation for its U-shaped structure combined with context information and fast training speed. The objective of our research was to build several semantic segmentation models with different U-Net-like architectures and investigate the impact of the optimizer model on the final accuracy and different validation metrics. The task of choosing the best model also requires the formulation of selection criteria for models obtained during training. For this purpose, it is necessary to investigate the dependence of the validation and test quality metrics of the models. To achieve the maximum accuracy in detecting defects, the model focuses on one of the most common defect types, that is, "scratch abrasion".

(Scratch abrasion:- These are slight injuries that happen when a sharp object, like a fingernail or thorn, scrapes along your skin the way a pencil scrapes across the paper.)

Related work:-

U2-Net, a straightforward yet powerful deep network architecture developed by Qin et al., comprises a two-level nested U-shaped structure applied to salient target detection (SOD). It offers the following benefits: thanks to the mixed receptive fields of various sizes within the proposed residual U-shaped block (RSU), it can capture a larger amount of contextual data at various scales. Additionally, the pooling operation employed in the RSU block increases the depth of the entire structure without significantly inflating the computational cost.

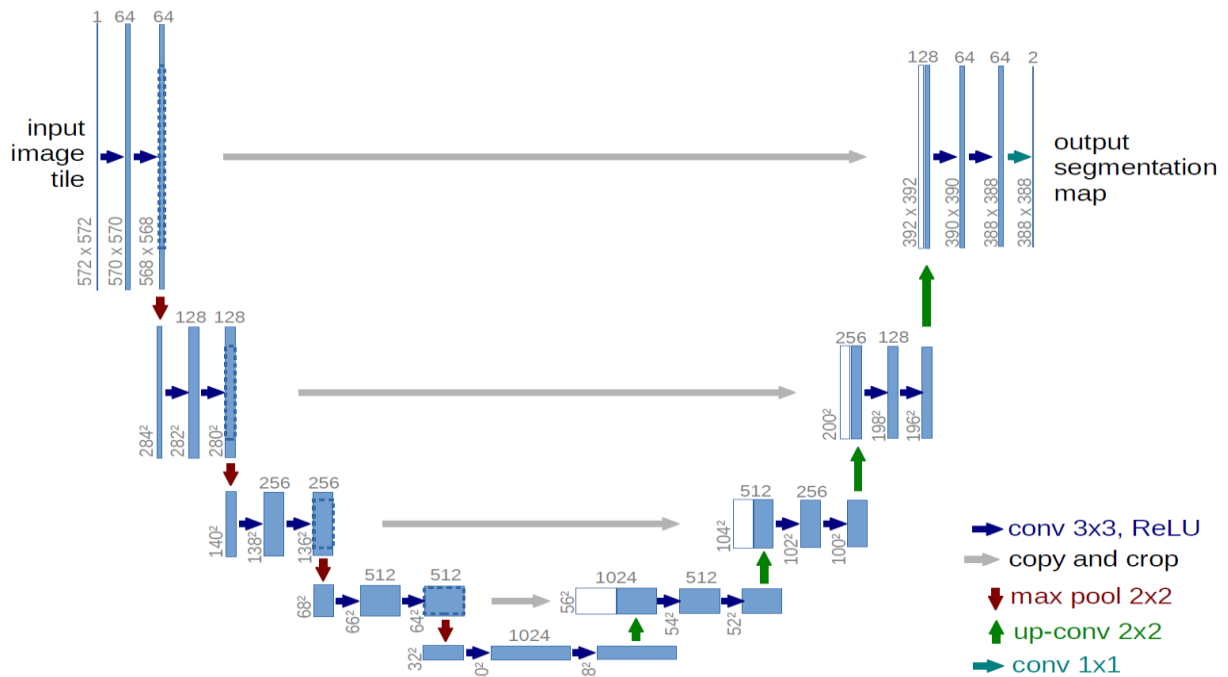


Fig.1 The architecture of U-Net

Since the inception of U-Net, its encoder-decoder-hop network structure has served as a wellspring of inspiration for numerous segmentation techniques in the realm of medical imaging. Within this context, deep learning technologies such as attention mechanisms, dense modules, feature enhancements, improved evaluation functions, and various fundamental U-Net structures have been seamlessly integrated into the domain of medical image segmentation, gaining widespread adoption. These diverse iterations of U-Net-related deep learning networks are meticulously designed to optimize

The general architecture of the basic U-Net neural network is shown in Fig 1. It is symmetrical and contains two main parts: The compression part i.e., the encoder (on the left), and the expansion part, i.e., the decoder (on the right). The compression part is a typical architecture of a convolutional neural network, which contains repetitive convolutions with a 3*3 kernel, followed by ReLu and max pooling operations. With each downsampling, the number of feature maps doubles.

As the image expands, it gradually enlarges to its original size. Each step of the expansion part increases the dimension of the feature map from the compression part. Combining the image with the convolution result of the previous layer provides for greater accuracy. At the end of each unsapling,

results, enhancing both accuracy and computational efficiency in medical image segmentation. This optimization is achieved through alterations to network structures, the incorporation of novel modules, and other innovative approaches. Nonetheless, it's worth noting that the majority of existing literature related to U-Net primarily introduces isolated new concepts, with only limited comprehensive reviews that consolidate the various adaptations of the U-Net structure for deep learning in medical imaging segmentation.

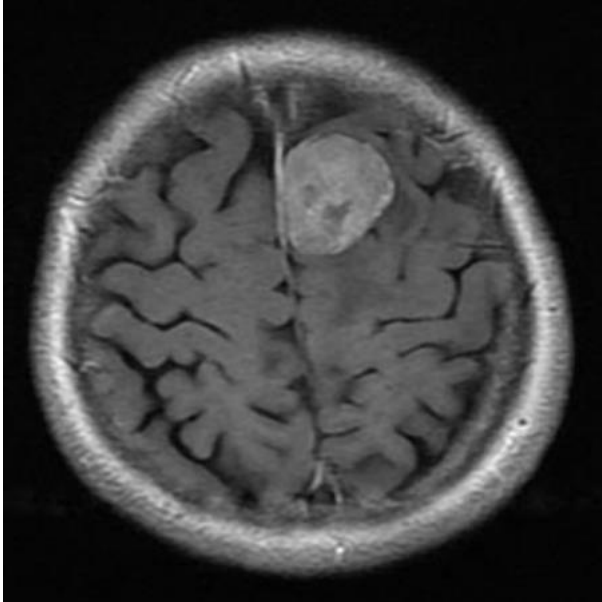
a convolutional with a 3*3 kernel and ReLu activation function is applied.

This approach eliminates the need, for models that determine the position of objects. It is a tool used not only in analyzing natural images and translating text but also in classifying and predicting images. Research has demonstrated that this algorithm is highly beneficial for identifying and locating tissues or organs and it can achieve a level of accuracy with limited computing resources. This is particularly advantageous when dealing with organs, like the pancreas.

In this paper, we enhance a framework known as the " convolutional network." We make

adjustments and expansions to enable it to function with several training images and deliver more accurate segmentations as depicted in Figure 1. The key concept is to augment a contracting network, with layers that replace pooling operators with upsampling operators.

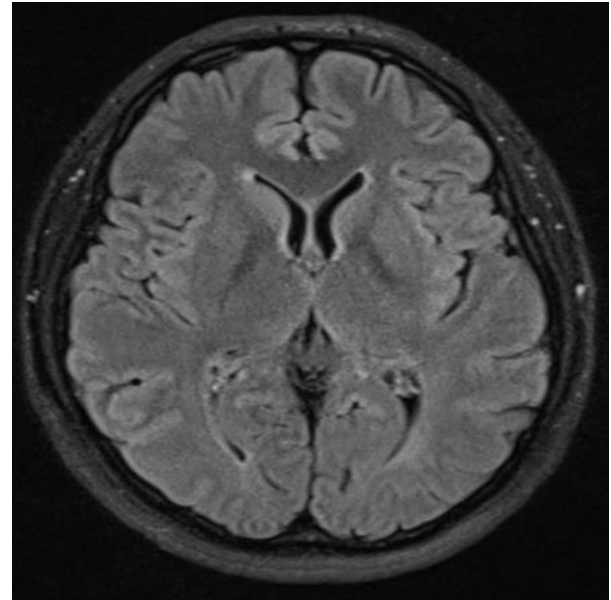
To achieve localization we combine high-resolution features, from the contracting path, with the output. By doing this a subsequent convolution layer can learn to create an output using this information.



With Tumor

The abnormal growth of malignant or nonmalignant tissues in the brain causes long-term damage to the brain. U-Net is one of the most common methods of detecting brain tumors. A brain tumor is characterized by the proliferation of brain cells. This disease is mainly caused by morbidity and cancer related conditions. Brain tumors are caused by malignant cells infiltrating brain tissues and growing abnormally. In secondary brain tumors, tumors that originate elsewhere in the body and then spread to the brain are classified as secondary brain tumors. The term metastatic brain cancer also applies to these cancers. In addition to lung, breast, skin (melanoma), colon, kidney, and thyroid gland cancers, the brain is a common site of metastasis for other types of cancer as well.

In the United States, there are approximately 787,000 people with brain tumor disorders, according to the National Brain Tumor Association. MRI is a common imaging method used before and after



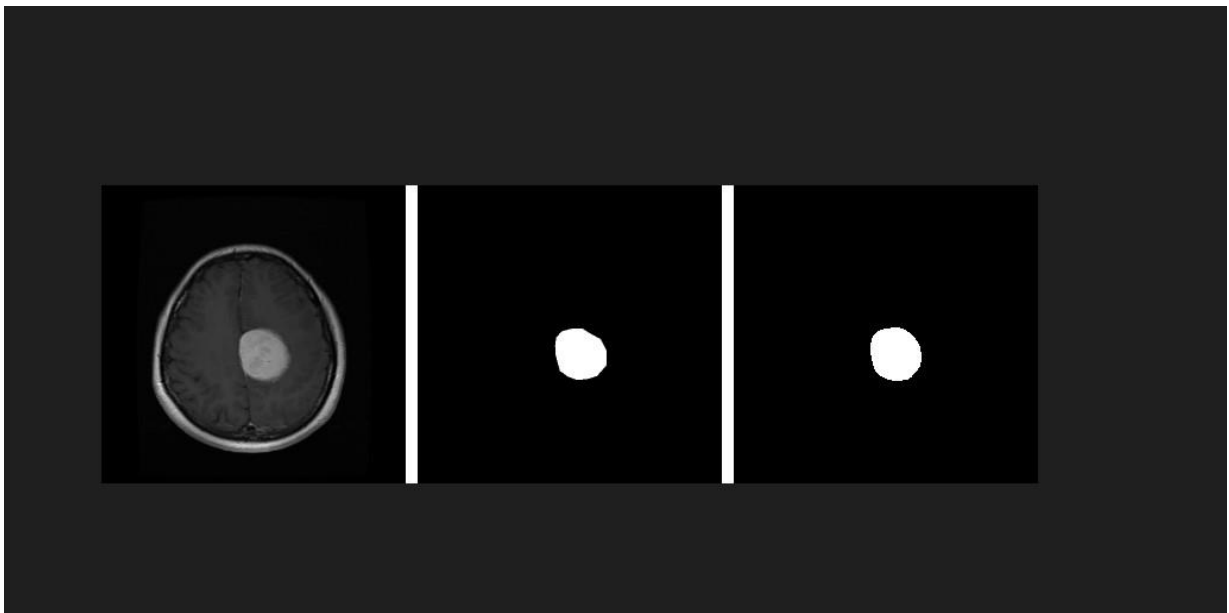
No Tumor

surgery, as it provides important information for treatment plan.

U-Net is also a common imaging method used before and after surgery as it segments the X-Ray picture to provide important information for treatment plan.

In U-Net the input(256,256,3) is taken as RGB layers, Convolution layer, Batch Normalization and Activation.

The use of Numpy, Glob, Shuffle, train_test_split helps clearly segment the X-Ray images for detection of the damage. Numpy packages can play with the images and images are used to read as array and Numpy is also a useful tool which manipulates array to work with them. Glob helps to extract image part and a mask part easily. Shuffle is used to shuffle the list of images on mask. Train_test_split is used to split the complete dataset into different parts i.e. training, validation.



Our results demonstrate the efficacy of the UNet architecture in accurately identifying tumors in medical images, thus providing a valuable tool for healthcare professionals in the early detection and diagnosis of medical conditions. The ability to convert the original grayscale medical images into binary RGB images, where tumor regions are distinctly represented in white, simplifies the interpretation and integration of our model into clinical workflows. This approach shows great potential in streamlining the diagnostic process and ultimately improving patient outcomes by facilitating early detection and intervention. The use of UNet for automated tumor detection holds promise for the future of medical image analysis and may play a pivotal role in enhancing healthcare delivery and patient care.

Our study focused on the development of a robust semantic segmentation model capable of accurately delineating tumor boundaries in medical images. The successful integration of semantic segmentation has enabled us to provide healthcare professionals with a valuable tool for improved diagnosis and treatment planning.

Our results demonstrate the effectiveness of this novel approach, showcasing the remarkable accuracy achieved in tumor localization and sizing. The application of semantic segmentation, which assigns semantic labels to each pixel in an image, not only allows for the precise identification of tumor regions but also offers insights into the specific types and characteristics of tumors.

The integration of semantic segmentation into medical imaging represents a significant step

forward in healthcare technology. It has the potential to revolutionize the way medical professionals approach diagnosis, leading to earlier detection and more tailored treatment plans. This research paper highlights the transformative impact of semantic segmentation in the field of tumor detection, emphasizing the potential to enhance patient outcomes and streamline clinical workflows.

It is well-established that deep neural networks require vast amounts of annotated training data to achieve high levels of accuracy. However, our work challenges this conventional notion by introducing an innovative approach that places a significant emphasis on the utilization of data augmentation. We harness data augmentation as a strategic lever to maximize the utility of the available annotated samples, pushing the boundaries of what is achievable with limited datasets.

Experiment(U-Net architecture):-

These variables are typically used in U-Net image processing for image input files to put the image Tasks where images are manipulated or used as input data.

```
IMG_WIDTH = 128
IMG_HEIGHT = 128
IMG_CHANNELS = 3
```

The code uses the TensorFlow library to define a neural network architecture known as a U-Net. U-Net is a convolutional neural network (CNN) architecture commonly used in image segmentation tasks, particularly in biomedical image analysis. It's called "U-Net" because of its U-shaped architecture.

This code is used as a "Contraction path" to put the input to draw the U-Net architecture as a semantic segmentation

```
#Contraction path
c1 = tf.keras.layers.Conv2D(16, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(s)
c1 = tf.keras.layers.Dropout(0.1)(c1)
c1 = tf.keras.layers.Conv2D(16, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c1)
p1 = tf.keras.layers.MaxPooling2D((2, 2))(c1)

c2 = tf.keras.layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(p1)
c2 = tf.keras.layers.Dropout(0.1)(c2)
c2 = tf.keras.layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c2)
p2 = tf.keras.layers.MaxPooling2D((2, 2))(c2)

c3 = tf.keras.layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(p2)
c3 = tf.keras.layers.Dropout(0.2)(c3)
c3 = tf.keras.layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c3)
p3 = tf.keras.layers.MaxPooling2D((2, 2))(c3)

c4 = tf.keras.layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(p3)
c4 = tf.keras.layers.Dropout(0.2)(c4)
c4 = tf.keras.layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c4)
p4 = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(c4)

c5 = tf.keras.layers.Conv2D(256, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(p4)
c5 = tf.keras.layers.Dropout(0.3)(c5)
c5 = tf.keras.layers.Conv2D(256, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c5)
```

➡ It defines a U-Net architecture with five levels, where each level consists of two convolutional layers (Conv2D), followed by a dropout layer (Dropout) and a max-pooling layer (MaxPooling2D).

➡ The architecture starts with an input tensor *s*, which represents an image. The code applies a series of convolutional layers with activation functions (ReLU), kernel initializers, and padding settings to extract features from the input image.

➡ After each pair of convolutional layers, a dropout layer is added to help prevent overfitting by randomly deactivating a fraction of the neurons during training.

➡ Following the dropout layer, a max-pooling layer reduces the spatial dimensions of the feature maps, allowing the network to capture hierarchical features at different scales.


```

u6 = tf.keras.layers.Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same')(c5)
u6 = tf.keras.layers.concatenate([u6, c4])
c6 = tf.keras.layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(u6)
c6 = tf.keras.layers.Dropout(0.2)(c6)
c6 = tf.keras.layers.Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c6)

u7 = tf.keras.layers.Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same')(c6)
u7 = tf.keras.layers.concatenate([u7, c3])
c7 = tf.keras.layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(u7)
c7 = tf.keras.layers.Dropout(0.2)(c7)
c7 = tf.keras.layers.Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c7)

u8 = tf.keras.layers.Conv2DTranspose(32, (2, 2), strides=(2, 2), padding='same')(c7)
u8 = tf.keras.layers.concatenate([u8, c2])
c8 = tf.keras.layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(u8)
c8 = tf.keras.layers.Dropout(0.1)(c8)
c8 = tf.keras.layers.Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c8)

u9 = tf.keras.layers.Conv2DTranspose(16, (2, 2), strides=(2, 2), padding='same')(c8)
u9 = tf.keras.layers.concatenate([u9, c1], axis=3)
c9 = tf.keras.layers.Conv2D(16, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(u9)
c9 = tf.keras.layers.Dropout(0.1)(c9)
c9 = tf.keras.layers.Conv2D(16, (3, 3), activation='relu', kernel_initializer='he_normal', padding='same')(c9)

```

It represents the decoder part of the U-Net architecture, which is responsible for upsampling and combining features from earlier layers to produce a high-resolution segmentation mask. In U-Net, the decoder is essentially the reverse of the encoder you mentioned in your previous code snippet.

➡ It defines the decoder part of the U-Net architecture, which consists of four levels (u6, u7, u8, u9). Each level performs the following steps:-

- **tf.keras.layers.Conv2DTranspose:** This layer performs upsampling or transposed convolution to increase the spatial dimensions of the feature maps. It uses a 2x2 kernel and strides of 2x2 to achieve this.

- **tf.keras.layers.concatenate:** This layer concatenates the upsampled feature maps with the corresponding feature maps from the encoder part of the U-Net. This is where the skip connections come into play, allowing the network to combine high-level and low-level features.

➡ The convolutional layers within each decoder level help generate feature maps that are progressively more spatially detailed, which is crucial for producing accurate segmentation masks.

Conclusion:-

Our research has introduced an innovative approach to brain tumor detection in medical images, leveraging the power of semantic segmentation, and specifically, the U-Net architecture. Our journey in this study began with the acknowledgment that the training of deep neural networks relies heavily on vast amounts of annotated data. However, we sought to challenge this conventional wisdom by emphasizing the implementation of data augmentation as a key strategy to maximize the utility of the available annotated samples.

The U-Net architecture, meticulously designed for semantic segmentation, played a central role in our research. This architecture, characterized by a contracting path for comprehensive context extraction and a symmetric expanding path for precise localization, proved to be a cornerstone in our pursuit of enhancing medical image analysis, particularly in the context of brain tumor detection.

In a world where continual advancements in medical imaging technologies have paved the way for more precise and efficient diagnoses, our research endeavors to contribute to the early detection of tumors, a critical factor in improving patient outcomes. Our pioneering approach has not only challenged the limitations of training data but has also demonstrated that, with the right strategies, it is possible to achieve superior performance even with minimal image datasets.

The utilization of Python programming and the U-Net architecture allowed us to outperform prior state-of-the-art methods in challenging competitions such as ISBI. This competition, focusing on neuronal structure segmentation within electron microscopic stacks, further underscores the real-world relevance and applicability of our methodology.

One of the key advancements in our research was the incorporation of residual units in our architectures. These units proved to be

effective in the training of deep models, significantly enhancing their performance. Moreover, the inclusion of recurrent residual convolutional layers facilitated the accumulation of valuable features tailored explicitly for segmentation tasks, further improving the accuracy and precision of tumor localization.

Empirical results unequivocally demonstrate the superiority of our segmentation architectures when compared to their counterparts. Our evaluation extended beyond the U-Net architecture to include a variant of a fully connected convolutional neural network known as SegNet, as well as residual U-Net models, underlining the robustness and generalizability of our approach.

In a broader context, the field of deep learning-based medical image analysis stands to gain valuable insights and innovations from our research. The potential implications are far-reaching, with the promise of streamlining diagnostic processes and enhancing treatment planning, particularly for patients affected by brain tumors.

As we look ahead, we envision a future where the fusion of cutting-edge technology and sophisticated algorithms, such as our U-Net-based semantic segmentation, will continue to redefine the boundaries of what is possible in medical image analysis. This research is a testament to the relentless pursuit of knowledge and innovation, with the ultimate goal of improving healthcare delivery and patient care. It represents a crucial step forward in our collective effort to combat the devastating impact of brain tumors, bringing us closer to a brighter and healthier tomorrow.

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17.U-Net-Based Medical Image Segmentation Xiao-Xia Yin,^{1,2}Le Sun,³Yuhan Fu,¹Ruiliang Lu,⁴and Yanchun Zhang

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