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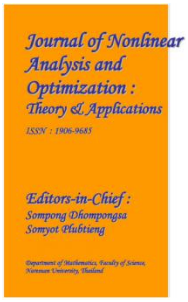

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BRAIN TUMOR DETECTION USING ATTENTIONGATE RESUNET MODEL

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ABSTRACT: Brain Tumor Segmentation is crucial for the treatment of MRI (Magnetic Resonance Image)brain tumors. It helps doctors in locating and measuring tumors and helps in developing treatment and rehabilitation strategies. Some methods which are based on the U-Net architecture have gained popularity for MRI brain tumor segmentation. Combing attention gate with U-Net architecture will enhance the ability of the model to more focus on the important or necessary features while suppressing or attenuating the irrelevant details. This paper presents the approach which combines ResUNet architecture with attention gate using VGG model as classifier. The research explores the effectiveness of an attention module which is called attention gate for brain tumor segmentation and detection.

Keywords: *Magnetic Resonance Image(MRI), Attention gate, U-Net,VGG,ResUNet*

1. INTRODUCTION

The nervous system, which regulates vital functions in our bodies, is made up of the human spinal column and brain. These functions include verbal communication, bodily locomotion, and cognitive processes. The existence of any abnormal proliferations within the Central Nervous System (CNS) may cause problems in an individual's normal functioning. It can lead to unclear speech or difficulty synchronizing body motions. Furthermore, it has the capacity to affect our speech, intellect, and bodily activities. Brain tumors can be malignant or benign. Prompt detection of brain tumors is critical for effective action, as they can have serious neurological implications if not treated soon. Traditional approaches for identifying brain tumors require the use of medical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT) scans. The incorporation of Machine Learning (ML) and image processing methodologies in brain tumor identification endeavors to tackle medical obstacles by automating the study of medical images. After the machine learning model has been trained, it can be used to interpret novel and unfamiliar brain

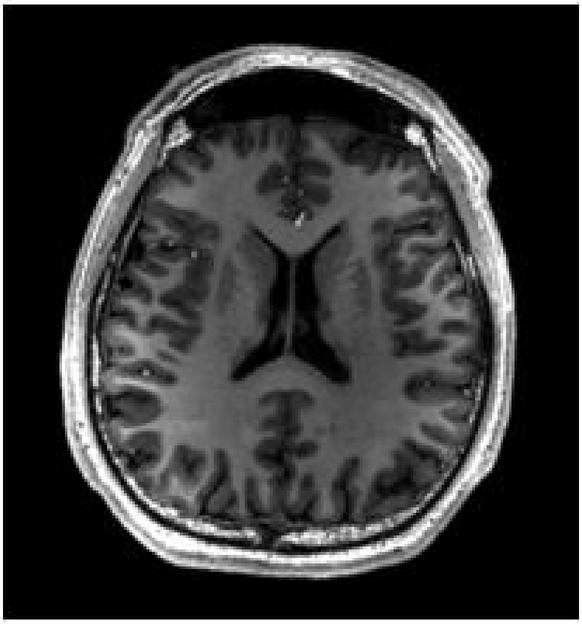

Figure 1 shows a magnetic resonance imaging (MRI) scan of the brain, as cited in [10].

The existing methods for detecting brain cancers using deep learning are mostly divided into two types: convolutional neural network (CNN) and fully convolutional network (FCN) approaches. CNN-based algorithms use small-scale images to segment brain tumors. A 3*3 convolutional kernel represents the dimensions of the convolutional filter used in CNN layers. FCN is a sophisticated semantic segmentation model that solves the problem of predicting each pixel independently. Deep neural network models like AlexNet, VGGNet, ResNet, and DenseNet have lately gained popularity in computer vision problems. These models have been widely used in medical image processing due to their ability to extract highly unique features. Researchers have presented U-Net-based topologies for brain tumor segmentation, which provide higher accuracy and performance. Attention gates may be easily integrated into deep neural networks like U-Net to improve classification and segmentation. Both FCN and U-Net designs are appropriate for medical image segmentation applications.

2. EXISTING SYSTEM

The researchers, led by Avigyan Sinha [1], suggested a way to improve brain tumor identification by testing various segmentation algorithms. The CNN architecture's parameters are slightly changed by using an ANN classifier and several segmentation techniques. Multilevel thresholding is the best strategy for the BRATS dataset.

Zahra Sobhaninia et al. proposed a neural network based on the LinkNet architecture. This technique entails training numerous LinkNet networks from various angles of the skull. A unique batch of images taken from a certain angle was used to train a second LinkNet network. This technique does not require any preprocessing steps.

The researchers, led by Madhupriya G [2], proposed a sophisticated method for identifying unwanted masses in the brain using a deep neural network and a probabilistic neural network (PNN). PNN uses the probability concept to perform the segmentation process, allowing the detection of unwanted masses in the brain. The input is segmented, and a two-path architecture is implemented with CNN and PNN.

Tonmoy Hossain and his colleagues [6] developed an extremely successful technique for segmenting and detecting brain tumors. There are two independent segmentation models here. The initial model used fuzzy c-means (FCM) for tumor segmentation and standard machine learning techniques for classification. In contrast, the second model focused deep learning approaches for detecting brain tumors. FCM is utilized for segmentation.

Lingling Flang[5] and colleagues developed a dual-path network dubbed Multi-Modal Feature Fusion. The Dual-path Network integrates a wide range of information using various kernel multiplexing techniques. The goal of this integration is to improve the model's ability to comprehend detailed aspects within the data. The MFF-DNet's basic structure includes a dual-path model that combines the DenseNet network with Feature Pyramid Networks (FPN). This combination allows for the incorporation of low-, middle-, and high-level characteristics, allowing the model to capture a wide variety of nonlinear structural properties in glioblastoma. As a result, segmentation is more accurate.
Geetanjali et al. developed a model to segment and classify medical images with the goal of discriminating between benign and malignant cancers. Includes preprocessing techniques aimed at increasing the quality of medical photos. K-means clustering is used for image segmentation. Following segmentation, the model uses a Support Vector Machine (SVM) classifier to categorize the segmented regions.

3. PROPOSED SYSTEM

The suggested system employs a deep learning approach that consists of two fundamental steps: image preprocessing and convolutional neural network (CNN) analysis. The Attention gate ResU-Net (AGResU-Net) is a model designed specifically for accurately segmenting brain tumors in medical images. This approach incorporates attention gate units and residual modules into the U-Net
to address issues such as small-scale tumors, complex architectures, and spatial information degradation during the segmentation process. The VGG model serves as the classifier during the classification procedure. Figure (2) shows the block diagram of our proposed system.

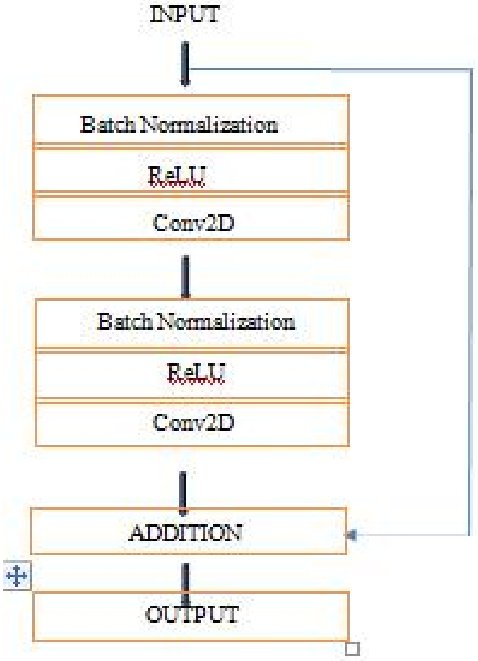

Figure 2 shows a block diagram of the proposed system.

1. Input: the neural network receives an image or a feature map from a preceding layer.
2. Batch Normalization (BatchNorm): (BatchNorm) standardizes input data inside a mini-batch. It ensures that the input's mean value is approximately equal to 0 and its standard deviation is approximately equal to 1. This improves the stability and speed of training by resolving issues like vanishing slopes. It is applied before the activation function (in this case, ReLu) to standardize the input.
3. ReLu (Rectified Linear Unit): activation function is used to introduce nonlinearity into the network. The function substitutes any negative numbers in the input with zero using the formula $f(x) = \max(0, x)$. The Rectified Linear Unit (ReLU)

4. Conv2D (Convolutional Layer): The input travels via convolution procedures, which involve sliding a group of filters (kernels) across the input feature map to extract local patterns. The convolutional layers accomplish feature extraction by identifying numerous properties such as edges, textures, and intricate structures within the input.

5. Addition: In this context, "Addition" refers to a skip or residual connection. The outputs of the second and first Conv2D layers are mixed. A defining property of a residual block, which is a crucial component of residual networks (ResNets). The inclusion of these two outputs helps to mitigate the issue of the vanishing gradient and makes it easier to acquire residual (or residual error) information.

6. Output: he ultimate output is the result of the processing that takes place across these layers. A feature map is a representation of input data that captures increasingly complex features as you move through the levels.

The input for the MRI image will consist of three encoder blocks, three decoder blocks, and a bridge connecting the encoders and decoders. Each encoding block includes Batch Normalization, ReLu, Convolution, and Addition. Each encoding block includes batch normalization and ReLU activation. We define a method that accepts the input shape as a parameter. Equation (1) represents the normalizing formula.

$$z' = \frac{z - \mu}{\delta},$$

(1)[9]

Where z and z' denote the input and normalized images, respectively.

The Rectified Linear Unit (ReLU) introduces nonlinearity by generating the input for positive values and zero for negative values. This technique allows for the recognition of detailed patterns and characteristics in medical images, which improves the model's ability to diagnose malignancies effectively.

During the decoding process, we move information from downsampled to upsampled data. We then combine this data with skip characteristics and use a residual block to improve the encoder blocks. To screen the characteristics, we use a classifier with a sigmoid function and a cost function to eliminate cumulative errors. We can determine whether or not the tumor exists by analyzing the output. If there is no tumor, it can be assumed that the individual is healthy. If a tumor is discovered, note its presence.

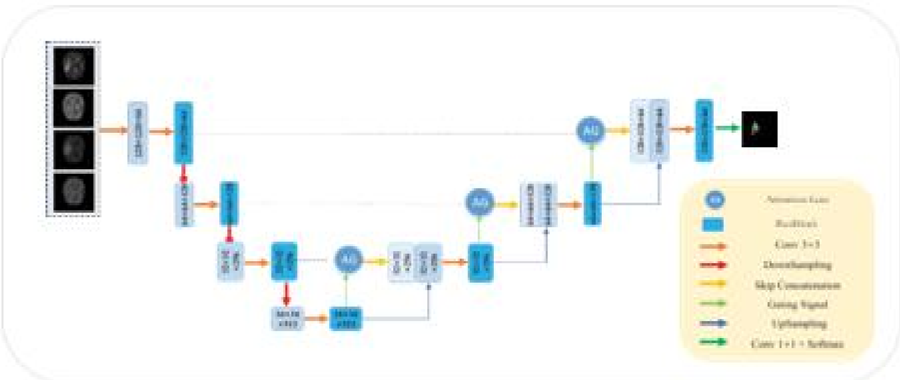

Figure 3 depicts the structure of the Attention Gate ResU-Net. The user's text is "[9]".

To get spatial information, the attention gate integrates data from both the down and up sample paths. Soft attention is used to selectively attenuate information in irrelevant spots within the connections.

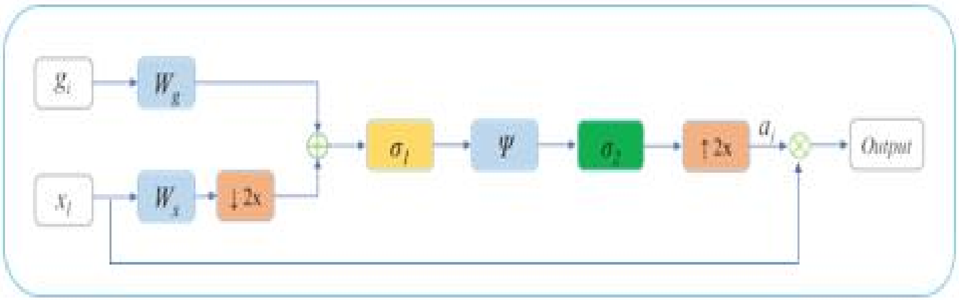

Figure 4 depicts the Fundamental Semantics of the Attention Gate, as stated in reference [9].

Each pixel in a single layer's feature map (xl) is evaluated using a gating signal (gi) to determine the areas of relevance. The attention coefficient (α) is a numerical value that ranges from 0 to 1. It is critical in recognizing and prioritizing regions relevant to the primary objective, while also suppressing any unnecessary or unrelated information. The resultant output (xout) is obtained by conducting element-wise multiplication between each element of the feature map (xl) and its corresponding attention coefficient (α). Equation (2) expresses the output of the attention gate.

$$x_{out} = x_l \cdot \alpha_i \longrightarrow (2)\ [9]$$

Equation (3) calculates the multi-dimensional attention coefficient as (3). The user's text is "[9]".

$$\alpha i=\sigma 2(\psi T(\sigma 1(\mathbf{W}T\mathbf{x}l+\mathbf{W}T\mathbf{g}i+\mathbf{b}g)+b\psi)) \longrightarrow (3)[9]$$

Residual Connections:

The U-Net architecture incorporates residual connections to enhance the flow of training data. These connectors allow gradients to transfer directly from the decoder to the encoder.

Attention Mechanisms:

The attention mechanism is a critical component of the Attention Gate Res-U-Net. It helps the model direct its attention to relevant portions of the image while suppressing unnecessary or disruptive features.

Gate Mechanism:

The Attention Gate Res-U-Net includes a gate mechanism that allows the model to control the passage of information from the encoder to the decoder. This aids in the preservation of relevant information while suppressing superfluous data throughout the segmentation process.

Skip Connections:

The Attention Gate Res-U-Net uses skip connections to connect encoder features at different spatial resolutions to their corresponding decoder features.

These linkages allow the decoder to retrieve high-resolution features from the encoder.

The machine is equipped with a 16 GB DDR4 SRAM, which provides efficient and quick data storage for a variety of computing tasks. Furthermore, it comes with a powerful 12 GB NVidia Tesla K40 GPU, which considerably improves its ability to do parallel processing and speed up graphics and machine learning tasks. With a big 50 GB of storage capacity, the system provides enough of space for storing greater amounts of data. Visual Studio, a comprehensive integrated programming environment, is used in conjunction with Python 3.9 to assist development. The packages include Keras, TensorFlow, and other components. Flask, a lightweight web framework, is also included, allowing for the easy creation of web apps and services on this well-optimized hardware combination.

4. RESULT ANALYSIS

The proposed solution for identifying brain tumors will increase performance. To detect brain cancers, we used a VGG model as the classifier and coupled an attention gate with the ResUNet architecture. The integrated approach accurately detected and classified brain tumors in MRI images. The introduction of attention gates into ResUNet increased focus on critical features while suppressing superfluous details, hence improving segmentation accuracy. This technique produces system output with superior performance and better precision.

Figure 4: Page for uploading

Figure 4 displays our proposed system's upload page, which allows the user to select an input image (MRI image) for further detection.

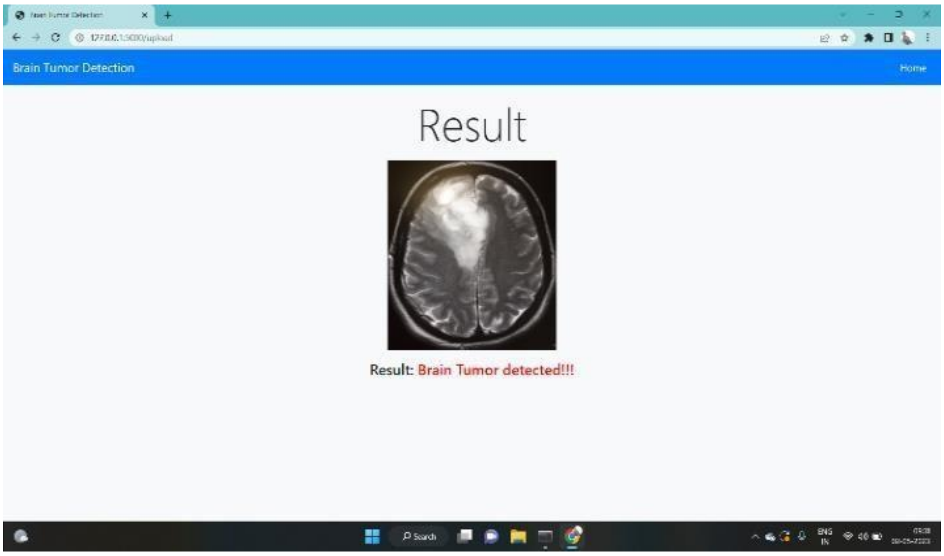

Figure 5 shows the outcome page.

Figure 5 illustrates the suggested system's output. If a brain tumor is present, the device will show the message "Brain Tumor detected"; otherwise, it will say "No brain tumor".

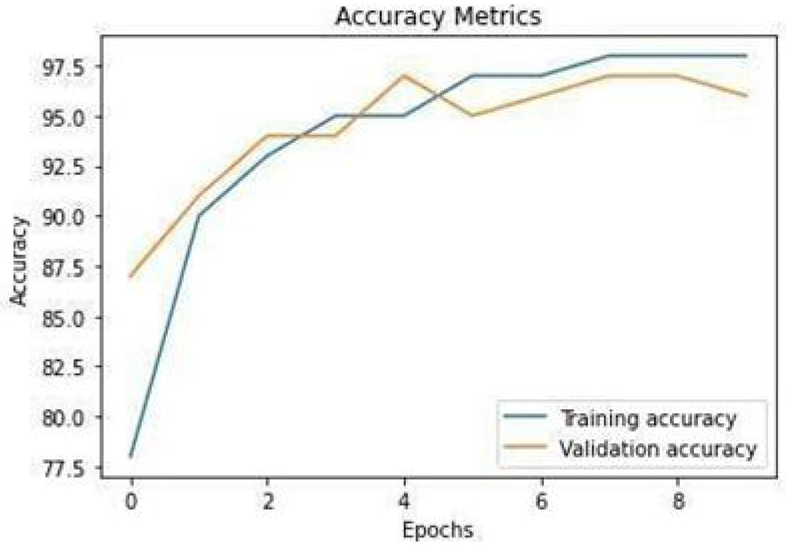

Figure 6 shows a graph representing the level of precision.

Figure 6 shows the link between epochs and accuracy. Accuracy is the ratio of correctly predicted instances to the total number of instances. An epoch is a single iteration across the whole training dataset.

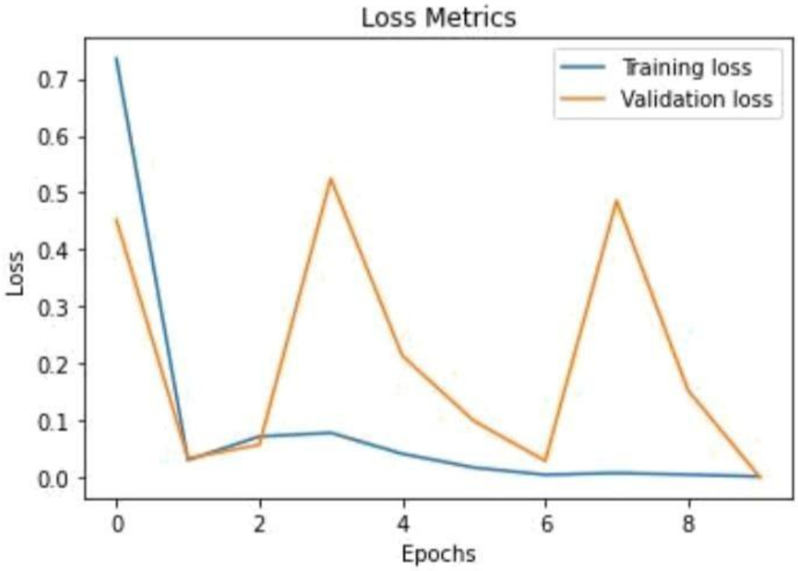

Figure 7 depicts a graph depicting the loss.

Figure 7 displays the relationship between epochs and loss in the form of a graph. Loss is the measurement of the loss value on the training data at the end of each session.

5. CONCLUSION

This paper introduces a novel AGResU-Net model that combines attention gates and residual modules into a simplified U-Net design. The primary goal is to evaluate the effectiveness of attention gates for brain tumor segmentation. AGResU-Net improves the segmentation of tiny brain tumors by incorporating multiple attention gate units into the skip connection. This enables for the distinction between significant and noise feature responses, while also emphasizing critical feature information. The efficacy of attention gate units is thoroughly tested with three reliable brain tumor datasets. The results show that AGU-Net and AGResU-Net outperform their respective baseline networks, U-Net and ResU-Net, as well as traditional segmentation algorithms for brain cancer. Nonetheless, AGResU-Net faces challenges in properly utilizing 3D data produced from X-ray information, resulting in the exclusion of precise configuration data and nuanced characteristics of the surrounding environment in various areas. To address this issue and improve segmentation accuracy, future research will look into the use of three-dimensional network designs.

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