# Brain Tumor Localization as a Service

Gopinath Achuthan
*Computer Science Department*
*University of Maryland Baltimore County*
Baltimore, United States
rx44815@umbc.edu

Rajlaxmi Biyani
*Computer Science Department*
*University of Maryland Baltimore County*
Baltimore, United States
rbiyani1@umbc.edu

Jhansi Sankaramaddi
*Computer Science Department*
*University of Maryland Baltimore County*
Baltimore, United States
jhansis1@umbc.edu

*Abstract*— **Deep learning methods are becoming stronger and prove to be more reliable in several computer vision fields with high accuracy. This paper mainly focuses on a web service we provide that gives brain tumor detection and localization using deep learning techniques from the Kaggle dataset: https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation.**

***Keywords— brain tumor, image classification, deep learning, detection, localization, image segmentation, resnet, resunet***

## I. INTRODUCTION

A brain tumor is a mass or growth of abnormal cells in the brain. Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some are cancerous (malignant). Brain tumors in humans can directly originate in their brain (primary brain tumors). It is also possible that cancer can originate in other parts of the body and then get spread in the brain area. (secondary, or metastatic, brain tumors).

Today, an estimated 700,000 people in the United States are living with a primary brain tumor. Predictions also say that over 87,000 more such cases will be diagnosed in 2020.

Brain tumors can be deadly and can significantly impact life quality and change everything for patients and their loved ones. Out of 700,000 Americans living with a brain tumor, 69.8% of tumors are benign, and 30.2% are malignant.

Brain tumors are associated with neurological disabilities, retardation and psychological problems, and an increased risk of death. Africans die of this disease more likely than others. They negatively affect people who suffer from them and are also a burden on the national economy as treating cancers is costly.

Patients undergo several types of cancer detection tests, including Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), to locate tumors in the brain. MRI is the most widely used clinical diagnostic and research technique. It is an efficient medical imagery tool with different methods(T1, T2, ARM) having each particular property is. Each an effective way to clarify the various tissues and obtain a 2D,3D, and 4D(3D+T) sight of a body part, especially the brain. MRI is based on the nuclear magnetic resonance (NMR) technique in which various tissues with high contrast can be observed due to various sequences.

To provide a high accuracy web service, we use a convolutional neural network model to detect and map the RI scan image's tumor location. Convolutional neural networks are chosen predominantly for supervised image classification. They are highly correlated with the amount of labeled training data. But they also work well with few labels compared to most other techniques and are also proven to outperform all other techniques even in such scenarios.

Convolutional neural networks have the ability to learn the characteristics though they are hand-engineered in the primitive filters. They will successfully capture the spatial and temporal dependencies in an image through the application of relevant filters. Their architecture performs a better fitting to the image dataset due to a reduction in the number of parameters involved and the reusability of weights. They reduce images to a form that is easy to process without losing features, which are critical for getting a good prediction.

## II. MOTIVATION

The brain tumor is one of the most dangerous diseases which require early and accurate detection methods. Most detection and diagnosis methods depend on neuro-specialists, oncologists, and radiologists for image evaluation, which is possible for human errors and time-consuming.

This service's prominent motivation is to provide a faster and high accuracy brain tumor detection and localize a tumor in the MRI scan image. In addition to that, to provide web service to people who don't have access to neurologists, oncologists, or radiologists who primarily detect the presence of tumors in the brain and suggest treatments for patients. Even today, so many rural areas and even urban areas in some backward countries do not have high-end facilities in areas that require intense research and funding.

Similar grounds of work are being done in the medical field only in areas like teledermatology, where some medical assistants go to underprivileged areas, take photos or scans a patient's skin conditions, and send them to dermatologists present at far distances to identify the skin condition and suggest some medication.

Our idea is to replace these specialists and provide the diagnosis using deep learning algorithms with more accuracy and efficiency. Tumor detection and treatments are costly methods. They require a lot of investments; hence, involving machine learning methodology to improve the work being done in this field will be a breakthrough.

The regular process is to send a report to a doctor from the radiologist who analyzes the scan and report's details to the patient. Normally this process will take a week or two unless it needs urgent attention.

In cancer treatment, diagnosis is of utmost importance. Many people succumb to it due to a lack of quality diagnosis and access to it. If it is diagnosed at the right time and cured efficiently, the survival chances are comparatively higher. The Late-diagnosis results in a reduction in survival chances. So, we aim to provide a web service in detecting a brain tumor with high accuracy and acquire the tumor's location faster.

## III. Problem Statement

To provide end-to-end web service to a user, the medical practitioners can upload an MRI scan image and get tumor detection and a tumor's mapping as in where exactly the tumor is located in the brain, which helps in deciding what treatment needs to be given and what are chances to cure. If the tumor is detected, then the location of a tumor is also mapped. Additionally, it allows the medical practitioners to take notes, save them for future use, and write the report from their observation through the service provided.

## IV. Service Architecture

Our expectations from this service were not to build a regular service that can just be used to detect brain tumors and make them as useful as possible. Keeping this in mind as one of the main focus areas, we have given a good amount of attention to our service's usability and user experience. From the front end to the back end, including the integration services, each part is made quite reliable through robust technologies and platforms.

While designing the user interface, we have maintained a few restrictions, such as mandatory user registration and user login process for the users to use the service. Along with these primary steps, the user must provide and validate some of his personal information, such as his qualification to use this service. As a matter of fact, Brain Tumor Localization service is not available for the general public, but it takes some basic qualifications to fulfill the eligibility criteria. Users must fall into one of the categories from different medical practitioners like radiologists, surgeons, lab researchers, etc.

Once all these requirements are met, the service will be ready to serve its purpose. The portal provides multiple useful features like recent activities feature, lifetime analysis history feature along with tumor detection and localization. The recent activities feature provides a way to quickly access recently performed activities like any recent upload of the MRI scan results, recently added/updated notes of the case history, etc.

The Lifetime analysis history tab lets the user go through all the cases he/she handled through our service in his/her lifetime. Additionally, he/she can update the notes for any of these cases as per his added knowledge about them. This feature plays an important role as it allows the user to review and retrospect on the actions taken for different cases, their takeaways, and their applications for such cases in the future.

Talking about storage management, we have tried to keep the service database design as modular and clean as possible. We have maintained tables to store user registration and login details. There is another table that contains all the different types of medical practitioners who can use the service. Apart from that, there is a table that stores the details about the analysis history of each MRI scan specific to the medical practitioners.

The other important part of the service architecture is the machine learning model deployed on the backend server. In the model, raw data is pre-processed and trained on the tensor flow and Keras package. The trained model is deployed and called from the backend server whenever the user uploads an image to check for tumor detection. The model part of the architecture is clearly described in more detail in section 6.

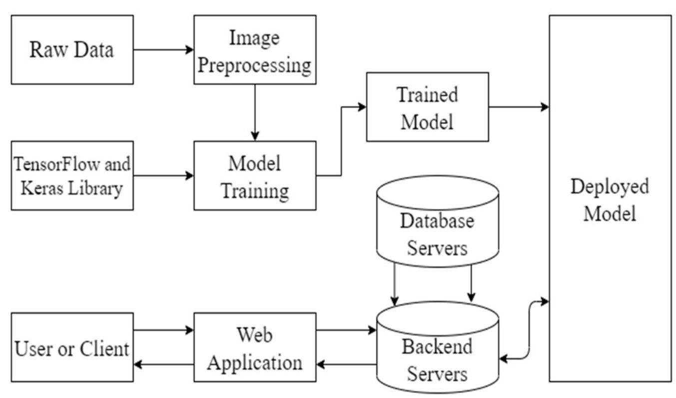


Fig. 1. Architecture Overview

## V. Deep Learning Techniques

Deep Learning techniques are introduced to mimic the human brain. A convolutional neural network (CNN) is a deep learning algorithm that takes images as input, assigns importance to them, i.e., learnable weights and biases to various aspects or objects in the image, and can differentiate one from another. The pre-processing required for convolutional neural networks is very less compared to other classification algorithms. With enough training, convolutional neural networks have the ability to learn the features or characteristics of the image through filters. They will successfully capture the spatial and temporal dependencies in an image through the application of relevant filters. Their architecture performs a better fitting to the image dataset due to a reduction in the number of parameters involved and the reusability of weights. They reduce images to a form that is easy to process without losing features, critical for getting a good prediction.

Here we describe the processes and techniques used in detecting brain tumors based on deep learning techniques, which are being used to detect the brain tumor from the MRI scan image and localize it if the tumor's detection is higher in probability.

*A. ResNet*

In CNN, without any intervention of hyperparameters, we can extract the features. But as CNN grows deeper, the vanishing gradient problem rises, which will negatively affect the neural network performance. The vanishing gradient problem occurs when the gradient is backpropagated to the earlier layers, resulting in a minimal gradient. Eventually, it is possible to become close to zero. This neuron is called dead neurons. The residual neural network or resnet includes *skip connection* features to activate the dead neurons to overcome this problem. Resnet works by adding identical mapping on top of CNN. The resnet building block technique is given below.

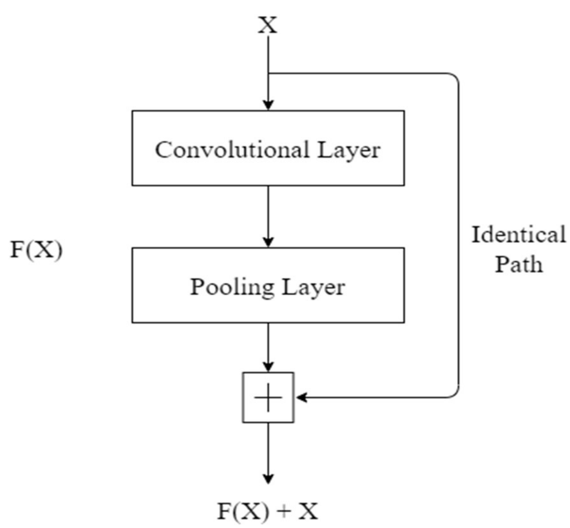


Fig. 2. Residual building block.

The CNN block consists of a convolutional layer and a pooling layer. On top of that input of the block is added to the output of the block. Even if the CNN block gradients become close to zero, the identical path will reactivate the path.

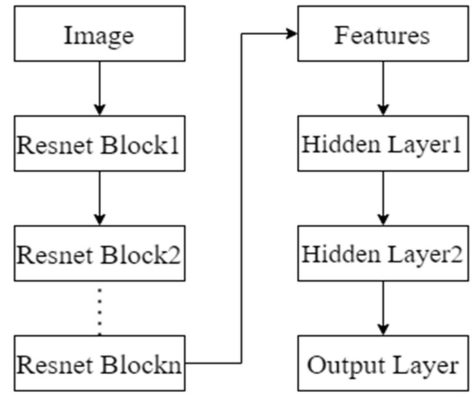


Fig. 2. Resnet Classification Model.

We know that ImageNet contains 11 million images and 11,000 categories. It is used to train a Resnet deep network [3]. We used transfer learning, a machine learning technique in which a network is trained to perform specific tasks and is being reused. Here, we exact features from the resnet model trained by 11 million images to perform our task. After extracting features from the already trained network, we can freeze the CNN model and initialize the network with pre-trained weights. Then, the fully connected neural network is added to the model's tail. The fully connected neural network is designed with hidden layers and an output layer that has two neurons. Next, retrain the deep learning network the weights for a fully connected network will be obtained for this task. This technique provides fast training progress. We do not have to train the model from scratch using randomly initialized weights.

*B. ResUNet*

ResUNet architecture combines UNet backbone architecture with residual block to overcome the vanishing gradient problems present in deep learning[5]. This architecture consists of three major parts. They are encoder or contracting path, bottleneck, and decoder or expansion path.

The contracting path consists of several contracting blocks, and each block takes an input that passes through the resnet block, followed by pooling. Feature maps after each block doubles, which helps the model learn complex features effectively. The bottleneck block serves as a connection between the encoder and decoder path. It takes the input from the encoder and then passes through the resnet block, followed by up-sampling convolution layers.

Each block takes in the up-sampled input from the previous layer in the decoder path and concatenates with the corresponding output features from the resnet block in an encoder path. Then it is followed by up-sampling convolutional layers. This helps to ensure that the features learned while contracting are used while reconstructing the image. That is, the dimension of the output is maintained in a way it is similar to the dimension of the input image.

## VI. Model

In this web service, the deep learning models are used in detecting and mapping the brain tumor. For our objective, the MRI scan dataset was obtained from the Kaggle source. The dataset consists of an MRI Scan image of the patient in TIFF format used to store the graphical image on a desktop and a spreadsheet containing the MRI image directories. The reason behind the availability of image directories in the spreadsheet is that the MRI scan image size is huge. It is nearly impossible to store the image's contents in an integer format in a spreadsheet. The spreadsheet consists of patient id, image path, and mask path. In this dataset, we have nearly 4000 MRI scan images. Before training the model, we split the dataset into three sections with a ratio of 70:15:15. This ratio is corresponding to the training data, validation data, and test data, respectively.

### A. *Model Pipeline*

The model pipeline diagram is given below.

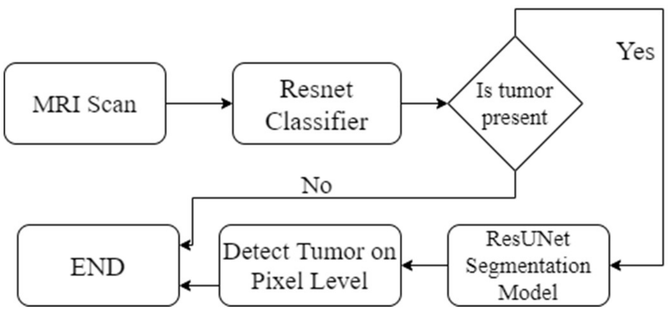


Fig. 1. Model Pipeline

As we can see, the input of the model pipeline is the MRI scan image. Then the image is preprocessed and given as input to the Resnet Image Classifier to detect whether the tumor is present or not. If the classifier is positive, then the image is given as input to the ResUNet image segmentation model is to localize the tumor from the image. If the classifier gave negative output (i.e., not a tumor), then the probability result obtained from the model is sent to the web service's front-end as mentioned.

### B. *Resnet Classifer*

As mentioned above, the first phase of the pipeline is a classification model. First, the input image is preprocessed by normalizing the pixel between 0 to 1. This step is necessary to smooth the gradient descent. The problem addressed here is the binary image classification. As mentioned earlier, the Resnet model is used to obtain the image features and send them to a full-connected neural network to classify the image to detect the tumor is present or not. Since it is a binary classification model, the output layer contains the two nodes and softmax as its activation function. The hidden layer uses as a Relu activation function, which is generally preferred for image classification problems. The resnet classification model provides us the probability value of where the tumor is present or not.

The performance analysis of the resnet model is given below.

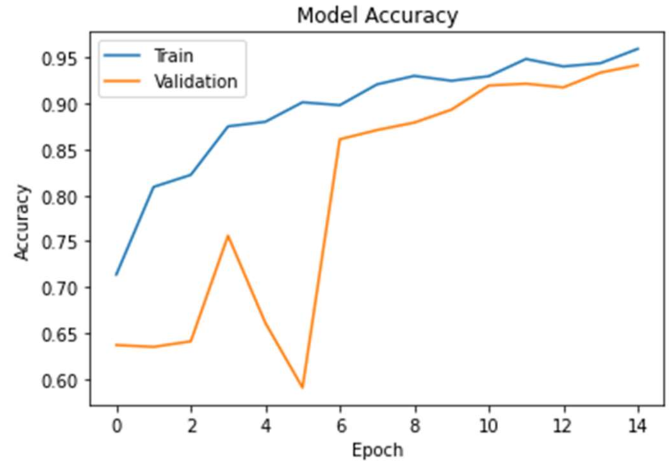


Fig. 2. Resnet Model's Accuracy graph.

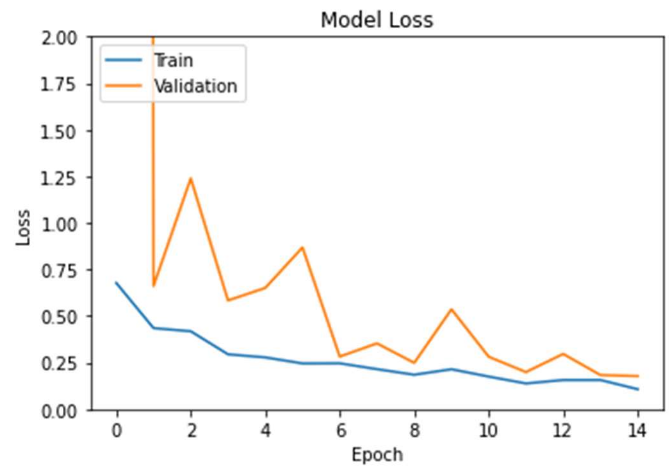


Fig. 3. Resnet Model's loss graph

From the observation obtained from the model's accuracy graph, we can say the validation data accuracy is above 90 percent when the training data accuracy is 95 percent. As the number of epochs increases, the performance of the model will also be increased. The validation data's loss is dropped quickly in one epoch from the model's loss graph. From this observation, we can say that the resnet model's performance as an image classification yields high accuracy for detecting the brain tumor.

The observation of this model with the test data is given below.

TABLE 1. Confusion Matrix

| | | Actual Prediction | |
|---|---|---|---|
| | | Tumor | Not a Tumor |
| System Prediction | Tumor | 383 | 2 |
| | Not a Tumor | 7 | 198 |

TABLE 2. Classification Report

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Tumor | 0.98 | 0.99 | 0.99 | 385 |
| Not a Tumor | 0.99 | 0.97 | 0.98 | 205 |
| | | | | |
| Accuracy | | | 0.98 | 590 |
| Macro Avg | 0.99 | 0.98 | 0.98 | 590 |
| Weighted Avg | 0.98 | 0.98 | 0.98 | 590 |

While evaluating the trained classification model using the test data, we observed that the accuracy of the model is 98.5%.

### *C. ResUnet Segmentation Model*

The second phase of the model pipeline is image segmentation. Before the segmentation, the model will decide whether to perform the segmentation or not. If the resnet model detects if the tumor is present, then the segmentation operation is performed. As mentioned earlier, the Unet architecture is based on the fully connected network, and it is modified in a way similar to an autoencoder. Instead of producing the same input image in the output layer, it will produce the brain tumor's mapping.

The segmentation model's input will be the preprocessed tumor detected MRI scan image. As mentioned before, the spreadsheet contains the path of a mask image. First, filter all the actual tumor present scan images and split them as before. This problem is similar to the regression problem. The metric used to train the model is a loss. But we need a custom loss function. Here we are using a focal tversky loss design from this paper [4] for better performance.

The output layer dimension will be the same as the input layer. The image segmentation must be treated as pixel-level classification. The output layer, which has a value greater than 0, will be treated as a tumor at a pixel level. The value 0 represents black in the image. After obtaining the tumor location in the MRI scan image, replace the located pixel on an original image with a bright color like red. The process is shown in below figure.

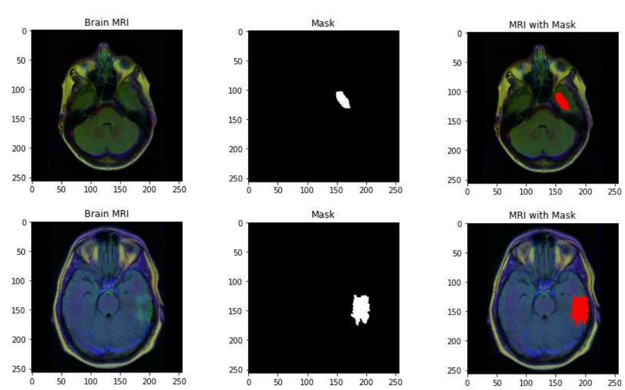


Fig. 4. Mapping the tumor in pixel level

## VII. Conclusion

From the observation obtained from the model, we can conclude that the accuracy of the brain tumor detection model is high, and the localization of the tumor can be obtained from the image segmentation model. Based on that, the web service we provide will enhance the lives of humankind.

## VIII. Future Work

In the future, this web service can be improved by increasing the input MRI scan image. More medical details other than the MRI scan can improve the accuracy of the service. Even though it is hard to interpret the deep learning black-box model, we can increase the trust of the medical practitioner by introducing explainable artificial intelligence to explain why the model predicts the tumor is present. The explainable ai domain is vast. It can be used for any number of machine learning problems. The best explainable technique for this model is Gradient-weighted Class Activation Mapping (Grad CAM). It allows us to understand how each class or target label is related to the hidden layers of the model.

## REFERENCES


[1] *Azhari, Ed-Edily Mohd, et al. "Brain tumor detection and localization in magnetic resonance imaging." International Journal of Information Technology Convergence and services 4.1 (2014))*

[2] Arunachalam, Murugan, and Sabeenian Royappan Savarimuthu. *"An efficient and automatic glioblastoma brain tumor detection using shift-invariant shearlet transform and neural networks." International Journal of Imaging Systems and Technology 27.3 (2017)*

[3] He, .Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016

[4] Abraham, Nabila, and Naimul Mefraz Khan. "A novel focal tversky loss function with improved attention u-net for lesion segmentation." *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE, 2019.

[5] *Z. Liu, R. Feng, L. Wang, Y. Zhong, and L. Cao, "D-Resunet: Resunet and Dilated Convolution for High-Resolution Satellite Imagery Road Extraction," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 2019, pp. 3927-3930, DOI: 10.1109/IGARSS.2019.8898392*

[6] Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." *Proceedings of the IEEE international conference on computer vision*. 2017