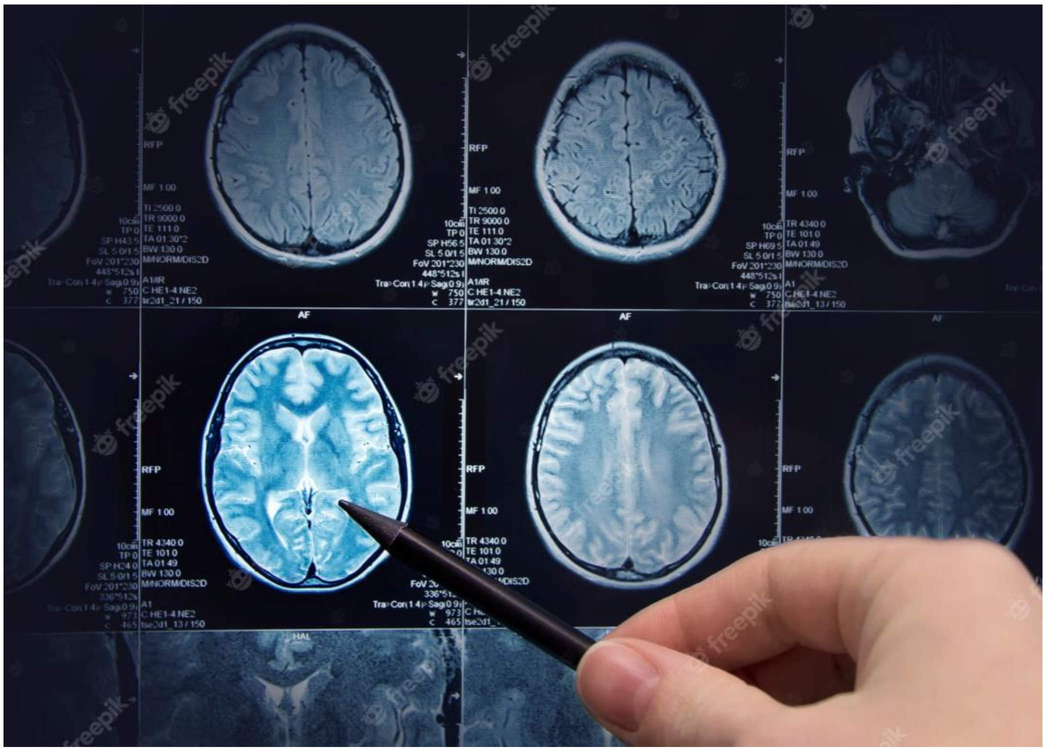
INTRACRANIAL HEMORRHAGE DETECTION



Introduction

A critical medical disease that needs immediate attention is intracranial hemorrhage, or bleeding inside the skull. It can come from a stroke, severe brain injury, or other medical disorders and is potentially fatal if addressed. For diagnosis and treatment planning, it is essential to be able to precisely identify and segment cerebral bleeding from medical imaging.

The ability for doctors to see the inside organs of the body without having to perform intrusive operations has transformed how we diagnose and treat medical disorders. In order to separate particular structures or regions of interest, binary segmentation is a frequent technique in medical imaging. Binary segmentation can be used to pinpoint the location of intracranial bleeding in the case of hemorrhage, which can help with diagnosis and treatment formulation.

In this article, we'll look at the problem of cerebral hemorrhage binary segmentation, the methods that have been utilized to solve it, and the prospective uses of this technology in healthcare in the future.

Background:

Medical imaging is the practice of using a variety of methods to produce images of internal organs and other body parts. Medical disorders can be identified, treatments can be planned, and illness development can be tracked using these images. X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are a few examples of common medical imaging methods.

The capacity to isolate certain structures or regions of interest within the images presents one of the challenges of medical imaging. Binary segmentation can be used in this situation. By isolating them from the backdrop, the process of binary segmentation can isolate particular structures or areas of interest within an image. Each pixel in the image is given a binary value (1 or 0), based on whether or not it is a part of the structure of interest.

Binary segmentation can be used to separate the location of cerebral bleeding from the surrounding brain tissue in cases of intracranial hemorrhage. This can help with the determination of the kind and extent of the bleeding as well as the formulation of the most suitable treatment plans.

The ability to isolate and analyze particular features or regions of interest within an image without being deterred by the backdrop makes binary segmentation a helpful approach in medical imaging. Additionally, it can aid in reducing the time and effort needed to examine medical images, which can be crucial in urgent cases like cerebral bleeding.

The challenge of intracranial hemorrhage binary segmentation:

Although binary segmentation is an effective method for medical imaging, detecting and segmenting cerebral hemorrhages can be difficult. This is due to a number of factors:

The appearance of hemorrhages can vary: Depending on where they are, how large they are, and other criteria, hemorrhages can appear in a variety of ways. It is challenging to create a one-size-fits-all strategy for cerebral bleeding detection and segmentation because of this diversity. Different segmentation methods may be needed for various hemorrhages, including intraparenchymal hemorrhages and subarachnoid hemorrhages.

Need for precise localization: Accurate localization of the site of bleeding within the skull is necessary in addition to the detection of hemorrhage. To accomplish this, the bleeding area must be precisely segmented and distinguished from nearby structures. However, this can be problematic since there are other structures nearby, such as blood arteries and bone, which might be tricky to remove from the area of the hemorrhage.

Image quality variations: The accuracy of binary segmentation is highly dependent on the caliber of the medical images. Finding comparable results across several imaging modalities can be difficult since variables like motion artifacts, noise, and picture resolution can all affect segmentation accuracy.

Despite these difficulties, binary segmentation approaches have significantly improved the identification and segmentation of cerebral bleeding. Machine learning algorithms and deep learning models are two techniques that researchers have developed to increase the precision and speed of cerebral hemorrhage segmentation. Large datasets of annotated medical pictures are frequently used in these methods to train the models and boost performance.

Approach

Intracranial hemorrhage (ICH) binary segmentation is an important task in medical imaging analysis that aims to accurately identify the presence or absence of hemorrhage in brain images. There are several approaches that have been used to address this challenge, including traditional machine learning algorithms, deep learning models, or a combination of both.

Data Gathering and Description:

To detect the presence of blood in the brain, a process known as intracranial hemorrhage binary segmentation is used. A collection of 82 patients' head CT images (jpg format) was gathered from Kaggle for this investigation, including approximately 30 image slices per patient. Both hemorrhagic and non-hemorrhagic pictures, as well as the corresponding masks, were included in the collection for hemorrhagic images. The goal of this data collection was to gather a diverse dataset of images for the segmentation model's training. There are 2183 normal images and 318 hemorrhagic images with 318 masks with image sizes 650x650.

Data Preprocessing:

The images were preprocessed by resizing and reshaping the images to 160x160x1 and normalizing the images by dividing them by 255. To balance the data, we utilize offline data augmentation techniques rotation (5), horizontal flip, and zoom (0.1) to get the same number of images normal and hemorrhagic, and in order to label normal images we just created black images and then concatenated all images in the same order as their masks in X and y we applied histogram equalizer and contrast stretching(range2~98) in order to help model, learn better and now the data are ready for training. The dataset was divided into train and test data with an 80/20 split, and the train data was further divided into train and validation data with an 80/20. we prepared a data generator for image segmentation by augmenting the training data with random transformations using online data augmentation. The fit () method is used to compute statistics of the augmentation process, and the flow () method generates augmented images and mask data in batches. The zip () function combines the two generators into a single generator that will be used to train the segmentation model with the fit generator() method. The batch-size and seed parameters are used to specify the number of samples in each batch and ensure the same random transformations are applied to the corresponding image and mask pairs.

Modeling and Evaluation:

This first model defines a U-Net architecture consisting of 4 levels of convolutional layers followed by max-pooling layers in the contracting path, and 4 levels of upsampling followed by convolutional layers in the expanding path. The output layer is a single-channel convolutional layer with a sigmoid activation function. It was trained using binary cross-entropy loss function and Adam as an optimizer with a learning rate of 10^{-5} and early stop with model checkpoint as callbacks to save the model and prevent overfitting.

The model has a high AUC (Area Under the ROC Curve) score of 0.94, indicating good overall performance. However, the IoU(Intersection over Union) score is low at 0.32, suggesting the model struggles with accurately segmenting the object of interest. The confusion matrix shows a large number of true negatives and a relatively small number of false positives, but a relatively high number of false negatives. The classification report indicates that the model has high precision and recall for the negative class (0), but lower precision and recall for the positive class (1). The weighted F1 score is high at 0.99 for the negative class, indicating good performance, but the lower F1 score for the positive class suggests the model could benefit from further improvement in its ability to correctly identify the object of interest.

The second model defines an architecture consisting of two branches: Branch 1 and Branch 2. Branch 1 applies multiple convolution and pooling layers to the input image to extract features, while Branch 2 performs a similar set of operations on the input. The outputs of Branch 1 and Branch 2 are combined using concatenation and then passed through multiple transposed convolution layers to perform up sampling. The final output of the network is passed through a sigmoid activation function to obtain a binary segmentation mask. We trained the model with the same as u-net with the default Adam optimizer.

The model has achieved higher AUC and IoU scores of 0.98 and 0.56, respectively. The confusion matrix shows a small number of false positives and false negatives. The classification report indicates that the model has high precision and recall for both classes, with an overall accuracy of 0.9978. The macro avg F1-score and weighted avg F1-score are 0.92 and 1.00, respectively, indicating good overall performance of the model.

Conclusion: Intracranial hemorrhage binary segmentation can be a valuable tool in clinical settings for identifying the presence of blood in the brain and improving patient outcomes. The success of the U-Net and custom architectures in this study demonstrates the potential of machine learning techniques for accurate and efficient segmentation of medical images.

However, further research is needed to evaluate the effectiveness of these models in larger datasets and in different clinical settings.

Deployment

Deploying a Deep Learning model for Hemorrhage Segmentation requires multiple components to work together. The project uses Flask, a popular Python web framework, to create a user-friendly web application that allows medical professionals to quickly and accurately diagnose hemorrhages in medical CT images. The project includes app.py, the main file that executes the Flask application, and model.py, which contains the Deep Learning model that uses the customized U-Net architecture to segment hemorrhages in the uploaded image. Finally, weights.h5 file which contains the latest weights for the custom architecture to directly make segmentations. Once the image is uploaded app.py file calls a function from model.py file which preprocesses the image and runs it through the model, it sends the result back to app.py, which displays the image with the segmented hemorrhages on the web using Flask and, HTML, JavaScript, CSS and Python scripts are used to enhance the user experience, and deployed on render.

Future Directions:

There are several potential future directions for further research and development in the area of intracranial hemorrhage binary segmentation:

Larger and more diverse datasets: While the current dataset used in this study is a good starting point, larger and more diverse datasets could help improve the performance of the model. This could include incorporating data from multiple hospitals, as well as incorporating images from different types of scanners.

Improving preprocessing techniques: While the current study used several offline data augmentation methods, there may be other techniques that could further improve the performance of the model. For example, using online data augmentation techniques during training could help the model better generalize to new data.

Exploring different architectures: While the U-Net and custom architectures used in this study were effective, there may be other architectures that could perform even better. For example, newer architectures such as EfficientNet or ResNet could be explored.

Clinical implementation: While this study showed promising results, further research is needed to determine the clinical impact of using intracranial hemorrhage binary segmentation in practice. This could include evaluating the model's performance on a larger scale, as well as conducting studies to determine how the model could be integrated into clinical workflows.

Extension to other medical applications: Intracranial hemorrhage binary segmentation is just one application of medical image segmentation. There may be other medical conditions that could benefit from similar approaches, such as lung cancer or breast cancer detection. Further research could explore the potential of using similar techniques for these applications.