Quality Evaluation of Skull Stripped Brain MRI Images

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Abstract

Since the 1980s, neurologists and neuroscientists have widely used brain MRI imaging to diagnose diseases and study the human brain. Different imaging modalities or sequences, such as T1-weighted (T1W) images, T2-weighted (T2W) images, and Diffusion-weighted images (DWI), can produce various kinds of brain MRI images. To promote collaboration and knowledge dissemination in neuroimaging research, more and more researchers are sharing neuroimaging data in open access data repositories. To ensure compliance with the Health Insurance Portability and Accountability Act (HIPAA), researchers often use skull-stripping tools to eliminate the image voxels representing the skull structure and facial features from the raw 3D MRI images before sharing the data.Skull stripping is an initial segmentation process that extracts brain tissues from a raw 3D MRI image of the brain, and various tools and algorithms have been proposed to perform this task. Although various algorithms and tools have been proposed to perform skull stripping for brain image segmentation, this task remains a challenging and labor-intensive process, even for expert radiologists. The accuracy of the segmentation results varies significantly among individuals, and there is no guarantee that facial features will be entirely removed from the processed images or that the voxels representing actual brain tissues will not be mistakenly removed. Due to the potential inaccuracies in the segmentation process, researchers must devote significant time and effort to inspect the quality of the segmentation results carefully.

Keywords: deep neural networks, CNN,

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1 Problem Statement

To protect patient privacy and comply with ethical guidelines, researchers commonly employ skull-stripping techniques to extract only the relevant brain image voxels and remove any data related to the skull structure and facial features from the raw 3D MRI images prior to data sharing. One objective of skull-stripping in MRI imaging is to ensure that facial features are removed to a degree that would prevent identification of the individual based on the remaining features in the stripped image. Additionally, it is important to assess whether any unintended removal of brain voxels occurred during the skull-stripping process, as this could result in the loss of crucial brain information.

1.1 Related Work

To prepare for this study, we conducted a literature review and consulted multiple research papers. Our primary focus was on the use of Deep Neural Networks for classification tasks. The quality of skull stripping can be affected by several reasons, including imaging artifacts, MRI scanners, and acquisition protocol, etc [2]. Over time, various methods have been developed for removing the skull from brain images. These include classical approaches, manual skull stripping, and deep learning-based techniques. Classical approaches are based on mathematical algorithms, while manual skull stripping involves the manual removal of skull regions from images. Deep learning-based approaches rely on the use of neural networks to automatically learn how to perform skull stripping. By considering the strengths and weaknesses of these different methods, researchers can choose the most appropriate approach for their specific needs. Skull stripping performed manually can be quite arduous due to various factors such as low image contrast, unclear boundaries of the brain in MRI scans, and the lack of intensity standardization. Additionally, it becomes even more challenging when dealing with brain MRI datasets that have varying acquisition parameters. In general, deep learning-based skull stripping approaches are divided into two distinct groups: 2D skull-stripping methods and 3D skull-stripping methods. Although 3D skull-stripping is thought to produce better results because contextual information between adjacent slices can be additionally used, it is computationally very expensive, so 2D skull-stripping has been more commonly adopted than the 3D method [3].

1.2 About Deep Neural Networks

Deep neural networks have become a powerful tool for image classification tasks in recent years.Deep Neural Networks have gained more and more popularity in the recent past because they achieve state-of-the-art performance for many applications [1]. These networks consist of multiple layers of interconnected nodes, which can learn to identify patterns and features within an image by processing large amounts of training data. Deep neural networks have been shown to achieve state-of-the-art performance on many image classification tasks, including object recognition and facial recognition. They are also widely used in applications such as autonomous vehicles, medical image analysis, and natural language processing. Before the rise of deep neural networks, traditional machine learning algorithms were widely used for image classification tasks. These algorithms typically involve a series of hand-crafted features extracted from the images, which are then used to train a classification model.One popular approach to feature extraction is to use a method called Histogram of Oriented Gradients (HOG), which calculates the distribution of gradient orientations in an image. Another common method is to use Scale-Invariant Feature Transform (SIFT), which identifies key points in an image that are invariant to scaling, rotation, and translation.Once the features are extracted, a classification algorithm such as Support Vector Machine (SVM) or Random Forest can be trained on the feature set to classify the images into different categories. These algorithms have been shown to be effective for many image classification tasks, such as face recognition and object recognition. However, the effectiveness of traditional machine learning algorithms is limited by the quality of the hand-crafted features used for classification. The manual feature extraction process is time-consuming and often requires domain expertise, making it difficult to apply to new types of images or tasks. Presently, there are several neural networks used for classification. Convolutional neural network (CNN) is a type of deep neural network is commonly used for image classification and other computer vision tasks. Recurrent Neural Network (RNN) is a type of deep neural network that is designed to handle sequential data, such as time- series data or natural language text. Generative Adversarial Network (GAN): is a type of neural network that is used for unsupervised learning tasks, such as image generation or image-to-image translation, Style transfer, Anomaly detection and more. CNNs has overcome other neural networks for image classification tasks .CNN is a type of deep neural network that is commonly used for image classification. CNNs are specifically designed to capture spatial relationships and patterns within input data, such as images, by exploiting the local correlation between neighboring data points. CNNs consists of multiple convolutional and pooling layers, with each layer learning increasingly complex features from the input data. The output of the final convolutional layer is typically flattened and passed through one or more fully connected layers. The final layer of the network typically uses a SoftMax activation function to produce a probability distribution over the possible output classes. Advantages of CNN over other neural networks are that they can efficiently extract spatial features and patterns in the data and can learn hierarchical representations of objects or patterns in the data. CNN can process their input data in parallel, as parallel processing is helpful in real time over sequential processing. CNNs can detect and recognize features in different locations within an image, regardless of their position or orientation. This property is known as translation invariance. 3D Convolutional Neural Networks (CNNs) have shown promising results in skull stripping tasks due to their ability to capture the spatial information present in 3D brain MRI images. 3D CNNs can analyze the entire 3D image volume simultaneously, which can help in preserving the continuity of the brain's edges and contours. This feature of 3D CNNs makes them suitable for handling complex and irregularly shaped brain structures, such as those seen in pathological cases. Additionally, 3D CNNs can also learn to identify subtle variations in intensity and texture that may be indicative of brain regions, thus making them effective for brain extraction even in cases with low contrast.

2 Dataset

The dataset provided contains 2,060 MRI scans of skulls with brain images.

- Containing personally identifiable information without any loss of brain features.
- Not containing personally identifiable information but with a loss of brain features.
- Not containing personally identifiable information with no loss of brain features.
- Personally, containing information and containing loss of brain features.

These scans have been categorized into four groups based on the presence or absence of personally identifiable information and the loss of brain features. The images in the dataset have dimensions of 256x256 pixels and varying depths, with the maximum depth being 150. The dataset is provided in a compressed .nii file format, which is commonly used for storing MRI scans. Each file in the dataset has been labeled in a separate CSV file.

3 Implementation

To create our dataset and model, we chose to use two widely-used open-source libraries in the field of machine learning: Keras and Tensorflow. These libraries provide a powerful and flexible framework for developing deep learning models.To extract data from the compressed .nii files in our dataset, we employed the nibabel python library. This library provides a simple and efficient way to read and write data in the NIfTI-1 file format, which is commonly used in neuroimaging research. By using this library, we were able to extract the MRI scan data quickly and easily from each file in our dataset.In addition, we utilized the matplotlib library to generate charts and images that helped us to visualize the data and results obtained from our script. We used these tools to explore and analyze our data, and to create visualizations of our model's performance.Overall, by using these powerful and widely-used libraries, we were able to develop a robust and effective deep learning model for analyzing our MRI scan dataset. Through careful analysis of our data and results, we were able to gain valuable insights into the characteristics of the scans and the performance of our model.

4 Data Preprocessing

Before building our model, we needed to construct a dataset by splitting the brain MRI scans into training and testing sets. We chose to use an 80/20 split, with 80 percent of the scans being used for training and the remaining 20 percent for testing. To ensure that the label file names matched the corresponding data being read in, we created an array of images that were paired with a corresponding array of class labels. The class labels were assigned integer values of 0, 1, 2, and 3 to represent the four categories discussed above. Initially, we attempted to use the full image size and depth for the model. However, we quickly realized that this was not feasible as TensorFlow was unable to handle the size of the model with a sufficient batch size. We needed to reduce the input size while maintaining a high quality of data to achieve high accuracies. To accomplish this, we explored various filtering methods and techniques. After much experimentation and analysis, we decided to reduce each 2D image to a size of 128x128 pixels and to include 75 of these 2D scans to form a 3D image. This approach allowed us to use a stronger model with a stronger batch size while maintaining a high quality of inputted data. Reducing the input size allowed us to use a deeper architecture with a higher number of trainable parameters, which ultimately resulted in better performance. With a smaller input size, we were able to use a larger batch size, which increased the number of samples processed per epoch and allowed for faster training times. Additionally, reducing the input size reduced the number of computations required, which improved the computational efficiency of our model.

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