BRAIN MRI ANALYSIS AND SEGMENTATION USING 2D-UNET ARCHITECTURE

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Abstract:
Deep Neural Networks have demonstrated amazingly positive execution in the field of computer vision issues - object acknowledgment, discovery, and division. These techniques have been used in the clinical picture examination area. Convolutional neural systems (CNNs), a remarkable part of profound learning applications to visual purposes, have earned significant consideration in the most recent years because of its advanced exhibitions in computer vision applications. They have accomplished tremendous growth in the areas of object acknowledgment, recognition and division challenges. Our attention is on models being utilized, information pre-handling and readiness and fittingly preparing the subsequent information or picture. The U – Nets are a very powerful CNNs which has accuracy near to humans. We have created and exploited this CNN architecture, U-Net and have done image segmentation for the brain Magnetic Resonance Images (MRI). The aim of our work is to fundamentally concentrate on the pre-processing of the MRI images, perform Skull Stripping using Deep CNN architecture U-Net and to perform image segmentation.
Keywords: Convolution Neural Network (CNN), Magnetic Resonance Imaging (MRI), Skull Stripping,

1. Introduction

The advancement in recent medical science is mainly due to the most advanced imaging techniques, which is used as an effective and efficient tool in diagnostics, treatment and in therapy. The advancement in the fields of artificial intelligence, machine learning, deep learning and computer vision has given enormous opportunities for building intelligent decision support system with increased accuracy, much reduced errors automated diagnosis and discovering new knowledge about the disease and its treatment. Processing of image data and predicting the abnormalities using the artificial intelligence of the computers has enhanced and improved the diagnostic confidence and the accuracy of image analysis process.

Image segmentation is one of the major process in medical image processing, which helps in segmenting the image into different portions and analyse in more detail pathologically with different accuracies and complexities. Over the decade various segmentation algorithms have been proposed and used on brain images. Rapid progresses have been made in exploring the brain anatomy with the help of magnetic resonance images (MRI). Computerized methods for MRI image segmentation, registration, and visualization have been extensively used to assist doctors in qualitative diagnosis. Brain MRI image segmentation is a very complex and difficult process as the brain tissues consists of many inconsistencies and abnormal tissues such as tumours. Artificial Intelligence makes the analysis of brain imaging less hassle and handy for handling large volumes of data. Neural data is much inconsistent, terribly complicated and has many different signals. Machine learning and deep learning algorithms have been extensively used to explore the brain image processing, diagnosis, treatment and classification of different strokes and tumours. Thus, Artificial Intelligence with its tremendous growth bridges the gap between the human capability and the computers.

Machine learning a subset of artificial intelligence was used in brain imaging in the previous years, now with the deep learning algorithms which have a higher capacity to learn than the machine learning algorithms, manages to improve the resolution and quality of the images. Machine learning's main strength lies in recognizing patterns that might be too subtle or too buried in huge data sets. Traditional machine learning algorithms suffer from insufficient training data and also overfitting and underfitting problems. Due to the extensive variation from patient to patient data, traditional learning methods are not reliable. Machine learning has evolved over the last few years by its ability to shift through complex and big data. When the size of the dataset and the complexity of images increase, the machine learning pattern recognition algorithms may give a low performance. So, this necessitates us to move on to deep learning algorithms.

2. Deep Learning in Brain Imaging

Deep learning has a trend to develop automated analysis in image processing, which is a breakthrough in science and technology. Deep learning which is also a subset of machine learning uses artificial neural networks that resembles to the cognitive structure of human brain. Availability of faster computers, cheap and faster GPU's and the availability of huge datasets has given advantage for the deep learning era. A variety of methods for image generation and image enhancement using deep learning have recently been proposed, ranging from removing image artifacts, normalizing/harmonizing images, improving image quality, lowering radiation and contrast dose, and shortening the duration of imaging studies.

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The basic computational unit in a neural network is the neuron, a concept inspired by the study of the human brain, which takes multiple signals as inputs, combines them linearly using weights, and then passes the combined signals through nonlinear operations to generate output signals.

Convolution Neural Networks (CNN) are the foundations of modern state-of-the-art deep learning based computer vision. It is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing in a ConvNet is much easier than the classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. These networks can take the imput as 3D image and has neurons arranged in 3D and produces volumnous output in 3D. The neurons arranged are similar to the neuron arrangement in brain and has a visual cortex.

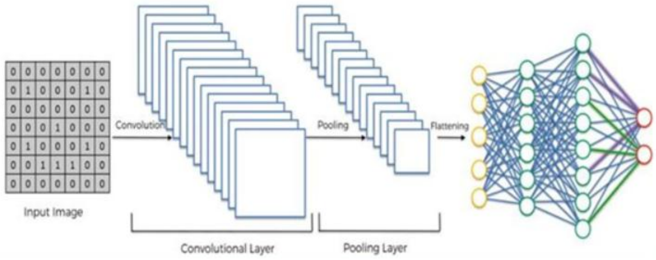

Fig 1 . Representation of Convolution Neural Network

The CNN s are being utilised in the field of medical image analysis. It is efficient in the process of segmentation, classification, object detection and recognition. The use of CNN s has grown in brain MRI image processing. The "fully-connectedness" of these networks makes them prone to overfitting data. Deep learning along with computer vision applications outperform human in identifying cancer in blood and tumours from MRI scans.

3. Objective

Despite there are too many algorithms and techniques for skull stripping and segmentation, still we have not found the best practice method due to the practical difficulties, low- contrast brain MRI images and absence of standardisation principles. We have proposed and implemented a 2D UNet architecture in CNNs which is a fully connected convolution network. This has a large number of feature channels in the up-sampling part, which allow the network to propagate context information to higher resolution layers. As a consequence, the expansive path is more or less symmetric to the contracting part, and yields a u-shaped architecture. It separates the objects and texture in an image which helps in tumour detection from MRI scan images. It helps in fast and precise segmentation of images.

4. Related Work

Brain MRI image analysis has traditionally been an important area of research involving tasks such as lesion detection and segmentation, tissue segmentation and brain parcellation on neonatal, infant and adult subjects. CNNs have given accuracy close to human performance for 2D images and are a powerful tool that extract hierarchy of features. Hence, we have advanced to use 3D CNNs on the biomedical analysis of data. Bharath Hariharan et al uses hyper columns at each pixel for vector activation of CNNs units above the pixel and performs fine grained localization task [1]. Jonathan Long et al proposed a Fully connected Convnet known as FCN for semantic segmentation. He says that the Convnets are built on translation invariance. Their basic components (convolution, pooling, and activation functions) operate on local input regions, and depend only on relative spatial coordinates [2]. Alex Krizhevsk et al proposed a 8 layered network in which five where convolution and three where fully-connected network with weights. This network maximized the multinomial logistic regression and reduced the problem of overfitting with million number of parameters. Thus, a deep CNN can give a best performance with supervised learning. But the network degraded in performance on removal of a single convolution layer [3]. Kleesiek et al. proposed an end-to-end 3D CNN approaches for 3D segmentation. But their network was not deep and has only one max-pooling after the first convolutions, so multiple scale structures where not analysed [4]. Milletari et al proposed a CNN model with Hough voting system. This network was not end-to-end, so it does not work for all types of structures [5].

4.2 Need For U-NET

Ozgun Cicek et al says that the U-Net architecture and the data augmentation of the u-net allows learning models with very good generalization performance from only few annotated samples. It properly applied rigid transformations and slight elastic deformations yielding biologically plausible images [6]. The U-Net architecture is built upon the Fully Convolutional and it gives better segmentation in medical imaging. The benefits of using U-Nets are that it is symmetric allowing the network many feature maps in the up-sampling path, which allows to transfer information. The skip connections between the down sampling path and the up-sampling path apply a concatenation operator instead of a sum. The skip connections intend to provide local information to the global information while up-sampling. The U-Net owes its name to its symmetric shape, which is different from other FCN variants [7]. U-Net is more successful than conventional models with its architecture and in terms pixel-based image segmentation formed from convolutional neural network layers and is more useful in the medical image analysis.

4.3 IMAGE SEGMENTATION

Simmons et al in his paper says that the inherent characteristics of the MRI acquisition process such as differences in the magnetic field, bandwidth filtering of the data or eddy currents driven by field gradients usually result in image artefacts that may also have a negative impact on the performance of the methods [8]. There is the need to remove spurious intensity variations caused by inhomogeneity of the magnetic fields and coils. In these cases, intensity correction of the MRI images is performed either before tissue segmentation, or as an integrated part of the tissue segmentation pipeline. A common technique to address this problem is to use bias-field correction [9]. Brain MRI datasets might have volumes acquired from different scanner vendors and from the same scanner but with different protocols. As a result, the volumes may exhibit non-uniform intensity representation for the same tissue types, i.e. intra class variability. To correct this problem, image normalisation algorithms are utilised. According to the literature, this intensity normalisation can be driven in two ways:

(i) Histogram matching
(ii) Normalise data to achieve zero mean and unit variance.

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In the former case, Urban et al. [10] and Kleesiek et al. [11] considered matching the histogram of all volumes to a subject in the training set, which may result in fused grey levels, while Pereira et al. [12] – based on the normalisation method proposed by Nyul et al. [10] – considered mapping to a virtual grey scale learnt directly from the data, so the undesired fusion of grey levels is avoided. Naturally, both normalisation strategies can be used one after the other one to improve the segmentation results. According to the results reported by Pereira et al. [13], the pre-processing step improved their result, obtaining a mean gain of 4.6%.

4.4 Pre-Processing Methods

The pre-processing plays a major role in the MRI brain image segmentation of brain and the steps in the pre-processing helps to detect various problems such as tissue volume analysis, brain mapping and analysis of anatomical structures and substructure of brain. The image quality and noise removal are the main aim for this pre-processing stage. In addition to the above discussed pre-processing methods, image registration between different MRI modalities is important depending on the dataset analysed. Image registration transforms different modalities of MRI into a common coordinate space. Many of them have applied image registration algorithms on their clinical trial dataset. For instance, Brosch et al. [14] applied a six degree-of-freedom intra-subject registration using one of the 3 mm scans as the target image to align the different modalities. Additionally, Kamnitsas et al. [15] applied affine atlas-based registration. Thus, we can see that the Deep CNN architectures are widely used for brain MRI for pre-processing data detecting and segmenting lesions and segmenting tumour whole tissue and sub-cortical structures.

4.5 SKULL STRIPPPING

Though there are many algorithms to perform skull stripping which is the process of removal of unwanted tissues other than the brain tissue from the MRI images, still we have not found the best solution to find the brain boundaries and have not found the standard way of organisation [16]. CNN-based algorithms are trained with known labelled data to learn the underlying mathematical description required for object or region detection, classification, and segmentation [17]. Generally, these algorithms require a vast amount of properly labelled data to train from scratch. However, biomedical image data is usually not sufficient for this challenge. Problems often worsen because labelling data requires a substantial manual effort from a brain anatomy expert to accomplish this tedious task [16]. So, we use a deep CNN architecture for skull stripping and for image segmentation tasks.

From the survey we understand that U-Net is convolution Neural Network that outperforms all other algorithms in the
process of image segmentation. In our work we have proposed a 2D U-Net architecture for performing skull stripping
and image segmentation.

5. About the Database

Data was collected from two sources, the Neurofeedback Skull-stripped (NFBS) and Simulated Brain Database (SBD). The Neurofeedback Skull-stripped (NFBS) storehouse is a database of 125 T1-weighted anatomical MRI checks that are physically skull-stripped. NFBS furnishes specialists with best quality level preparing and testing information for creating AI calculations. The store contains information from 125 members, 21 to 45 years of age, with an assortment of clinical and subclinical mental side effects. For every member, the storehouse contains:

- Basic T1-weighted anonymized (de-confronted) picture
- Skull-stripped picture
- Brain Mask

Simulated Brain Database (SBD) contains a lot of reasonable MRI information volumes created by an MRI test system. This information can be utilized by the neuroimaging network to assess the exhibition of different picture investigation techniques in a setting where the fact of the matter is known. The SBD contains mimicked cerebrum MRI information in three symmetrical perspectives (transversal, sagittal, and coronal), depending on two anatomical models: ordinary and different sclerosis (MS). For both of these, full 3-dimensional information volumes have been re-enacted utilizing three groupings (T1-, T2-, and proton-thickness (PD) weighted).

The images from both datasets were resized to matching dimensions of 128 x 128 x 1. The images are in 3 dimensions, but we sliced out the 2-dimensional images from the middle to work with due to memory limitations in hardware. Anti-aliasing was performed along with resizing of the images. The extra dimension was added to indicate there exists only a single channel in the image and fit into our convolutional neural network. Anisotropic diffusion filter was applied to remove noise. This technique reduces image noise without removing important parts of the image content such as edges, lines, and other details important to interpret an image. The images were then split into two sets for training and validation. The images were stacked into one array in NumPy format and stored as NPY files for easy retrieval in future.

6. Pre-processing

Pre-handling of images in MRI is a basic process in image diagnosis. For CNNs, providing the pre-processed data is a pivotal advantage in accomplishing great execution. The pre processing tasks are explained below.

6.1 Normalisation

Normalisation function is applied to the image. Since a neural network works better with values in range [0,1], the default min and max values are 0 and 1 in the functionality. We can also use z-score normalisation, but it doesn't help in better classification of the images. Normalisation of the image content does not affect the way the image will be interpreted and doesn't do any radical changes to the pixel details. It is to Scale down the range of the intensity values of pixels in an image. It also helps view an image in proper contrast.

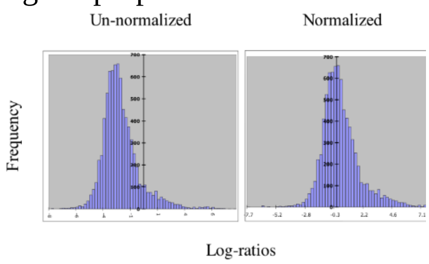

Fig 2: Intensity ranges

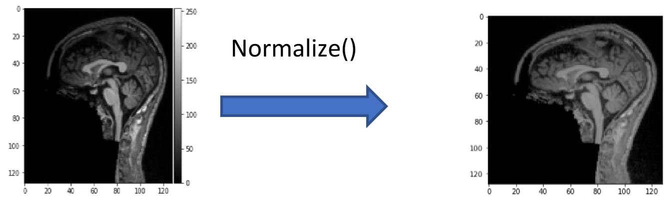

Fig 3: Normalization of an Image

6.2 Image Registration

Image registration helps to organise and put the different sets of data into one coordinate system. Medical imaging always makes use of this technique for image analysis. Registration helps in providing an order to compare data obtained from different sources and methods. The basis for image registration was homography. Homography is a simple 3x3 matrix which maps collineation between two images. Homography is calculated on planar images. Let's say (x1, y1) is a point in first image and (x2, y2) is a point in another image. Then the homography relates them in the following way:

$$\begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = H \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \cdot \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix}$$

If we know the homography, we can apply it to the pixels of an image to obtain a warped image that is aligned with another image. Homography is calculated using key-point detectors or feature points. They are all available in OpenCV – SIFT, SURF and ORB.

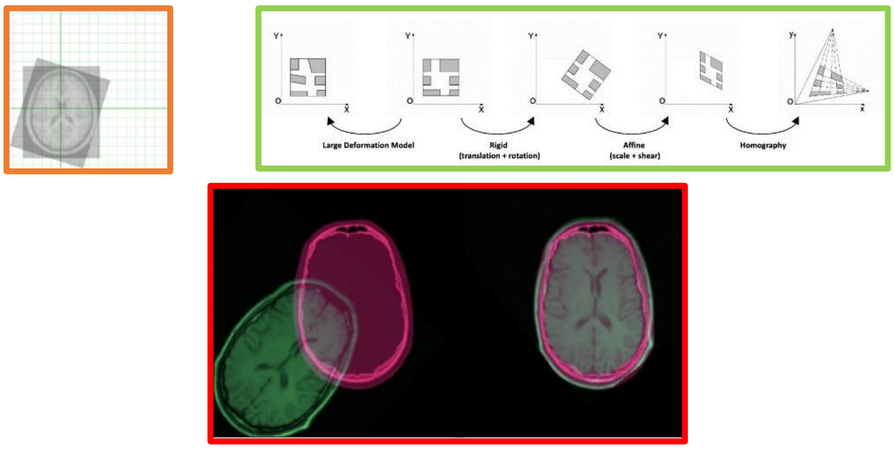

Fig 4: Image Registration Process

The basic steps in calculating homography is as follows: -

- Read the images
- Detect features in the two images (using ORB, SURF or SIFT). Set a MAX_FEATURES constant to limit number
  of features.
- Detect key features and compute descriptors.
- Find the matching features in using a measure of similarity. We used hamming distance measure.
- Calculate homography. It is important to have a minimum of 4 corresponding points between two images to calculate H
- After calculation of H, we can transform the image.

The image registration process is not necessary if we are making use of a FCN (Fully convolutional neural network), since a convolutional network gradually down samples an image and focuses more on the context rather than the location of the relevant features in an image. But proper alignment of images helps in creation of a good data that might be useful to other people.

6.3 Bias Field Correction

A bias field is a signal that would usually disrupt an old MRI scans with noise or certain interference values. N4 Bias Field Corrector algorithm from SimpleITK library has been implemented to remove such distortions if present.

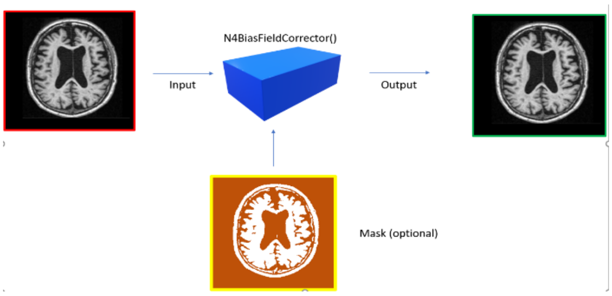

Fig 5: N4 Bias Field Correction Process

6.4 Skull Stripping

The way toward extricating the mind tissue from non-cerebrum one is alluded to in the writing as skull stripping.

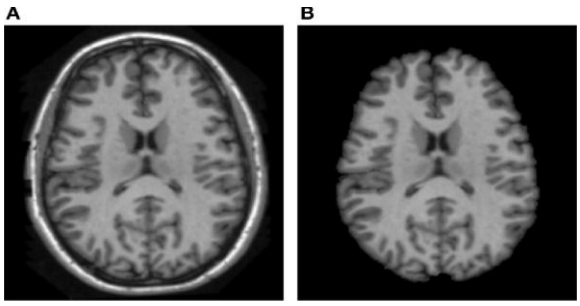

Fig 6: A. Original Image B.-Skull-stripped Image

We perform skull stripping and tissue segmentation using an FCN called as UNet..

7 CNN for Image Segmentation

UNet, developed from the customary convolutional neural system, was first planned, and applied in 2015 to process biomedical pictures. A general convolutional neural system concentrates its assignment on picture arrangement, where info is a picture and yield are in one name, yet in biomedical cases, it requires us not exclusively to recognize whether there is an illness, yet in addition to restrict the territory of variation from the norm. The reason it can localise and distinguish borders is by doing classification on every pixel, so the input and output share the same size.

7.1 UNet – Convolution Operation

A convolutional operation takes two inputs – A 3d volume (nin x nin x channels) and a set of 'k' filters (called as kernels) each with size (f x f x channels). A typical kernel is of size 3 x 3 x channels. The output of a convolutional operation is a 3d image of size (nout x nout x k).

The relation between n_{in} and n_{out} is given as: -

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{s} \right\rfloor + 1$$

n_{in}: number of input features

n_{out}: number of output features
k: convolution kernel size
p: convolution padding size
s: convolution stride size

The convolution operation helps find relevant features in the receptive field i.e. the area where the filter is looking at.

7.2 Max Pooling Operation

Max pooling operation helps reduce the size of the feature map so that we have fewer parameters in the network.

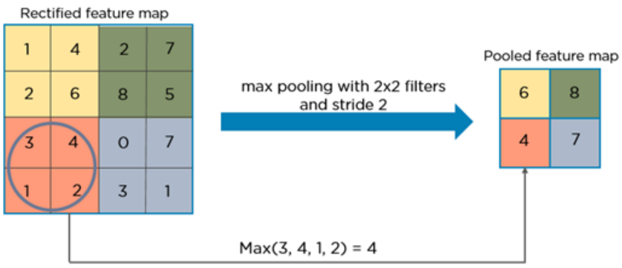

Fig 7: Max Pooling Operation

The idea behind max pooling operation is to retain only important features (max valued pixels) from each region and throw away irrelevant information. The information that best explains the context of the image will be retained. This operation, like convolutional operation, reduces the size of the image. Reduction of image size is known as down sampling. This basically means a high-resolution image is being converted to a low-resolution image. Both Max pooling and Convolutional operation down-sample a feature map of an image. By down sampling, the model better understands "WHAT" is present in the image, but it loses the information of "WHERE" it is present.

3.3 Deconvolution

As we have performed segmentation to perform skull stripping and tissue segmentation, we need a high-resolution image as an output with all our pixels classified. A regular convolutional network will lose all the information of the location of the information. Hence, we need to up-sample the image to obtain our high-res image. We make use of transposed convolution in UNet.

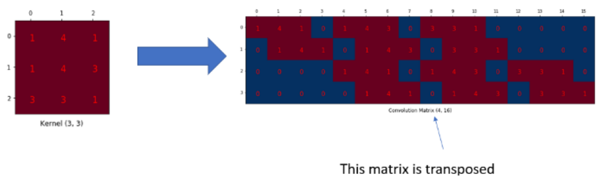

Fig 8: Deconvolution Operation

Deconvolution is the exact opposite of the normal convolution operation. The 3x3 kernel is rearranged into a 4x16 matrix.

8 Implementation Details

We created a 2-layer convolution UNet architecture, using the keras library. The image values ranged from 0 to 1 and the size was 128x128x1. Due to hardware limitations, we performed operations on 2D images instead of 3D images. The defined UNET architecture will be used to train several models for skull stripping and tissue segmentation.

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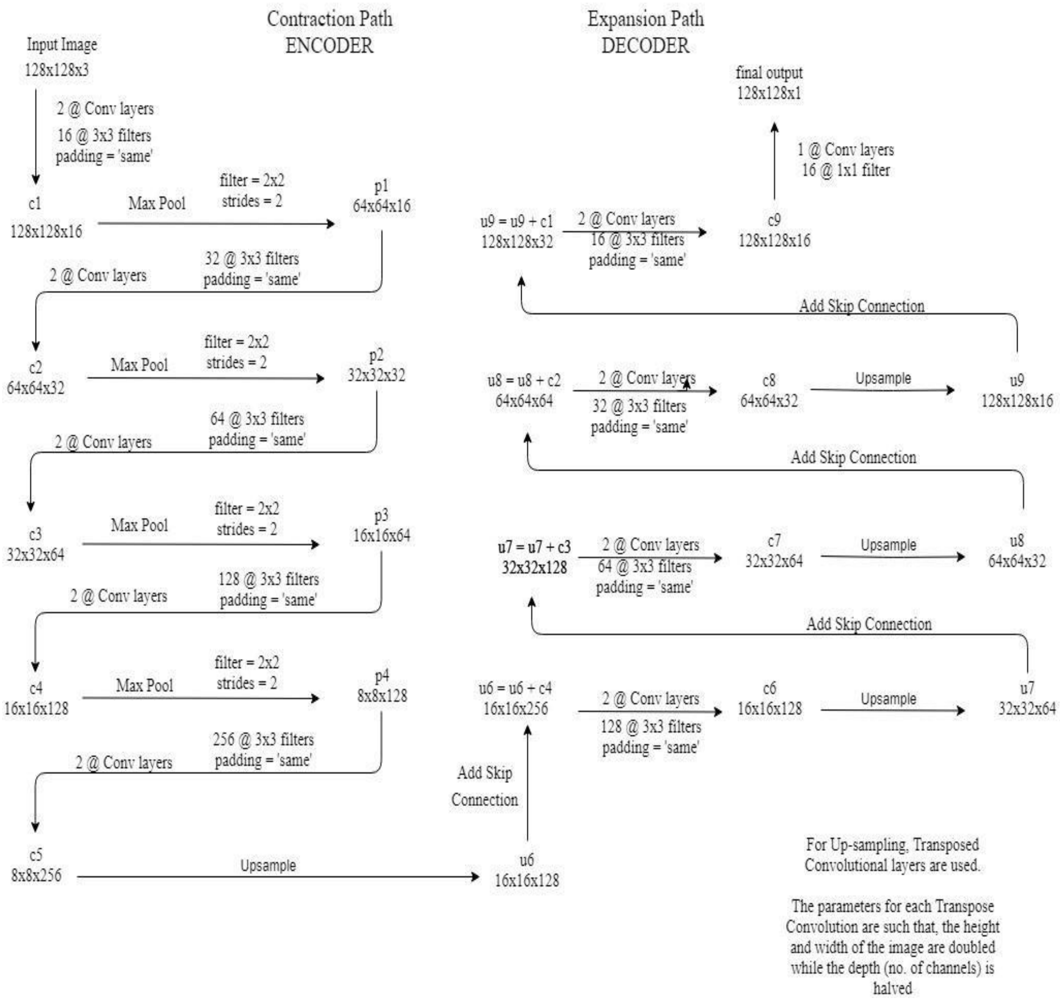

Fig 9: UNet convolution architecture

The model is trained over a batch of 87 NFSB image dataset with batches of 10 images going through with duration of 10 epochs for learning. The masks are labelled using statistical conventions of calculating lower bound using mean and standard deviation. For prediction the model is used to generate mask from a validation set. For tissue segmentation we extracted grey matter, white matter, and cerebrospinal fluid ground truth images. Generation of appropriate image masks was done. The model was trained with 10 images dataset of Brain web. All the best trained model weights were saved in an hdf5 file. The predicted masks are then applied to the image to extract the relevant tissues of the skull, grey and white matter from the image. The pipeline that was used in our implementation is given below.

Fig 10: Implementation Pipeline

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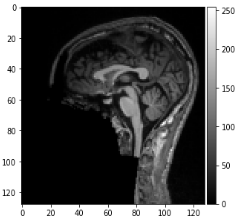
8. Implementation Steps with Results

8.1.1 Pre-Processing

A) Normalisation



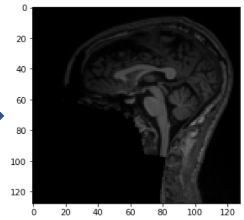
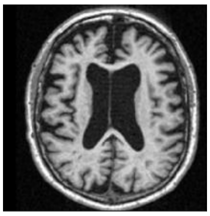
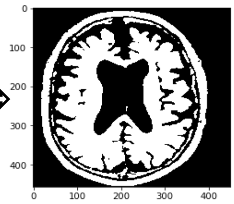


Fig 11 A Fig 11 B

Image in Fig 11 A with values in range [0,255] is normalized to Fig 11 B of range [0,1].

B) N4-Bias Field Correction





12A: Normal Image Fig 12B: Otsu
Threshold Mask

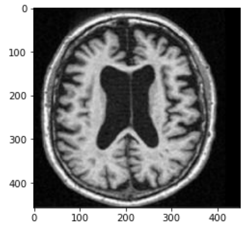
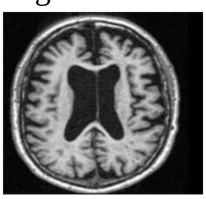


Fig12 C: Bias Field corrected Image

C) Image Registration

Using a reference/placeholder image to realign any distorted or misaligned dataset image according to the reference image using feature extraction methods. There are many algorithms for that we calculated using ORB features.



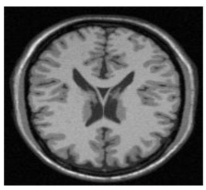


Fig13A: Image to be Fig13B: Alignment
Image
Registered

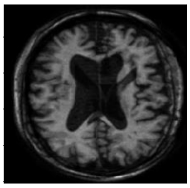


Fig13C: Aligned Image using Image Registration

D) Skull Stripping

This is a process of removing of the non-brain tissues and cranial bone off the image to improve the performance and speed of the model.

Fig 14 A: Sagittal View of the Brain

Fig 14 B: Ground Truth Sagittal Mask For reference

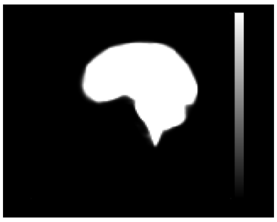


Fig 14 C: Model Predicted Mask

Fig 14D: Image after application of Mask with Skull Stripping with UNet

These are the pre-processing steps involved for all the images in the dataset.

8.2 Image Segmentation

We then performed the segmentation of grey and white matter with UNet Model. The process involves the following steps.

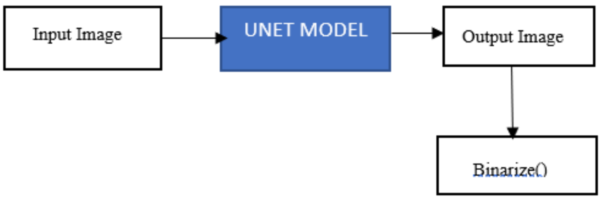


Fig 15: Processing with UNet

A) Grey Matter Segmentation

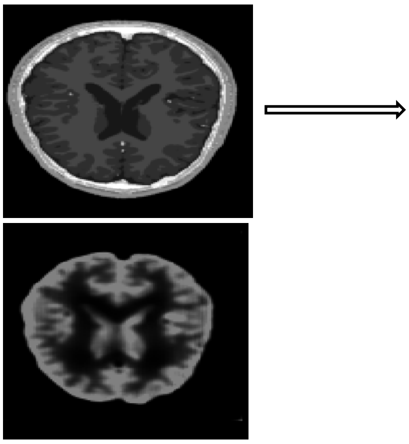


Fig 16A: Grey Matter Image
Image for Prediction

Fig 16B: Predict
with UNet

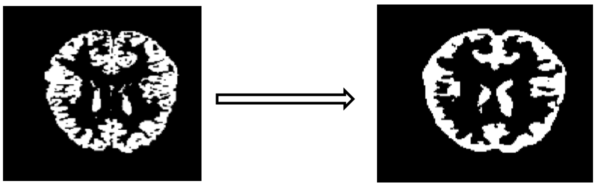


Fig 17A: Ground Truth Generated
Mask
Image

Fig 17B: Mask
from Predicted

B) White Matter Segmentation

UNet models trained to identify White matter and Cerebrospinal Fluid regions of the brain generate masks and then the binarized masks are put together to form the coloured segmented image.

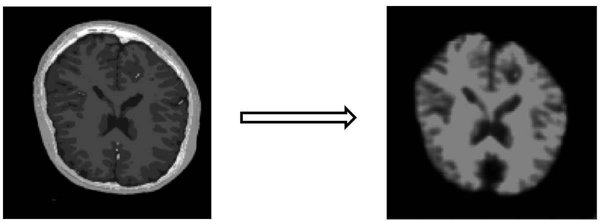


Fig 18A: Trained Image
Matter

Fig 18B: White
Predicted with UNet

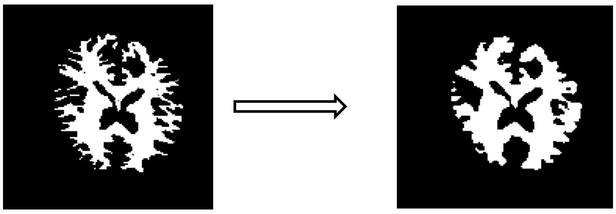


Fig19A: Ground Truth Fig 19B: Mask Generated
Mask from Pred
Image

C) Cerebrospinal Segmentation

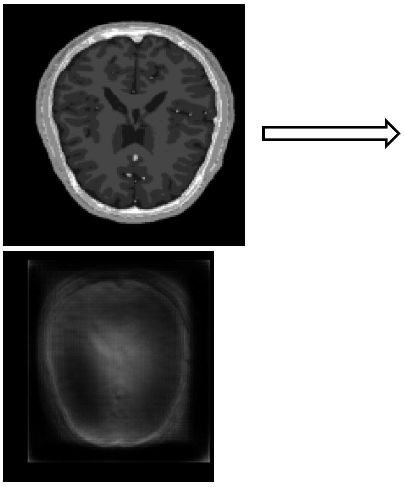


Fig 20A: Trained Image Fig20B: Predicted

Image

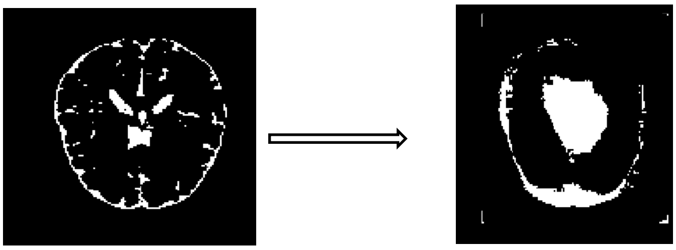
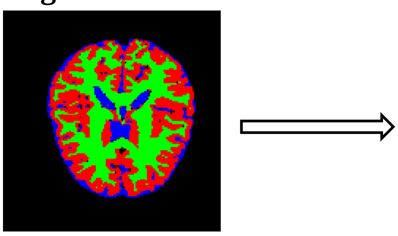


Fig 21A: Ground Truth Fig 21B: Mask Generated
Mask from
Predicted Image

D) RGB Segmented Images



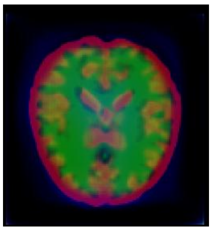


Fig 22A: Ground Truth Fig 22B : Mask
Generated
Mask From Predicted
Image

9 Benefits

UNet works with very few training samples and provides better performance for segmentation tasks. It learns from the examples provides sampling of images of different size. As there are large number of feature channels in the up-sampling part, it allows the network to propagate context information to higher resolution layers. Biomedical Segmentation and image analysis have become more accurate and reliable with the advancement of Deep CNNs. The full connected CNNs reduces human effort in pre-processing and they automatically learn from their inputs

10 Conclusion

Deep Convolution Neural Network shows a fully automated skull stripping process and shows a significant increase in accuracy in skull stripping and segmentation. The network has been constructed from the scratch and trained with the dataset obtained from NFBS. The UNet architecture which we have built and used has provided greater advantage in image segmentation as it takes into account multiple parameters. Thus, we have analysed our brain MRI dataset with this Fully Connected CNN architecture and have obtained good results.

11 Future Work

In our work, we have explored and used 2D U-net architecture for skull stripping and segmentation. As our future work we will expand our work with 3D-Unets and will increase the efficiency and accuracy. There are also many variants of this architecture available so we will try to enhance our work with other FCNNs and will compare the results with one another. Thus, these CNN architectures solve the problem of segmentation and tissue analysis in the field of bio medicine.

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