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DEEP LEARNING TECHNIQUES FOR SKULL STRIPPING OF BRAIN MR IMAGES

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Abstract- The subject matter: this article analyzes and designs a system based on deep learning to strip the human Skull into three views. The goal was to design a system that separates the Skull, keeps the brain based on MRI images, and allows the three sections to work in a 3D system. The tasks to be solved Skull stripping in three axes (axial, sagittal, and coronal) together to obtain a 3D image and test the system on other data that the system has not been trained on to ensure its efficiency in isolating the human Skull The methods used are: The proposed system used two stages for the work: the first is image processing based on deep learning technology by relying on the CLAHE filter to do equalization of the images, i.e., work on lightening the dark areas and darkening the light areas and using normalization. Moreover, the use of deep learning technology on a pre-trained model (EfficientNet-B0) for the training process and the use of hold-out methods to divide the data into training, testing, and evaluation. Moreover, to evaluate the work efficiency using the scale (dice coefficient) and the dataset using NFBS for training and testing and IBSR for only testing, the Results were obtained: The results obtained for the NFBS dataset from the training are (accuracy =98% and F1-score=98.4%) and from the test are (dice-score = 99.9%), and the results of the external test data set IBSR are (dice-score = 99.9%). Conclusions: The process of isolating the Skull is an essential step in diagnosing diseases of the human brain, and the image processing process is an essential step to prepare the data that will be trained on, as well as the strategy for transforming the efficient-b0 model's training into the structure of the u-net model in terms of in-depth training on a large variety of languages with good accuracy and testing processes. External data is used to assess whether a system is operating efficiently.

Keywords: Skull, Stripping, MRI, Deep Learning, Dataset, 3D.

1. INTRODUCTION

Brain extraction is the technique of extracting signals from tissues other than the brain from magnetic resonance imaging (MRI) data. This practice is also known as skull-stripping. This is a crucial part of many neuroimaging analysis pipelines and helps protect the identity of brain scan data. Skull removal accuracy facilitates subsequent neuroimaging analysis [1]. Brain tissue identification in structural magnetic resonance imaging (MRI) is impacted by the presence of the brain skull, which can lead to severe errors, especially in patients with brain tumors [2]. Traditional cranium stripping techniques are frequently adapted to images with specific acquisition characteristics, for instance, near-isotropic resolution and T1-weighted (T1w) MRI contrast, which are common in research settings [3]. However, existing techniques are not sufficiently adaptive to different image types, including stacks of thick slices obtained with fast spin-echo (FSE) MRI in clinical situations. Recently, Learning-based methods for extracting the brain have grown in popularity. However, they all have identical drawbacks: They are only useful for the kinds of images seen before throughout the training process. Perform reliable skull-stripping with a variety of imaging protocols [4]. Based on MRI images and deep learning, this paper proposes a system for cranium removal.

2. MEDICAL IMAGE

In separating the Skull, two types of medical images are being worked on, and the following is Table 1. showing the two types and explaining the differences between them.

3. RELATED WORK

In (2019) [8] In order to train a model utilizing a more manageable amount of data, it is important to first remove any tissue that is not brain-related from brain scans that were taken using magnetic resonance (MR) imaging. Compared to training on the reduced dataset, training on the entire dataset did not significantly improve. This suggests that there was no significant additional variability added to the supplementary data. As a result, we are of the opinion that additional progress can only be made by the incorporation of new data sourced from sources other than the NFBS dataset. Compared to the test and evaluation, the training procedure had a high success rate of 90%. In [9] introduced, a source-free adaptation method. Its success applied entirely to the skull-stripping task on multi-site age datasets without needing target domain annotations or simultaneous access to image inputs for both the source and target domains.

Table 1. Differences between CT and MR images [5] [6] [7]

CT	• Definition: Computed tomography (CT) is a computerized X-ray imaging technique that employs a fast-rotating, narrow beam of X-rays to create cross-sectional images, or "slices." Tomographic imaging provides more data than X-rays. The computer machine can "stack" multiple slices to generate a three-dimensional (3D) patient image, simplifying identifying essential components and potential cancers or anomalies. • Domain: Detection of Diseases like (COVID-19 and Sars) • Advantage and disadvantage: With a 15 to 20-minute analysis time and high-quality images. However, the need for radiation exposure and using a contrast material (dye) in most cases may make it inappropriate for patients with severe kidney disease.
MR	• Definition: MR image of a subject in a magnetic field tunnel. This aligns all body protons' quantum spins. The fluctuating magnetic field pulse disrupts this alignment. Electromagnetic waves are emitted when protons reach equilibrium. Images will vary depending on fat content, chemical composition, and stimulation sequences to disrupt protons. T1, T1C, T2, and FLAIR sequences are prevalent. Moreover, the machine's computer can "stack" several slices to create a three-dimensional (3D) image of the patient, making it easier to identify essential components and possible cancers or anomalies. • Domain: Detection of Diseases like (tumors and Alzheimer's) • Advantages and disadvantages: MRI is non-invasive and radiation-free. Contrast agents based on gadolinium, used in X-rays and CT scans, are more likely to trigger an allergic reaction than those based on iodine used in MRIs.

A method consists of a segmentation grid, a shape dictionary, and an automatic shape code. With the help of a shape dictionary, the Shape Auto Encoder makes full use of prior anatomical knowledge to improve unreliable segmentation results on the target domain. In [10], Using two CNNs for automatic segmentation (extraction) of the brain and lesions, a method was created for measuring lesions in the MRIs of multiple sclerosis patients. This method was accomplished using magnetic resonance imaging (MRI). The proposed method accurately segmented lesions with comparable reproducibility to cutting-edge software tools and manual segmentation. Skull-stripped (brain cover) manually for NFBS data) of the brain and lesions, a method for quantifying lesions in MRIs of multiple sclerosis patients was developed.

The proposed method accurately segmented lesions with comparable reproducibility to cutting-edge software tools and manual segmentation. Skull-stripped (brain cover) manually for NFBS data. To reduce the running duration, an epochs algorithm was not used to stop the system when the result was stable and the rate of change was minimal. Unmentioned is the number of trained and verified images and the no-partition technique. In [11] a method of orthogonal moment preprocessing is presented here to enhance the results of convolutional neural network segmentation of the entire brain in magnetic resonance images. This method transforms the original image into one that has orthogonal moment qualities by using kernel windows that are based on orthogonal moments. An epochs algorithm was omitted to stop the system when the result is stable and the change in results becomes negligible, thereby reducing the system's running time. The quantity of trained and verified images, as well as the partitioning method, are not specified.

4. PROPOSED SYSTEM

Because of its ability to capture both internal and external structures with high spatial resolution, MRI is the most effective imaging method for studying brain tissue in depth. This makes it possible to detect even the smallest changes in these structures [12]. MRI is widely used in medical sciences for various applications, particularly in the analysis of brain images. Therefore, a system was proposed to separate the skull based on deep learning, image processing processes, and working in a three-dimensional and one-dimensional system. The following is a diagram showing the structure of the proposed system.

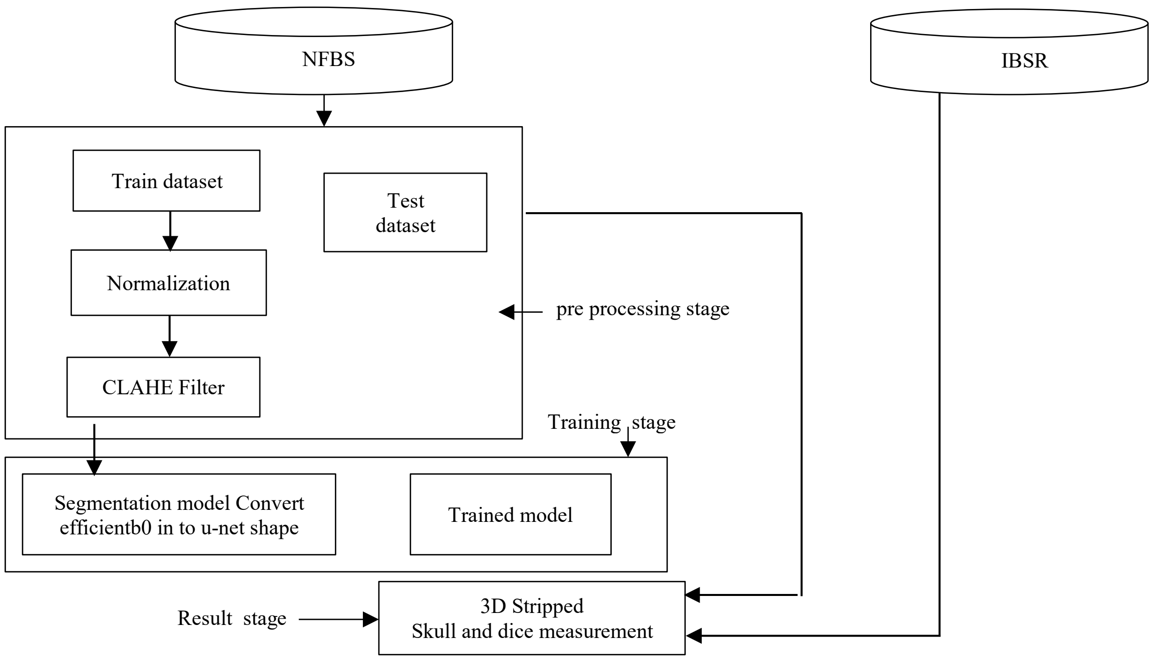

Figure 1. The proposed system's component diagram

5. DATASET

5.1. Dataset in Proposed System

Two datasets have been used in the proposed model (NFBS) Neurofeedback Skull-stripped for taring and testing and another (IBSR) for evaluating the model.

5.1.1. Neurofeedback Skull-stripped (NFBS) Repository

Comprises 125 T1-weighted MRI scans manually skull-stripped to remove non-brain tissues [14]. This pre-processing step facilitates the processing and analysis of the NFBS dataset. Also, it serves as a high-quality gold standard for training and testing data for creating AI computations [15].

The dataset includes scans of 125 participants, aged between 21 and 45, exhibiting clinical and subclinical psychiatric symptoms. For each participant, the repository includes the following:

1) A structural T1-weighted anonymized (de-faced) image.
2) A skull-stripped image.
3) A brain masks.

The images have a resolution of 1 mm3 and are stored in NiFTI format (nii.gz). Additionally, the repository contains a customized BEaST library tailored to the NFBS dataset. This dataset is valuable for researchers investigating brain structure and function and developing new treatments for psychiatric disorders. Figure 2 shows an example of dataset NFBS.

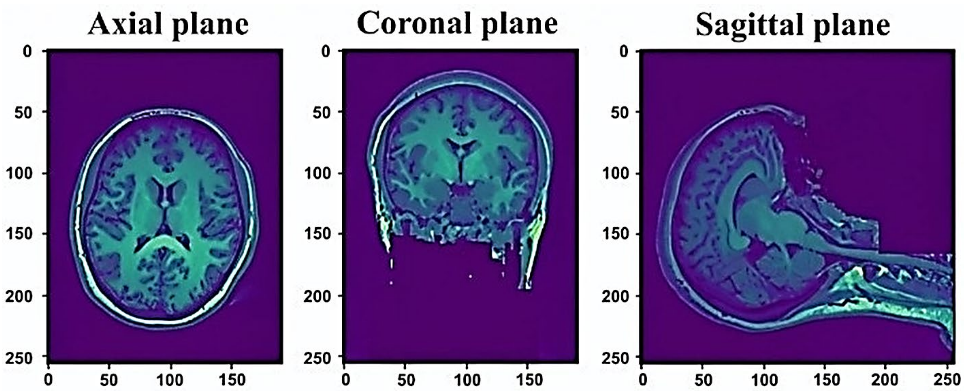

Figure 2. Examples of NFBS dataset

5.1.2. The Internet Brain Segmentation Repository (IBSR)

The IBSR v2.0 dataset is an MRI brain dataset accessible to the public [13]. The data set collection includes high-quality T1-weighted images of 18 participants with manual white matter, gray matter, and cerebrospinal fluid segmentation. The Center for Morphometric Analysis at Massachusetts General Hospital, in conjunction with the Brigham and Women's Hospital, is responsible for developing this dataset. The initial release of the dataset was in 1999. Since then, it has been widely used in developing brain imaging and analysis techniques, including image registration, segmentation, and shape analysis. The images within the IBSR v2.0 dataset have a resolution of 256×256×124 voxels and a voxel size of 1×1×1.5mm.

Expert neuroanatomists conducted the manual segmentations, which have demonstrated high inter-rater reliability. Figure 3 is an example of a dataset IBSR. Table 2. summarizes the training and testing divided based on cross-validation technical and scikit-learn library.

Table 2. Summarize training and testing data

	Training	Testing
NFBS (Training and Testing) (125 cases)	112 (90%) (case) (Deal with it 100%) (Divided into training and validation based on 80-20) (90 training -22 validation)	13(10%) (case) (Select 13case to evaluate to get the shuffling data)
	8.1.1 (8 equal training, one equal validation, one equal testing)	
IBSR (Testing) (18 cases)	Testing	
	All cases for external evaluation	

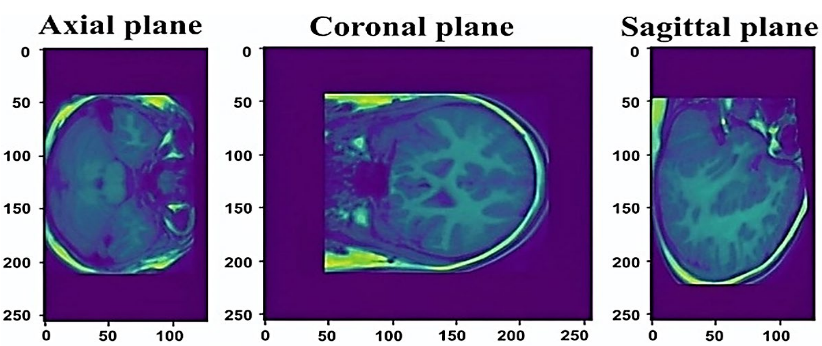

Figure 3. Example of dataset IBSR

5.2. Image Processing

The process of pre-processing once has three stages, and this dictates an explanation of these stages of treatment

5.2.1. Normalization and CLAHE Filter

Normalization is a procedure in image processing that modifies the range of pixel density values. Examples of applications include images with low contrast due to sunlight. Normalization is occasionally referred to as variance stretching or histogram stretching. In the proposed system, the interpretation of images was standardized. The contrast-limited adaptive histogram is CLAHE. The equalization filter is a non-linear image processing technique used to enhance an image's contrast [16], as depicted in Figure 4.

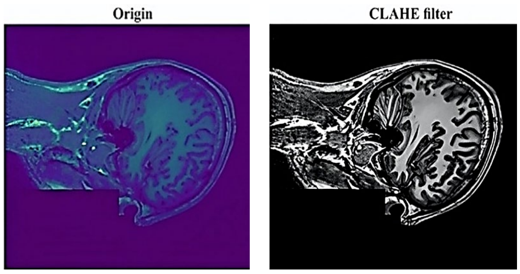

Figure 4 Original and enhanced image (NFBS dataset), sagittal axis

In the proposed system, this type of filter was used to obtain a balance in the colors of the image, as it works to lighten the dark areas and darken the light areas, and thus the features of the brain and Skull will be highlighted.

5.2.2. Resizing and Rotation

Step (Resizing) is essential and is based on choosing the best size for the neural network. Therefore, before removing the Skull, i.e., training, the image size must be changed from (256×256) to (128×128). This size was adopted based on practical experience, the experience of more than one size, and its impact on the results and Rotating images (90 degrees) anti-clockwise because the original images in the NFBS dataset were rotated (90) degrees clockwise.

5.3. Training Model-Based Segmentation Model

Skull stripping has been performed on enhancement images by constructing a model based on segmentation models using efficientnetB0, which is known as a Python library that provides a collection of neural network models for image segmentation tasks. The library is built on top of the Keras (Tensorflow) framework and includes a variety of state-of-the-art models for image segmentation. The u-Net architecture adapts Efficient-Net for segmentation tasks designed explicitly for semantic segmentation tasks. The encoder-decoder technique forms the foundation of the U-Net architecture. This approach consists of a contracting path to collect context and an expanding path to offer exact localization information. In the case of medical imaging, U-Net is particularly effective. Transforming Efficient-Net to U-Net architecture can leverage the strengths of both architectures for a better-performing segmentation model. The efficient feature extraction capabilities of Efficient-Net can help capture relevant information. In contrast, the spatial information provided by the U-Net architecture can help improve the accuracy and localization of the segmentation. To convert Efficient-Net B0 into U-Net, the input/output layers must fit the U-Net structure. U-Net has contracting/expanding paths that extract features via down-sampling/up-sampling. A segmentation model is used to modify network parameters, add layers, and introduce skip connections for reusing extracted features, which helps preserve information during up-sampling.

It is necessary to define the input and output layers, as shown in the following:

- Define the input layer as: (shape= (None, None, 1))
- Add convolution layer with the parameters: Conv2D (3, (1, 1)) (input_)
- The output is the base model (efficient-netB0) combined with the above steps (a, b).

The "Efficient-B0" neural network uses a method of incremental improvement. Experimentation with subsequent neural network architectures follows the initial convolutional neural network. Each unit has seven individual blocks. These blocks include a variety of sub-blocks whose number grows from one block to the next the basic structure now contains an additional category. Input, hidden, and output layers are the typical components of a "convolutional neural network" components. The "outputs and inputs" of the intermediary layers of a feed-forward neural network are obscured by the convolution operation and the final convolution of the system. Each layer in a feed-forward network gets the results from the layer above it and uses those inputs to produce new results. Table 3. summarizes the many levels of the neural network method and shows how it all works.

Using the principle that progress is incremental yields a very effective neural network. After the first "trunk" convolutional neural network, all following experiments are initiated from the same point. Each consists of seven units. Incrementing from EfficientNetB0 to EfficientNetB7, these blocks also include variable sub-blocks. The processing and understanding of digital images are the focus of the AI subfield known as computer vision. Deep learning for image segmentation is essential for computer vision. Image segmentation is the process of breaking a digital image up into several fragments. It seeks to classify pixels according to their similarity, which might be determined by a pixel's color, intensity, texture, or other features. Deep learning for image semantic segmentation has numerous applications, including object recognition, medical image analysis, etc. Many deep-learning image segmentation methods exist, such as thresholding, region expansion, and clustering algorithms. Clustering techniques combine pixels that are somehow connected. Region-growing algorithms grow regions outward from a seed point until they hit a boundary. To separate a picture into the foreground and background, thresholding methods require a threshold value. Image segmentation is a complex procedure because it can be challenging to define what constitutes a "similar" pixel and because there might be significant changes in color, intensity, and texture within an object.

Table 3. An overview of neural network layers

"Layer"	No. of layers	Characterization
Input layer	1	All CNN feedback is included in this report. When processing data using a neural network, it is common practice to have the pixel matrix represented by the data.
Conv2D	105	As the following layer in a deep CNN, filtration is applied to the initial picture or other inputs after the convolutional layer extracts visual information.
ReLU	29	Multilayer neural network non-linear activation function (MLN). ReLU, a neural network activation function, is non-linear. Unlike the standard sigmoid function, this one provides each neuron with the same probability value (>50% if X > 0) ("and 0 if X is negative"). Because the action is zero for negative X and positive X, it cannot be considered linear. Thus, it is curved.
Average Pooling	27	The term "aggregate averaging" refers to averaging each patch of a feature map. This demonstrates that the sample was obtained by down sampling. The mean value of each square on the feature space is two by 2 pixels.
Dropout	19	Dropout is a training method in which randomly chosen neurons are disregarded. Instead, they are eliminated at random. This indicates that their influence on activating neurons downstream is eliminated in anterior lane, but weight of neurons in posterior lane remains unchanged.
Flatten Layer	2	Convert data to a one-dimensional array, then insert it into the subsequent layer. Finally, flatten the output of the conv layers into a single, colossal attribute vector. This layer is coupled to the overall classification model through a "fully-connected layer."
Dense	1	The results of the convolutional layer are fed into this layer so that it may be used to recognize pictures. Every layer of a neural network comprises individual cells called neurons. Activation functions are non-linear functions that produce the weighted average of their inputs. The weighted average is conveyed by an activation function, which is a function that produces the weighted mean of its inputs.
sigmoid	1	Applying a sigmoid function to the input such that the output is constrained within the interval [0, 1]. Create a binary cross-entropy loss output layer or a custom training loop to use the sigmoid layer for binary or multilevel classification problems.

Additionally, certain things might be connected, making it hard to segment using earlier methods, and here comes the use of deep learning. The deep learning U-Net semantic segmentation method is a fantastic method for segmenting images. Automatic feature extraction from data via deep learning algorithms can be used to segment the data. Furthermore, complex qualities that are challenging to specify explicitly can be learned using deep learning models. The EfficientNetB0 was the foundation for the segmentation models, as was mentioned in Chapter 3. As its name suggests, EfficientNetB0 is much smaller than the other models and has fewer trainable parameters, making it an excellent choice for applications with limited computing resources (although this advantage is more pronounced during model training than during model deployment), Table 4. shows the model summary of the proposed model.

Table 4. Proposed model layers summary

Model Name: Segmentation Model		
Layer (type)	Output Shape	Param #
input_2 (Input Layer)	[(None, None, None, 1)]	0
conv2d (Conv2D)	(None, None, None, 3)	6
EfficientNetb0 (Functional)	(None, None, None, 1)	10115501
Total params: 10,115,507 - Trainable params: 10,071,507 Non-trainable params: 44,000		

5. RESULT AND DESICCATION

In the proposed system, scales were relied on in the subject of skull separation: accuracy and (dice measurements). The following are the equations for the scales adopted in the system:

- Dice Score: The evaluation of this contest is based on the average dice coefficient. The dice coefficient compares the pixel-by-pixel agreement between a predicted segmentation and its corresponding ground truth. The dice coefficient equals twice. Therefore, a relevant criterion for judging whether or not a suggested method of cranial strapping is successful is the ratio of the overlap area to the total number of pixels in both images. The dice score equation is:

Dice Coefficient = 2 × divided by the total number of pixels in both images, the Area of Overlap. The formula is given by:

$$\frac{2\times|X\cap Y|}{|X|+|Y|} \tag{1}$$

where, X is the predicted set of pixels, Y is the ground truth.

If both X and Y are vacant, the Dice coefficient is 1. The score on the leaderboard is the mean of the Dice coefficients for each test image.

- Loss: The loss function is a method for evaluating the accuracy of an algorithm's dataset modeling. It is a mathematical function of the machine learning algorithm's parameters and deep learning. The discerption loss is:

$$l(\hat{y},y)=i(\hat{y}\neq y) \tag{2}$$

where, i corresponds to the indicator function. Which means that the output is one of the inputs evaluated to be true. Alternatively, if the input is evaluated as false, the output is 0.

- $F1$-Score: The harmonic means of accuracy and recall, the flowing equation denotes $F1$, and the equation is:

$$F1=\frac{2\times TP}{2\times TP+FP+FN} \tag{3}$$

- Accuracy: Accuracy is how closely an expression or measurement matches an actual value. It also involves accuracy. Some fields, like science, define it more precisely. Equation (4) means as:

$$\text{Accuracy}=\frac{\text{Total of correctly number of image}}{\text{Total namber of image}}\times 100\% \tag{4}$$

Figure 5 shows result of loss and $F1$ in the dataset *NFBS*. However, the model shows average $F1$-scores of 98.2% and $F1$-scores validation of 97.8%. The number of epochs stops at epoch 21 because of the Early stopping function, where there was no improvement on the $F1$-scores validation for the subsequent ten iterations (as set in the patience parameter). Table 5 summarizes the result of a proposed system based on testing data.

Figures 7 and 8 show the proposed system's final result in skull stripping. Noted. The proposed trained model can extract the brain from the skill of any image in any plane with a high accuracy dice coefficient. The proposed system has an optional choice for predicting a single plane or three planes simultaneously (as 3D); the predicted dice coefficient is calculated upon the output of the trained model, which is the mask of the brain and the ground truth.

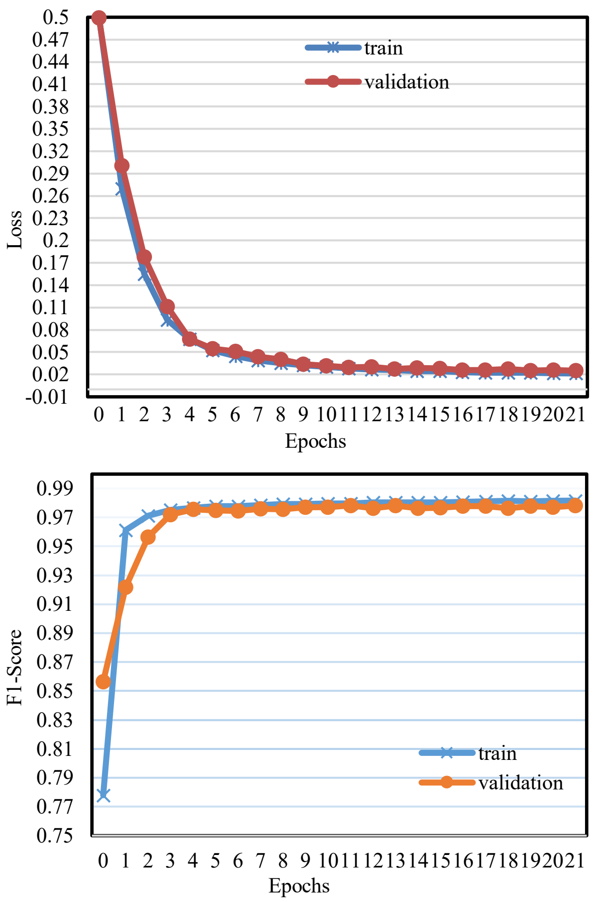

Figure 5. Loss and $F1$-score in the proposed system in the NFBS dataset

Table 5. Result summarized

Accuracy	$F1$	Dice-score
98%	98.4%	*NFBS*=99.9%
		IBSR=99.9%

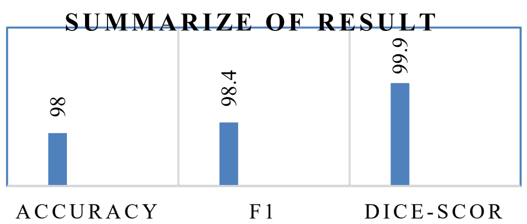

Figure 6. Summarizes of result in the proposed system

6. CONCLUSION

Cranial stripping plays a vital role in medical image analysis. It is a necessary pre-processing step for removing non-cerebral tissue, which enables obtaining a clear and accurate image suitable for further processing. In this paper, we propose to use the hash model with the netB0 architecture to make efficient u-net technology, and this led to the generation of a robust system to automate the skull stripping process. (23) The basic idea is to create in-depth training. The u-net model is unsupported in the proposed system because its layer is low, so (segmentation) was used to make the netB0 train in a (U) shape. The result was the ability of the system to separate any segment of the MRI without training on it. It was verified. This is done through IBSR external data, which confirms the system's efficiency. Therefore, three parts were made together and displayed in a 3D manner to facilitate the diagnosis task for the doctor. The three sections were exposed together, and the accuracy of the skull separation was up to 98%.

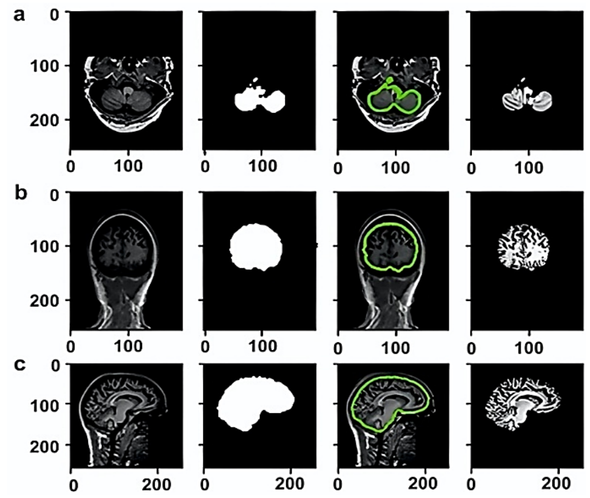

Figure 7. Example of the result in three clips in NFBS (detection and stripping Skull), a. Axial, b. Coronal, c. Sagittal plane

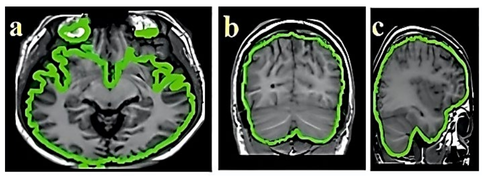

Figure 8. Example of the result in three clips in IBSR (detection), a. Axial, b. Coronal, c. Sagittal plane

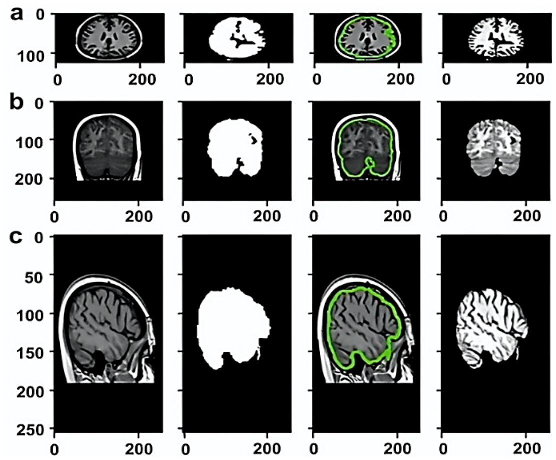

Figure 9. Example of the result in three clips in IBSR (Skull stripping)

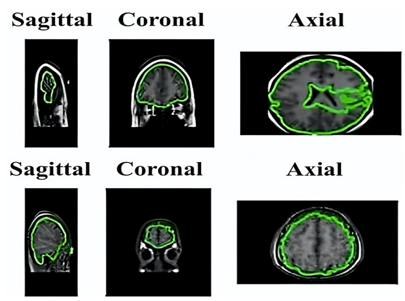

Figure 10. The 3D result of the proposed system

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