STM JOURNALS

Journal of
Multimedia Technology & Recent Advancements

ISSN: 2349-9028
Volume 11, Issue 3, 2024
September–December
DOI (Journal): 10.37591/JoMTRA

https://journals.stmjournals.com/jomtra

Review JoMTRA

A Split and Merge UNet: A Deep Learning Assisted UNet Model to Segment Corpus Callosum of Brain for Automatic Autism Detection

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Abstract

In recent years, deep learning techniques have shown remarkable performance in various image analysis applications, particularly in the domain of medical image processing. Among these, image segmentation plays a critical role, as it helps in isolating and analyzing specific regions within medical images. The proposed study focuses on segmenting the corpus callosum, a vital structure in the human brain, using a novel optimization technique known as the Split and Merge algorithm, combined with the UNet architecture—a fully connected neural network widely recognized for its effectiveness in biomedical image segmentation. Autism, a neurodevelopmental disorder that affects social communication, behavior, and cognitive functioning, is typically diagnosed in children between the ages of 2 and 5. Research has identified the corpus callosum, the largest white matter structure in the brain, as a potential biomarker for detecting autism, especially through MRI scans. Structural abnormalities in the corpus callosum have been correlated with autism, making it a key focus in early diagnosis. This work introduces an automated approach to detecting autism by leveraging the Split and Merge UNet segmentation methodology. The proposed system aims to accurately segment the corpus callosum region from MRI images, facilitating the early detection of autism. By combining the precision of the Split and Merge algorithm with the robust learning capabilities of UNet, this methodology promises to offer an efficient and reliable tool for medical professionals, ultimately aiding in the timely intervention and treatment of autism.

Keywords: ASD, MRI, UNet, segmentation, split and merge classification, ABIDE

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Received Date: May 03, 2024
Accepted Date: October 01, 2024
Published Date: October 18, 2024

Citation: Nagashree N., Amarnath Patil, Ananya Rao G.R., Sanjana R.S. A Split and Merge UNet: A Deep Learning Assisted UNet Model to Segment Corpus Callosum of Brain for Automatic Autism Detection. Journal of Multimedia Technology & Recent Advancements. 2024; 11(3): 1–9p.

INTRODUCTION

Autism is a collection of complex abnormalities known as autism spectrum disorder (ASD). It is a highly diverse neurodevelopmental condition with various causes and trajectories and is characterized by a range of symptom severities and several associated comorbid disorders. ASD is a spectrum of disorders rather than a single disorder; therefore, it is called an autism spectrum disorder [1]. The main challenge in identifying autism is its inherently difficult neuroanatomy. From the anatomy of the brain, autism can be detected in some major structures, namely, the front portion of the brain, parietal region, limbic regions, and cerebellum. Evidence indicates that various aspects of cerebral morphology differ in individuals with ASD, including volumetric (such as cortical thickness and regional area) and geometric (such as cortical shape) features. Additionally, different morphological characteristics may result in distinct neuropathological and genetic characteristics. For example, cortical thickness is thought to reflect dendritic arborization, whereas cortical surface area is associated with the number of columns in the cortical layer. In contrast, geometric features such as cortical folding patterns may indicate abnormal intrinsic and extrinsic connectivity. Therefore, investigating the connections between these cortical features could offer valuable insight into the causes of ASD. It can be concluded that differences in the area of the corpus callosum of the brain may be shrinking or enlarging, resulting in autism in children, and the difference in the volume of white matter and gray matter in the brain also affects autism. Image segmentation involves partitioning of a digital image into several regions. The purpose of segmentation is to transform the image representation into a format that is more meaningful and simpler to analyze [2]. Segmentation helps in object location and finding image boundaries. Hence, image segmentation helps to detect many diseases using MRI brain imaging.

This is considered a challenging problem owing to the poor contrast, various types of noise, and indistinct or missing boundaries often present in medical images [3]. Autism can be detected using brain imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). MRI scans are noninvasive and do not involve radiation, making them safe for the human body. MRI scans are dependent on radio frequency and magnetic waves [4]. The images extracted through MRI were in the Diacom format and 3D representation of images. Brain images can be represented in several ways. To obtain several views, an image slicer was used to convert 3D images into 2D images to slice images into various views. The detection of autism is very challenging; however, only psychiatrists, neurologists, or child specialists can detect it. In addition, it is not a single segment or part of the brain that is affected by autism [5]. It is not a good idea to diagnose autism by only observing abnormalities in one portion of the brain. There are several other parameters. Structural brain analysis and behavioral analysis. In structural brain analysis, many parameters must be considered, including various parts of the brain. Research shows that an autistic brain has abnormalities in white matter, gray matter, cerebrospinal fluid, and deformation in the corpus callosum.

Therefore, there is a need for an effective medical image segmentation method that features minimal user interaction, rapid computation, accuracy, and robust segmentation results [6]. In contrast, image segmentation techniques are based on edge- and region-based partitions. Several frequently employed algorithms include edge-based methods; artificial neural network-based segmentation techniques; physical model-based approaches; region-based methods (such as region splitting, growing, and merging); and clustering methods (including Fuzzy C-means clustering, K-means clustering, and Expectation Maximization) [7–10]. Image segmentation presents several challenges such as creating a unified approach that works across all types of images and applications. Choosing the right technique for a specific type of image is also a complex issue, making it unlikely to be a universally accepted method for segmentation. Segmentation remains a critical and difficult problem in image analysis and computer vision [11]. EmanAbdel-Maksoud researched brain segmentation methods using a clustering technique [12]. Despite intensive research in brain segmentation, it is still a challenge; therefore, research has been conducted on how to go deeper with convolutions approaching deep learning networks [13].

ASD typically affects the human brain, leading to challenges in speech, social interaction, communication, and motor skills, and can be diagnosed by experts starting from around two years of age or even earlier, with recent advancements [14]. Studies have shown that using a large-capacity CNN for training offers advantages over traditional neural network methods for classification tasks because it does not require extensive training of base CNN models [8–10]. Many networks in the literature use a divide-and-conquer approach for training. In contrast, architecture focuses on using images selected by experts, which enhances recognition accuracy [6, 7, 11, 12].

Desai and Dinesh [7] concluded that fine-tuning the entire network during the final training phase can improve the training accuracy; however, this approach was not practically implemented because of high computational costs. Research explored various metrics for evaluating segmentation methods for autistic brains and introduced a new metric to assess the effectiveness of segmentation algorithms [14]. A genetic thresholding-based algorithm for MRI image segmentation to detect autism and dementia was presented [15]. Recently, Convolutional Neural Networks (CNNs) have advanced significantly for the automatic detection of Autism in both MRI and fMRI brain images [1, 16]. Additionally, detecting eigenvalues from feature points extracted from brain images has contributed to automatic autism detection. Several deep learning techniques such as UNet, modified UNet, Dense UNet, Transnet, and several other CNN algorithms have performed better with medical images [17].

This work proposes a new architectural framework called the split-and-merge technique in combination with the UNet architecture to optimize the feature extraction phase. Split-and-merge is a semi-supervised neural network training method to obtain better features from the image to be trained [18].

Recently, convolutional neural networks (CNNs) have been a better performance factor because they use multiple layers, hence termed deep learning [19–23]. Image analysis has many challenges in brain medical image applications because images are subjected to various preprocessing stages, resulting in different algorithms [24]. As ASD is a behavioral problem, both the structure and function of the brain need to be studied for the automatic detection of diseases. An automated tissue segmentation method has been proposed to identify regions of gray matter, white matter, and cerebrospinal fluid [25].

Hyde et al. [26] proposed the application of supervised machine learning to ASD [27]. This study offers a thorough review of approximately 45 studies, including those on classification algorithms. Given that autism is a behavioral disorder, both structural and functional brain analyses are crucial for the development of classification algorithms. Rong Chen et al. [28], in their recent publication, reviewed recent advances in the understanding structure of the brain and analyzed why structural analysis plays a significant role [25, 27]. As highlighted in numerous studies, feature detection is a critical step in autism detection. The process begins with Haar feature detection, which has been used for facial feature recognition [24, 25]. Several studies have proposed various machine learning and deep learning methods that utilize the ABIDE dataset to obtain MRI images of individuals with autism. An effective neural network classifier has been employed in these approaches [27].

In this study, a recent segmentation method called panoptic segmentation is adopted [26]. It is the semantic segmentation phase, which provides a better understanding of specific parts of the image and is particularly well suited for MRI brain images. This type of segmentation helps preserve more details in MRI. The LWBNA-UNet method was adopted for image classification and segmentation, which yielded a Dice coefficient of 0.992 [28].

MATERIALS AND METHODS

Materials

In this study, brain MRI images of autistic and non-autistic subjects from the consortia of 17 different medical universities, ABIDE I and ABIDE II, were used. Around 100 images, out of which 71 were autistic and the rest of the normal images were considered for the initial experiments. These are resting-state MRI findings along with phenotypic data.

The resting-state fMRI images obtained were 3D; therefore, we sliced the 3D images into 2D using an image-slicing tool, and various slices of the images were considered. The slices obtained are of 3 forms. Three different slices of the MRI images are shown in Figure 1.

Image pre-processing: Since the images containing 2D slices have noise and it is a challenging task to perform segmentation and further classification, scull stripping is performed on all the images taken for the experiment. The image is mathematically represented as I(x, y) with a matrix of order MXN. Initial pre-processing is done by applying the skull stripping method and the result is shown in Figure 1.

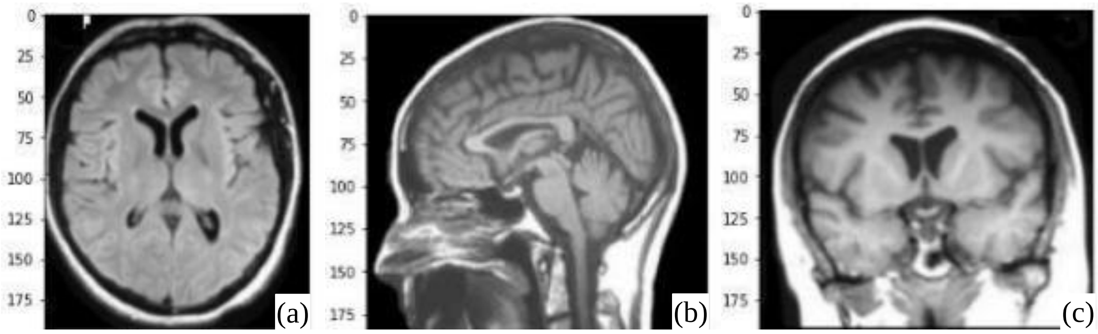

Figure 1. Three different slices of the brain, (a) axial, (b) sagittal, and (c) coronal views of brain.

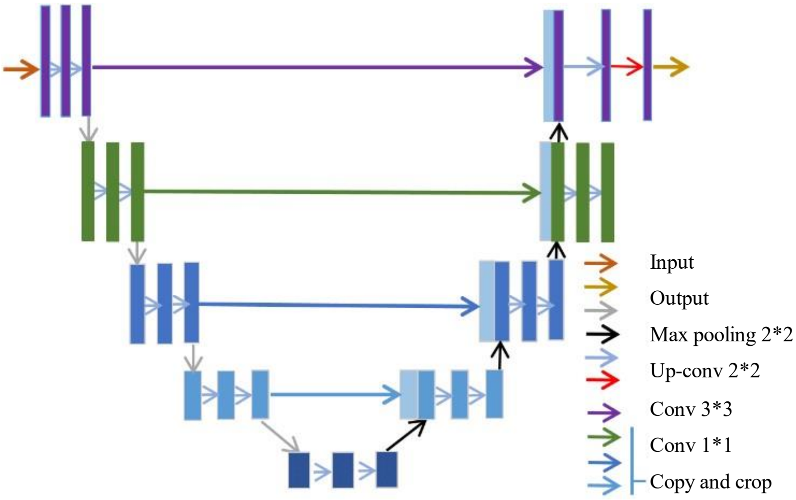

Figure 2. UNet architecture [10].

Proposed Architecture

Convolutional Neural networks are used for efficient classification and segmentation of all given images. This method includes both training and testing phases. Initially, all images taken for observation were in the training phase using the neural network model. In biomedical imaging, such as brain imaging, the structure itself is too complex to signify; hence, several levels of optimization are involved. UNet architecture proposed by Olaf Ronneberger, Philipp Fischer [18], and Thomas Brox in 2015 in the paper —U-Net: Convolutional Networks for Biomedical Image Segmentation [27] is shown in Figure 2 which is a fully convolutional neural network developed for biomedical image segmentation. The model contains a series of layers, constructing sampling and upsampling.

In the encoding part, convolutional layers are represented as a network pattern. We used a feature-extraction algorithm as a convolution filter to generate feature maps in the input image. Thus, the feature points obtained in the coordinate matrices must be vectorized [29]. To increase the effectiveness of UNet, an optimization approach was incorporated. Split and merge are AI-based optimizations that efficiently reduce the computational cost and time required to train the network. A modification of the UNet architecture for training the images is shown in Figure 3. It is an image optimization technique in which only the useful features of the images are considered, whereas the rest are neglected so that it improves the execution time of the UNet technique.

Split and Merge Method

This is an artificial intelligence (AI) technique used to segment images. The data or input image is represented as a quadrant tree, which is split into four quadrants. After repeated splitting until uniform features are obtained, uniform quads are merged, depending on the similarity of the region in the input image. The technique is continued until no more splits and mergers are possible [30].

1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	0
1	1	1	1	2	1	1	0
1	1	1	1	2	3	1	0
1	1	1	1	2	3	1	0
1	1	1	1	1	2	1	0
1	1	1	1	1	1	1	0

(a)

1	1	1	1	1	1	1	2
1	1	1	1	1	1	1	2
1	1	0	0	1	1	1	1
1	1	0	0	0	0	0	0
1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1
1	1	1	1	3	2	1	1
1	1	1	1	0	0	0	0

(b)

1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	0
1	1	1	1	2	1	1	0
1	1	1	1	2	3	1	0
1	1	1	1	2	3	1	0
1	1	1	1	1	2	1	0
1	1	1	1	1	1	1	0

(c)

1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	0
1	1	1	1	1	1	1	0
1	1	1	1	2	1	1	0
1	1	1	1	2	3	1	0
1	1	1	1	2	3	1	0
1	1	1	1	1	2	1	0
1	1	1	1	1	1	1	0

(d)

Figure 3. (a) Input matrix representation; (b) 1st Split; (c) 2nd Split; (d) 3rd Split.

The steps of the algorithm are as follows:

- *Step 1:* Represent the input image and divide the image into four square quadrants.
- *Step 2:* If a quadrant is not homogeneous, it is further split into four quadrants until a homogeneous square is obtained.
- *Step 3:* Based on the homogeneity criteria of the image, merge each quadrant.
- *Step 4:* Repeat the above steps until no more splits or mergers are possible.

The proposed work relies on an evolved architecture called the fully convolutional network [10]. This architecture was modified and enhanced to function with a limited number of training images while providing more accurate segmentations. The brainchild of this work is to perform encoding and decoding of UNet modeling to segment the image successively [31].

- *Encoder:* UNet architecture has two parts, the first part of architecture is the encoder, and the rest half is the decoder. In the encoder, a trained classification network that runs through multiple layers of convolutions is adapted to sample the feature representation of the given input image.
- *Decoder:* It is used for reverse sampling with previous convolution operations.

In the proposed methodology, the input image is divided into several layers, called convolutions, and the CNN method is applied. The convolution filter used for this process is the feature extraction of the individual layers of the image. Furthermore, in the UNet approach, each layer is represented as an encoder layer of the networks [32]. A modified form of UNet was proposed, that is, alpha-beta pruning, which is an AI optimization algorithm for dimensionality reduction. The process involves constructing a tree network of all the layers of the input image, and only the essential images are retained. The remaining image layers are pruned to reduce the time complexity of the UNet algorithm. The dimensionality-reduction architecture is shown in Figure 4.

EXPERIMENTS AND RESULTS

The proposed method was implemented using Python library. Initially, the dataset for autism was obtained from the ABIDE dataset. Thus, the obtained MRI brain images are 3D images of the brain that must be converted into 2D representations using image slicing. Various 2D views of the images, such as sagittal, transverse, and partial views, were obtained. While converting from 3D to 2D, all views of the 2D image have to be collected and used for further processing. The reason behind this is that in some views, the corpus callosum will look clearer; in other views, white and gray matter will have better visibility. Therefore, to obtain better segmentation results, all views of the brain were considered. Figures 5–8 show the brain MRI 2D image of different views.

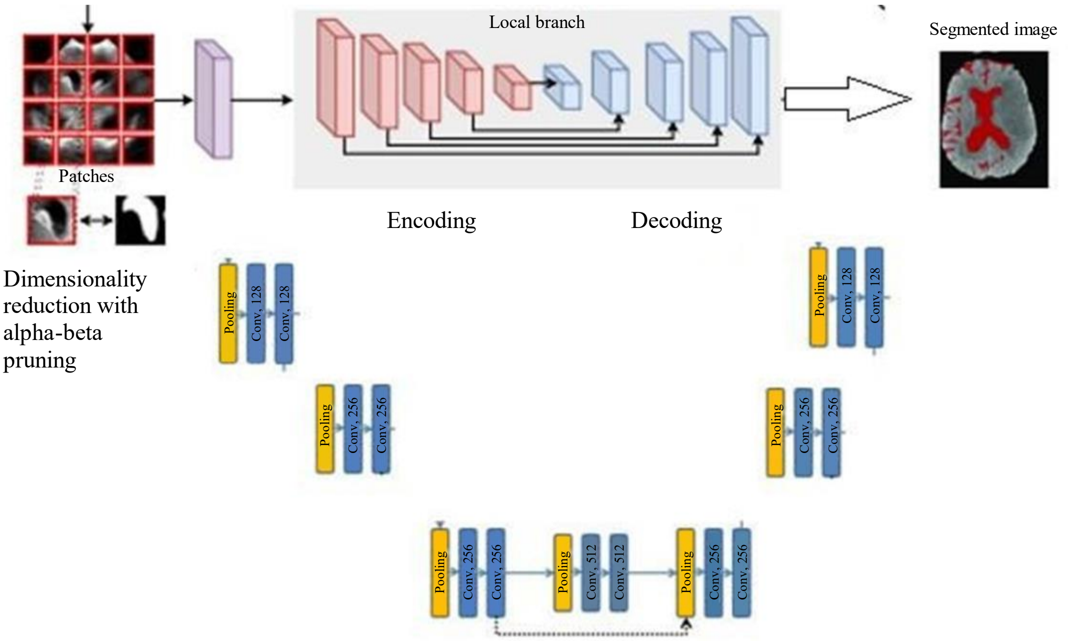

Figure 4. Modified UNet with split and merge.

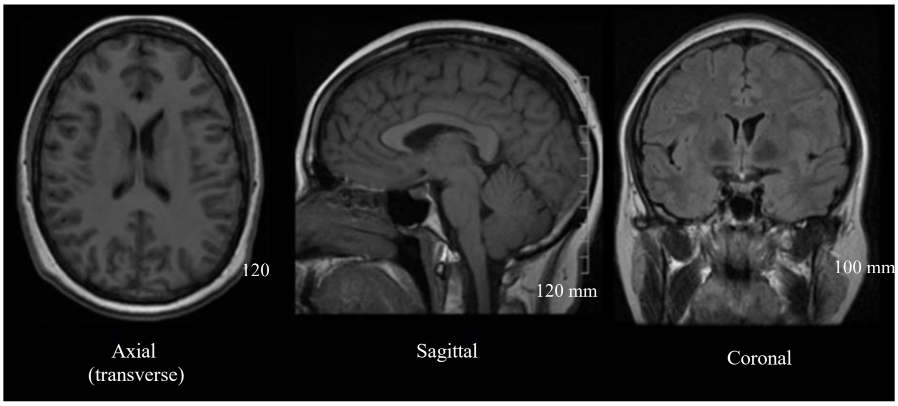

Figure 5. Image pre-processing; converting from 3D to 2D.

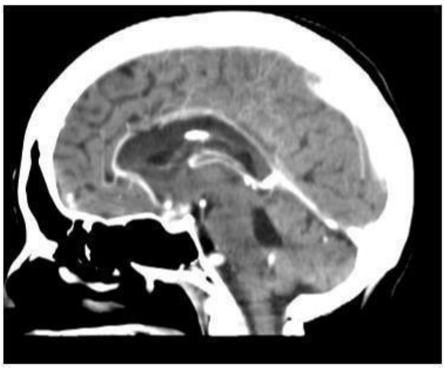

Figure 6. Binarization.

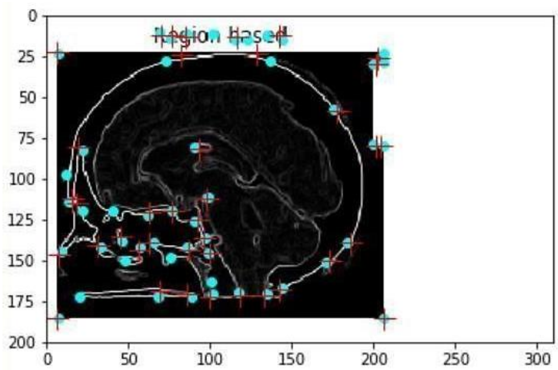

Figure 7. Feature point extraction.

Journal of Multimedia Technology & Recent Advancements
Volume 11, Issue 3
ISSN: 2349-9028

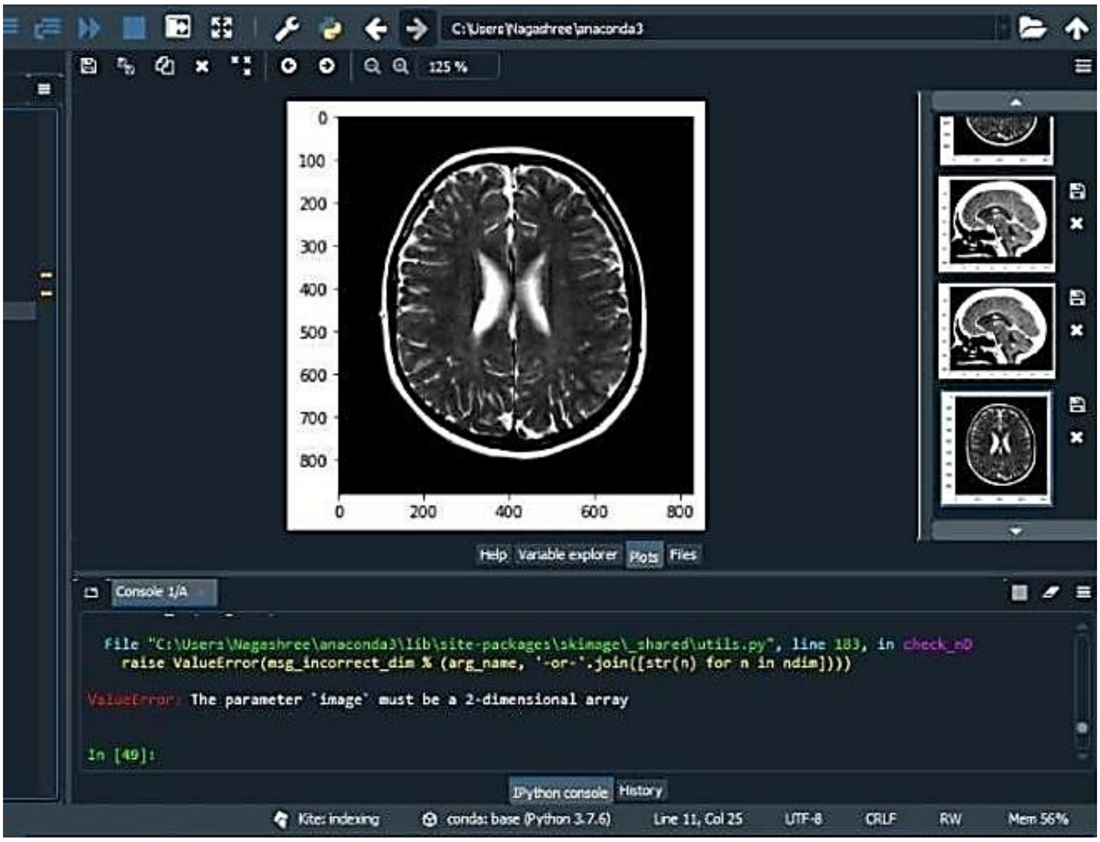

Figure 8. Result of image segmentation using split merge UNet.

Table 1. Dice coefficient.

S.N.	Method	Dice coefficient
1	UNet	0.9
2	ResNEt	0.87
3	TransNet	0.88
4	Alphabeta UNet	0.91
5	Split and Merge UNet	0.9927

PERFORMANCE EVALUATION

The Performance of the methods was evaluated using pre-trained models such as UNet, ResNEt, and the proposed Split and Merge UNet for classification and detection. The proposed approach yielded a better Dice coefficient of 0.9924 compared to the other methods. Table 1 presents the dice coefficient values of the various models. The Dice coefficient of the proposed model is nearly equal to 1, which indicates the efficiency of the segmentation method.

CONCLUSION

Automatic detection of autism using an image segmentation approach is a tedious task, as with structural brain imaging, it is very difficult to identify autism. Through gene expression, a phenotype can achieve one variant of autism detection; also, nowadays lot of CNN methods have been proposed which are very efficient for biomedical image segmentation. The proposed method uses the split-and-merge optimization technique along with the UNet approach, which yields better results. The conventional UNet algorithm has many layers with a series of decoders and encoders to achieve results. In the UNet framework, multiple layers are reduced by an AI technique called split and merge, which attempts to reduce the dimensionality of the feature map generated from the input images, thereby increasing the speed of segmentation of biomedical images.

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