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Infant's MRI Brain Tissue Segmentation using Integrated CNN Feature Extractor and Random Forest

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Abstract— Infant MRI brain soft tissue segmentation become more difficult task compare with adult MRI brain tissue segmentation, due to Infant's brain have a very low Signal to noise ratio among the white matter_WM and the gray matter _GM. Due the fast improvement of the overall brain at this time , the overall shape and appearance of the brain differs significantly. Manual segmentation of anomalous tissues is time-consuming and unpleasant. Essential Feature extraction in traditional machine algorithm is based on experts, required prior knowledge and also system sensitivity has change. Recently, bio-medical image segmentation based on deep learning has presented significant potential in becoming an important element of the clinical assessment process. Inspired by the mentioned objective, we introduce a methodology for analysing infant image in order to appropriately segment tissue of infant MRI images. In this paper, we integrated random forest classifier along with deep convolutional neural networks (CNN) for segmentation of infants MRI of Iseg 2017 dataset. We segmented infants MRI brain images into such as WM- white matter, GM-gray matter and CSF-cerebrospinal fluid tissues, the obtained result show that the recommended integrated CNN-RF method outperforms and archives a superior DSC-Dice similarity coefficient, MHD-Modified Hausdorff distance and ASD-Average surface distance for respective segmented tissue of infants brain MRI.

Keywords- infant; cnn; random forest; feature; tissue.

I. INTRODUCTION

Non-invasive method such as MRI- Magnetic resonance imaging , PET-positron emission tomography, X-ray and CT-computed tomography have almost all developed in recent decades, the images captured from the infant's brain could be used to identify and diagnose brain disorders and abnormalities. In ancient practice, a physician, neurosurge, or pathologist diagnoses defects by manually gathering data from the image, which is time-consuming and susceptible to misinterpretation related to human inconsistency [11]. The assessment and recognition of abnormalities that contribute to an accurate diagnosis is a time-consuming and complex process. Researchers have proposed automated approaches to assist physicians in making the accurate diagnosis in order to improve diagnostic accuracy.

The segmentation of newborns' brain regions is a crucial step in diagnostic imaging investigation. The segmentation stage, which refers to splitting irregular parts of an image, is important for identifying abnormalities in medical imaging. The neonate mapping may be used to evaluate this texture's organization as well as the development and wellbeing of the newbornAnbeek, P. et al. [27]. Schizophrenia is an illustration of an alternative to faulty fetal growth brain development, the effects of which manifest in adulthood. By analysing several newborn tissues, it is possible to prevent this condition from developing childhood brains.This may also be accomplished by comparing the atlas of newborns that are healthy to other baby atlases. In general, computerized surgery, diagnostics, and medical research all heavily rely on medical image segmentation. The real brain model is created using these textures, which comprise soft and tough textures. One of the most crucial uses of machine learning and image processing in medical imaging systems, disintegration gives professional doctors a powerful tool for illness diagnosis and enables early disease identification and therapy. The cerebrovascular fluid (CSF), grey matter (GM), and white matter (WM) are the three linear and detachable tissues that make up the human brain bare R.J.et al. [28]. While the surface of the brain is made mostly of GM, tumors resemble WM [35].

Methods depend on magnetic resonance imaging are used to study the morphology of various body components (MRI). Its non-invasive qualities and the high spatial resolution, which effectively reveals smooth texture variations employed in the volume analysis of brain smoothness, such as neurological disorders, are the reasons for employing this form of imaging in its non-ionizing radiation. Without requiring surgery or incision, clinicians may reach the inside organs and architecture of the human body using these images [36].Recognizing image elements, which forms the foundation for treatment, is one of the fundamental components of medical image analysis. In order to increase the precision of disease detection, computer systems are used, and image segmentation is crucial for identifying illnesses. The segmentation procedure is the method used to disclose the item in the image. Based on the kind of image that is being utilised, the segmentation process has a variable architecture. Problems with medical picture segmentation include feature matching, strong image resolution, and noise brought on by imaging. Despite these issues, segmenting medical imagery is crucial for diagnosing illnesses. The capability to identify the illness and assess its severity is one of the key drivers behind the medical picture segmentation method [37].

The ability to suggest a segmentation model that might be noise-resistant, identify weak boundaries, etc. is still not attainable despite the advancements achieved in the segmentation of medical images. Pre-defined information is arranged into associations and the edges of medical pictures are then recognized. The fact that this approach takes a long time and requires user participation to identify the key regions is one of its biggest drawbacks. Because the pixels were labeled, the pictures were segmented. Each segment's surrounding regions, which are based on variations in greyscale levels, must be significantly different from those of the segment. Consequently, small variations in the brightness levels of the pixel are retrieved from the texture in the perspective of the segmentation procedure. Finding every pixel in two-dimensional (2D) images or every voxel in three-dimensional (3D) images is the foundation for segmenting a specific item [31,38,39]. The capacity to identify the illness and assess the treatment plan using the segmentation method is a key factor supporting the process of medical image segmentation. Cells that exhibit abnormal development in the brain's surface make up a brain tumor. A malignant tumor in the nervous system is cancer that begins in brain cells, presses on the tissue surrounding the brain as it grows, and manifests as signs and symptoms in the body. Because they are located in a region of the brain that is linked to tissues that are extremely essential for the body's vital activities, brain tumors have a malignant structure. Additionally, brain tumors have an intrusive form and harm the human brain's most vital organ . More reliable image fragmentation might reduce the inaccuracy brought on by human behavior [32,40]. Recent research and MRI images show that the poor textural difference between the WM and GM areas at roughly 6 months of life makes segmenting brain imaging of this age a difficult problem. A technique to segment brain images is required in order to properly detect the kind of tissue and shape of the illness in medical imaging, as the techniques used to assess the size and layout of illnesses in the naked eye have significantly larger mistakes and take a lot of time [1,33,34].

In resent year, several researchers used the deep convolutional neural network to enhance the accuracy for infant brain segmentation [1, 2].The intensity distributions of gray white matter (WM) and matter (GM) overlay more and low CNR ratio that in the infant brain,due to myelination and maturation made manual labelling challenging [10]. As a result, the amount of tissue class labels is extremely restricted. Its quiet an open challenge to develop accurate soft tissue segmentation algorithms for infant MRI brain segmentation [3, 10, 29, 30].

II. NOVELTY OF RESEARCH WORK

Novelty of this work lies in extraction of important features using convolutional neural networks-CNN. The advantages of CNN for feature extraction is to have prime features required for accurate segmentation of brain tissue of infants. A neural network called CNN extracts the features of the input images, while a different neural network categorizes the characteristics. The feature extraction network uses the input image as a starting point. The neural network uses the extracted features for classification. Along with this tissue segmentation and classification is performed by random forest. For image enhancement wavelet transforms is utilized, which removes noise from brain MR images of infants. In medical images preservation of edges and are of prime importance this can be achieved in preprocessing stage.

III. CHALLENGES

Recent progress in MR image acquisition, automated brain segmentation continues to remain challenging. Irrespectively of the application, there are considerable difficulties with the MR images that make segmentation challenging. The intensity of the various tissue class varies progressively throughout the image space rather than being uniform. Non-uniform radio-frequency (RF) fields, reception sensitivity, electrostatic activities with the body, and intensity inhomogeneity/non-uniformity are the causes of this phenomenon Belaroussi et al.[17] Imaging

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systems with higher fields generate higher notable intensity variation. The accurate delineation of tissue borders is further complicated by partial volume (PV) effects Tofts [18] which include the merging of various tissue types in a single voxel. Due to the restricted image resolution, voxels that contain multiple tissues have an intensity that reflect the variation of tissues represented in the voxel. The image is commonly also affected by noise, which can come from the body's electromagnetic field and small irregularities in the electronics used for reception Weishaupt et al.[8]. Fetal and neonatal brain MRI segmentation is significantly challenging to segment automatically than adult brain segmentation. Furthermore, domain-specific difficulties are present in the infant brain MR images.

- Due to the fetal/infants brain's compact size and the quicker scanning times, there is a lower contrast-to-noise ratio Prastawa et al. [20].
- Compared to adults, there are more motion artifacts to be identified. Unsedated newborns and infants exhibit substantial instability, which demands for the the use of rapid or several brain acquisitions to compensate for the motion. Mismatched image slices and ghosting effects are motion artifacts that emerge along the phase-encoding direction Rutherford et al. [19].
- In contrast to adult data, infant MR analysis revealed an inversion of white matter and gray matter contrast. In the T2-weighted images, the white matter, which is essentially unmyelinated in the newborn brain, appears brighter than gray matter, however in the adult data, gray matter has higher intensity levels than white matter. The cerebrospinal fluid-cortical gray matter boundary's merging of cerospinal fluid and gray matter results in intensities that approach the white matter intensity profile Xue et al. [21].
- Neonatal brain grows so rapidly, there are huge differences in the form and appearance of its structures. Faster cortical ribbon bending and the creation of dense gray matter structures. However, white matter myelination is an ongoing cycle in the growing brain and becomes increasingly obvious in various white matter locations. Due to these variations in anatomical features, proper registration of participants with varied scan ages is difficult.
- Absence of atlases with manual labels with various scan ages. It takes a lot of effort and requires specialised anatomical skill to manually delineate complex structures. Manual brain atlasing is exceedingly limited during the prenatal phase, in contrast to the adult brain's atlas resources. The lack of atlases and the diverse variety of brain appearances present a difficulty for segmentation approaches since there is a deficiency of training data.

IV. RELATED WORK

Tushar H. Jaware et al. [3] developed hybrid method for infant MRI brain tissue segmentation and classification, consist of CNN neural network and sparse auto encoder. Such as deep convolutional neural network (DCNN) with sparse auto encoder and self-organized map (SOM) as the framework for fragmenting and classifying newborn brain images. In order to eliminate the unnecessary segmentation near segment boundaries. Additionally, an input image's EWT and GLCM-based texture attributes are used.Tissue segmentation of nearby 6 months of age is very difficult than adult, so Toan Duc Bui et al. are Motivated by the stated purpose [4] they proposed a 3-Dimenttinal cycle GAN –Seg architecture, for accurate white matter-WM and the gray matter-GM and also cerebrospinal fluid-CSF tissue segmentation of infants. Generally, Infants MRI brain tissue segmentation method used uni-scale symmetric convolutions, which are inefficient to accurate tissue segmentation.

To overcome this problem, Zeng Zilong et al. [5] propose a framework for brain MR images of infants using a 3D mixed-scale convolutional neural networks -CNN network (3D-MASNet). Yue Sun et al. [6] developed algorithm for cerebellum tissue segmentation of infant. They utilize a confidence map-directed semi-supervised transfer learning architecture.

T H Jaware et al. [22] proposed a hybrid model for infant tissue segmentation and classification. Initially, they apply a wavelet filter bank on input images after segmented images into different classes. Lastly, they classify tissue using fuzzy based support vector machine. B Suranyi et al. [23] the proposed method in which histogram normalization and feature generation are used and, all MRI images are supplied to 6 machine learning algorithms, which use them as training and test data in accordance with the leave-one-out procedure. Utilizing statistical techniques, the classification algorithm output is assessed.

S Pasban et al. [24] developed deep neural network hybrid of VGG-16 and U-Net for infant tissue segmentation, initially they employ Fourier transform for pre-processing the input raw images and using hybrid convolutional neural networks -CNN model they segment tissue into three class.

Y Sun et al. [25] build a framework for semi-supervised transfer learning that is guided by a competence map for the tissue segmentation of infant’s cerebellar MR images between the ages of 24 months and 6 months.

T H Jaware et al. [26] suggest a fully automated, pipeline-based Neural Tree method that makes use of useful local similarity factors such tissue proximity, connection, and structure, the segmentation of infant brain MRI. The suggested approach and at the proposed site do not call for physical

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cooperation or the use of an atlas. Summary of existing infants brain tissue segmentation method illustrate in Table 1.

V. SEGMENTATION

Generally, convolutional neural networks -CNN have every neuron in a feature space map are linked meagrely to a specific set of neurons in the former network layer, this contrasts from the connectivity in such an ANN. Convolutional neural network is made up of three layers: convolution, pooling, and fully connected (FC) layer[12]. CNN are inspired with the notion of basic and complicated cells in the brains. It has seen wide applications in image vision and images segmentation.
We use the keras sequential model to do deep learning feature extraction. Then have used the pre-trained network as an arbitrary feature extractor, allowing the input picture to advance to the next layer before resting and accepting its outputs as our features. Only two convolutional layer with by Max Pooling layer used with 32×32×3 filter size and activation function is sigmoid.

A. *Convolutional Layer*

Convolutional layers have been used to retrieve multiple input features. Each subset of features is mainly composed of rectangle neurons. The convolutional kernel is a collection of weights carried by neurons in the same feature map. Convolutional kernels are typically generated using random matrices

B. *PoolingLayer*

Down-sampling is implemented with the use of pooling layers. The pooling layer's function is to combine related features in a specific situation to enhance recognition reliability [8].

C. *Fully Connected Layer*

FC layers are integrated in a CNN structure. If the size of the input vector represent with M and the overall size of the generated vector is N, this vector of the lth layer is determined as bellow [7, 8].

$$x_j^l = f\left(\sum_{i=1,..,M} x_i^{l-1} \times w_{ij}^l + b_j^l\right), j = 1, \dots, N, \tag{1}$$

There are several well-known CNN models, including LeNet-5, Google Net, AlexNet, and Net in System [14, 15].

D. *Random Forest Classifier*

In classification and segmentation, the selecting of a classifier is important. Due to the minimal, shrinking gradient, and overfitting issue in the training process, it is challenging for the conventional CNN architecture, which is built associated with softmax to provide optimal classification performance [13].

the random forest classifier is a decision tree-based ensemble learning approach. Numerous different sets can be used to achieve training results for each tree. Based on the voting result of each class final classification can be obtained. The random forest classification model is shown in Figure 1

TABLE I. SUMMARY OF SEGMENTATION METHOD

Author	Dataset	Tissue segmented	Algorithmic uniqueness	Performance parameter
T. H. Jaware et al.[3]	Newborns (38–42 weeks age), children (4–17 years) and adults (35–71 years).	CGM, SGM, UWM, MWM, Bm, Cb, CSF	Atlas free hybrid based on SOM-DCNN with sparse auto encoder	Dice similarity coefficient, Modified Hausdorff distance, Absolute volume differ
T.D. Bui et al.[4]	6-month-old infants images	CSF,GM,WM	3D-cycleGAN-Seg architecture	Dice similarity coefficient, Modified Hausdorff distance, Absolute volume difference
Z.Zeng et al.[5]	Dataset of the iSeg-2019 Grand Challenge brain MR images of 6-month-old infants	CSF,GM,WM	The 3D-MASNet (3D-Mixed-Scale Asymmetric Convolutional egmentation Network) framework	Dice similarity coefficient, Modified Hausdorff distance, Absolute volume difference
Y,Sun et al.[6]	6-month-old subjects	CSF,GM,WM	Architecture for semi-supervised transfer learning	Dice similarity coefficient, Modified Hausdorff distance, Absolute volume difference
T. H Jaware et al [22]	Newborns that are less than 28 days old	GM, WM, CGM, MWM, UWM, CSF, BS, CB and VENT.	Atlas free hybrid based wavelet filter bank	JSD, MSD, DC, MHD, AVD,
B Suranyi et al.[23]	iSeg 2017 challenges	CSF,GM,WM	Compare with 6 different algorithm	Dice score Sensitivity (TPR) Precision (PPV) Overall accuracy
S Pasban et al.[24]	iSeg-2017challenges	CSF,GM,WM	Hybrid CNN model	DISC and ASC
Y Sun et al. [25]	24 months and 6 months infants	CSF,GM,WM	Semi-supervised Transfer Learning	Dice ratio
T. H. Jaware et al.[26]	MRBrainS13 challenge	WM , GM , CSF, BM MWM	atlas-free pipeline based Neural Tree approach	DC, MHD, AVD

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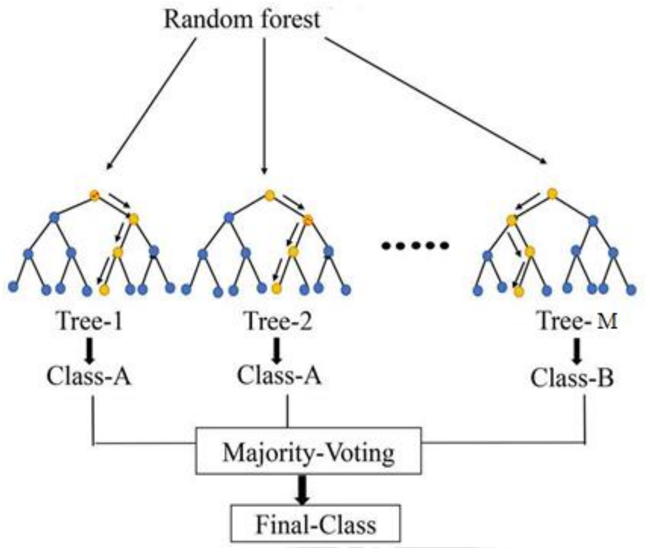

Figure 1. Random forest classifier model.

VI. MATERIAL AND METHOD

In this section we discuss data set and proposed convolutional neural networks random forest (CNN-RF) Integrated method. Firstly, discuss data set use for tissue segmentation. Secondly, proposed method which is divided in following steps, filtering, feature extraction and segmentation (classification).

A. Dataset

In this work we use iSeg-2017 dada set [1]. The aim of the iSeg-2017 competition is to evaluate automatic and semi-automatic methods for segmentation and measurement of infant brain tissues using T1w and T2w brain of MRI data. In training data it consist of T1w- and T2-w images of 10 infant subjects and testing consist of 13 infant subjects of T1w- and T2-w images.

B. Proposed Method

The integrated CNN-RF proposed method presented in Figure 2, this method include initially preprocessing, extracted feature based on CNN and final tissue segmentation based on ensemble random forest classifier[9].

Initially pre- processing is required to enhance images. In this work, we used the wavelet base denoising method for enhancing infant brain MRI images for feature extraction. The feature was were extracted using deep learning CNN sequential model, this net consist of 7 layers, the input layer consists of a size of 512 by 512 pixels. Last layer is fully connected, over the feature extracted by the convolution layer, implementing a general purpose classifier. We generated 32 filter feature bank from CNN net, fully connected layer CNN was changed by a random forest classifier to segment or classify tissue of input pattern. Finally, Random forest classifier segmented infant brain MRI tissue in 3 classes such as white matter-WM, cerebrospinal fluid –CSF, and gray matter-GM shown figure 3.

VII. RESULT

To estimate the toughness of the proposed CNN Random forest integrated method, we utilized the iSeg2017data [1]. The iSeg-2017 dataset involves of 10 subjects for Training with ground truth labels and for testing 13 subjects without ground truth labels. The performance of 5 subject were compared with the ground truth. Calculate mention below three performance evaluation metrics, using public assessment tool.

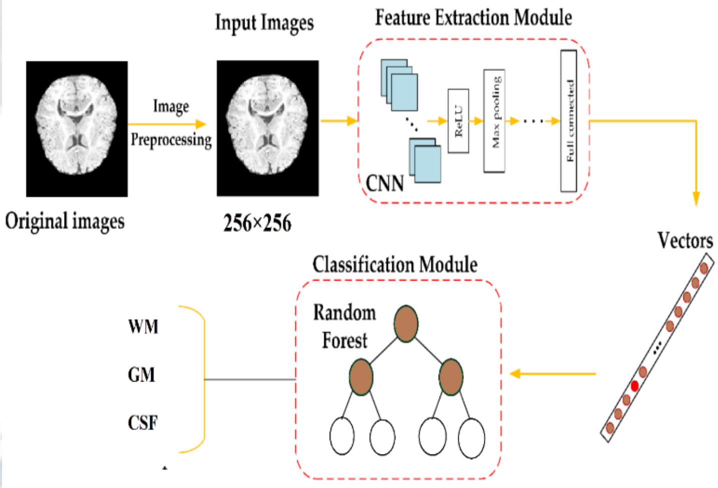

Figure 2. Proposed intergrated CNN-RF method.

1) Performance evaluation metrics: For evaluating our segmentation simulation result, we utilize various performance assessment measures, which are detailed below.

a) (DSC) Dice similarity coefficient: To evaluate the similarity among the segmentation consequence S and label GT G, the Dice similarity coefficient (DSC) states as:

$$DSC = \frac{2|S\cap G|}{|S||G|} \tag{2}$$

Whereas S and G represent the binary segmentation markers produced manually and measurably, respectively, and $|S \cap G|$ represented the magnitude of the node of S and G. A greater DSC values indicated that the segmentation accuracy is excellent.

b) (MHD) Modified Hausdorff distance: MHD is defined as follows to determine the distance between segmentation and ground truth constraints

$$MHD(S,G) = max\ (h95(S,G), h95(G,A)) \tag{3}$$

To avoid the sensitivities to outliers, just use 95th percentile of the Hausdorff distance.

Where $h_{95}\ (S,G) =\ 95\ \mathrm{KK}_{a\in s}\mathrm{min}_{g\in G\|g-a\|}$.

c) (ASD) Average surface distance: The ASD error is the third measurement metric, which is defined as

$$ASD = \frac{1}{2}\left(\frac{1}{n_A}\sum_{s\in surf(S)} d(S,G) + \frac{1}{n_G}\sum_{g\in surf(G)} d(g,s)\right) \tag{4}$$

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Where $surf(S)$ and $surf(G)$ represent the external of the segmentation output S, GD G, correspondingly. n_S represent total amount of points in the segmentation, and n_G indicate ground truth surface.

The Euclidean distance between such a point a on the boundaries of surface S and the surface G is determined by d(S, G), average surface distance with such a lower value means higher segmentation accuracy.

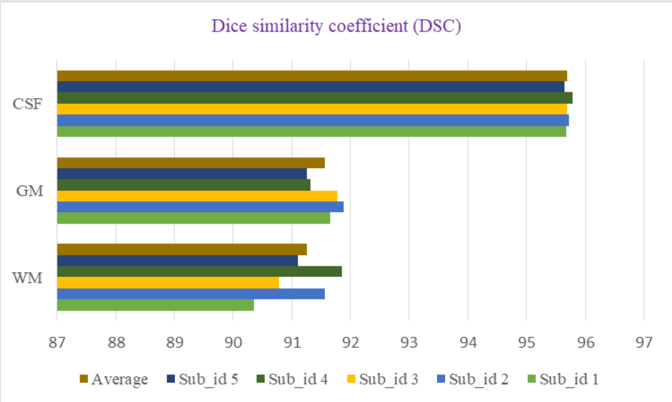

Figure 3. Dice similarity coefficient (DSC)

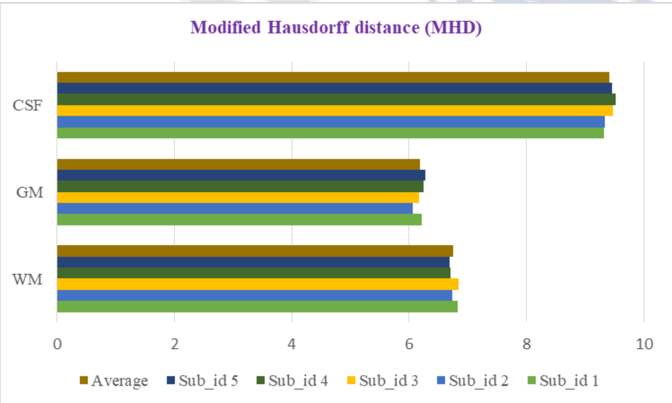

Figure 4. Modified Hausdorff distance (MHD)

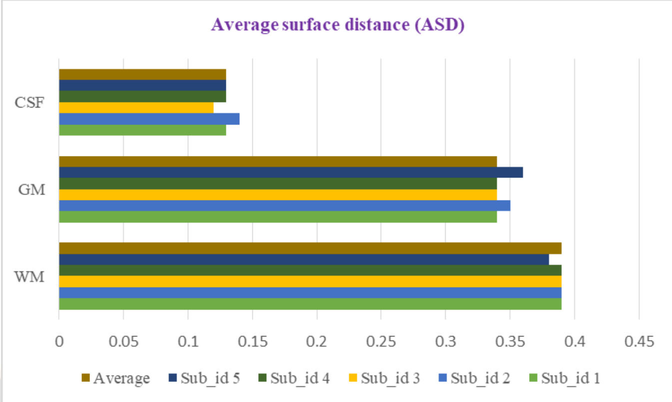

Figure 5. Average surface distance (ASD).

VIII. DISCUSSION

We utilized sequential CNN model and random forest classifier instead of deep learning model which required less computation power. It allowed the proposed approach perform much better. The iSeg-2017 database was used to evaluate the approach. The DSC, MHD and ASD measures of the method for the three classes of WM, GM, and CSF 90.35, 91.65, 95.68, 6.82, 6.22, 9.32, 0.39, 0.34 and 0.13 , respectively.

Table 2 represent the performance evaluation metrics values of coefficient-DSC, Modified Hausdorff distance-MHD and Average surface distance -ASD of white matter tissue, gray matter tissue and cerebrospinal fluid respectively. Bottom line bold value indicate average of the five subjects.

TABLE II. PERFORMANCE EVALUATION METRICS.

Subject_id	WM			GM			CSF		
	DSC	MHD	ASD	DSC	MHD	ASD	DSC	MHD	ASD
Sub_id 1	90.35	6.82	0.39	91.65	6.22	0.34	95.68	9.32	0.13
Sub_id 2	91.57	6.73	0.39	91.88	6.06	0.35	95.72	9.34	0.14
Sub_id 3	90.78	6.84	0.39	91.78	6.17	0.34	95.69	9.48	0.12
Sub_id 4	91.86	6.71	0.39	91.32	6.24	0.34	95.78	9.52	0.13
Sub_id 5	91.10	6.69	0.38	91.25	6.28	0.36	95.65	9.46	0.13
Average	**91.25**	**6.75**	**0.39**	**91.57**	**6.19**	**0.34**	**95.70**	**9.42**	**0.13**

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TABLE III. SIMULATED RESULT OF T1 AND T2 IMAGES.

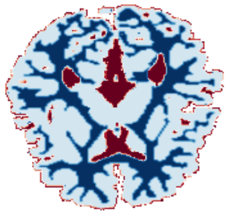
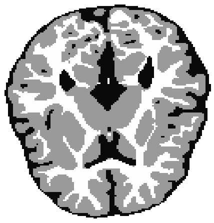
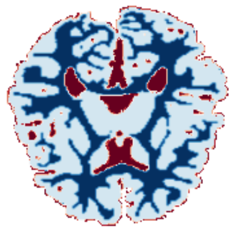
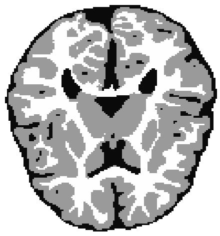
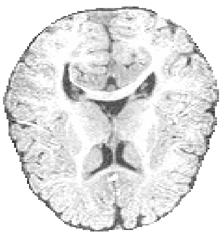
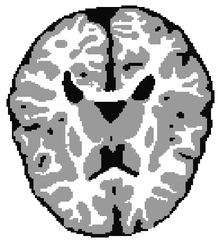
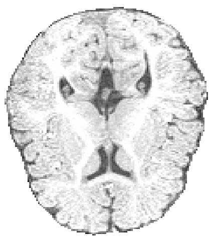
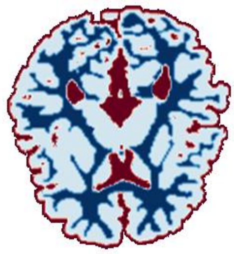
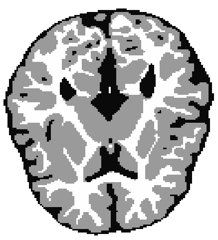
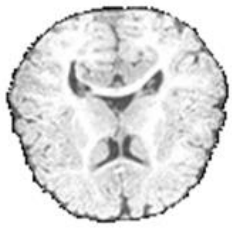
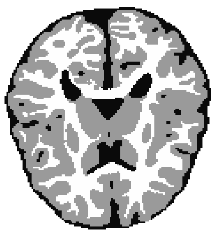
Subject_id	Input Image	Segmented Result	Mask
Sub_id 1			
Sub_id 2			
Sub_id 3			
Sub_id 4			
Sub_id 5			

TABLE IV. COMPARISON WITH EXISTING METHODS BASED ON DSC

Method	CSF	GM	WM
3D-cycleGAN-Seg [3]	85.01	90.73	90.31
But Semi-supervised transfer learning [6]	90.50	90.08	90.14
Our Method	**95.70**	**91.57**	**91.25**

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Table 3 shows the simulation result of segmentation of soft tissue, first column consist of Sun_id, we used total 5 subject. Second column shows input image and reaming column consist of segmented result and ground truth respectively.

Figure 3 to 5 shows the Dice similarity coefficient-DSC, Modified Hausdorff distance-MHD and Average surface distance -ASD values respectively represent using bar graph of the proposed dataset on tissue segmentation corresponding to WM- tissue, GM-tissue and CSF.

Table 4 illustrates a comparison of the proposed system with the existing algorithms. The dice values are, based on the data, significantly higher than the comparison method. When compared to earlier segmentation approaches, the proposed CNN-Random Forest based segmentation method provides better DC. Limitation of this CNN – Random forest method is suitable only for small data set means small training and testing data set. But its work fine on small dataset. We advise combining different transfer learning architecture with a random forest classifier to achieve better results with large data sets.

IX. CONCLUSION

The purpose of this research was to evaluate the efficiency and accuracy of random forest machine learning algorithms in the challenge of segmenting MRI images. The objective was to identify the 3 major categories of brain tissue in skull-striped brain MRI images of 6-month-old newborns. The optimum solution for a segmentation method flow is the Random Forest algorithm, which would improve the results when assisted by supplementary features extracted. The proposed automated system have higher Dice similarity coefficient (DSC) with cerebrospinal fluid tissue proposed method outperformance with exiting approaches.

REFERENCES

[1] Wang, L., Nie, D., Li, G., Puybareau, E., Dolz, J., Zhang, Q., Wang, F., Xia, J., Wu, Z., Chen, J.-W., Thung, K.-H., Bui, T. D., Shin, J., Zeng, G., Zheng, G., Fonov, V. S., Doyle, A., Xu, Y., Moeskops, P., Shen, D. (2019). Benchmark on automatic six-month-old infant brain segmentation algorithms: The ISEG-2017 challenge. IEEE Transactions on Medical Imaging, 38(9), 2219–2230.

[2] Bui, T. D., Shin, J., & Moon, T. (2017, September 11). 3D densely convolution networks for volumetric segmentation. arXiv.org. Retrieved March 7, 2022.

[3] Jaware, T. H., Khanchandani, K. B., & Kalal, D. (2019). An atlas-free newborn brain image segmentation and classification scheme based on Som-DCNN with sparse auto encoder. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 8(1), 49–64.

[4] Bui, T. D., Wang, L., Lin, W., Li, G., & Shen, D. 6-month infant brain MRI segmentation guided by 24-month data using cycle-consistent adversarial networks. 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI).

[5] Zeng, Z., Zhao, T., Sun, L., Zhang, Y., Xia, M., Liao, X., Zhang, J., Shen, D., Wang, L., & He, Y. (2021, January 1).3D-masnet: 3D mixed-scale asymmetric convolutional segmentation network for 6-month-old Infant Brain Mr Images. bioRxiv. March 7, 2022.

[6] Yue Sun, Kun Gao, Sijie Niu, Weili Lin, Gang Li, Li Wang, The UNC/UMN Baby Connectome Project Consortium,. (2020, October 4). Semi-supervised transfer learning for infant cerebellum tissue segmentation. SpringerLink. March 7, 2022.

[7] Yunjie Chen, Yuhang Qin, Zilong Jin, Zhiyong Fan, Mao Cai,"A triple residual multiscale fully convolutional network model for Multimodal Infant Brain Mri Segmentation",(2020). KSII Transactions on Internet and Information Systems, 14(3).

[8] Bui, T. D., Shin, J., & Moon, T. (2019). Skip-connected 3D Dense Net for volumetric infant brain MRI segmentation. Biomedical Signal Processing and Control, 54, 101613.

[9] Sukanya, & Dubey, G. (2020). Segmentation and detection of road region in aerial images using hybrid CNN-random field algorithm. 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence).

[10] T. D. Bui, L. Wang, W. Lin, G. Li and D. Shen, "6-Month Infant Brain Mri Segmentation Guided by 24-Month Data Using Cycle-Consistent Adversarial Networks," 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI), 2020, pp. 359-362.

[11] Chelli N. Devi, Anupama Chandrasekharan, V.K. Sundararaman, Zachariah C., "Alex,Neonatal brain MRI segmentation: A review,Computers in Biology and Medicine,"Volume 64, 2015, Pages 163-178.

[12] M. A. Mufti, E. A. Hadhrami, B. Taha and N. Werghi, "Automatic target recognition in SAR images: Comparison between pre-trained CNNs in a tranfer learning based approach," 2018 International Conference on Artificial Intelligence and Big Data (ICAIBD), 2018, pp. 160-164, doi: 10.1109/ICAIBD.2018.8396186.

[13] Cao G, Wang S, Wei B, Yin Y, Yang G (2013) A Hybrid Cnn-Rf Method for Electron Microscopy Images Segmentation. J Biomim Biomater Tissue Eng 18:114..

[14] C. Mohamed, B. Nsiri, S. Abdelmajid, E. M. Abdelghani and B. Brahim, "Deep Convolutional Networks for Image Segmentation: Application to Optic Disc detection," 2020 International Conference on Electrical and Information Technologies (ICEIT), 2020, pp. 1-3.

[15] Víctor Vives-Boix, Daniel Ruiz-Fernández, "Synaptic metaplasticity for image processing enhancement in convolutional neural networks,"Neurocomputing,Volume 462,2021,Pages 534-543.

[16] Boubakeur Belaroussi, Julien Milles, Sabin Carme, Yue Min Zhu, Hugues Benoit-Cattin, Intensity non-uniformity correction in MRI: Existing methods and their validation, Medical Image Analysis, Volume 10, Issue 2, 2006, Pages 234-246.

[17] Tofts, P. (2003). Quantitative MRI of the Brain: Measuring Changes Caused by Disease. Wiley.

[18] Schatton, T., Murphy, G., Frank, N. et al. Identification of cells initiating human melanomas. Nature 451, 345–349 (2008).

[19] Counsell, S. J. and Rutherford, M. A. (2002). Magnetic resonance imaging of the newborn brain. Current Paediatrics, 12(5):401–413.

[20] Marcel Prastawa, John H. Gilmore, Weili Lin, Guido Gerig, Automatic segmentation of MR images of the developing newborn brain, Medical Image Analysis,Volume 9, Issue 5,2005, Pages 457-466.

[21] Hui Xue, Latha Srinivasan, Shuzhou Jiang, Mary Rutherford, A. David Edwards, Daniel Rueckert, Joseph V. Hajnal, Automatic segmentation and reconstruction of the cortex from neonatal MRI,NeuroImage,Volume 38, Issue 3,2007, Pages 461-477.

[22] Tushar Jaware, Kamlesh Khanchandani & Ravindra Badgujar (2020) A novel hybrid atlas-free hierarchical graph-based segmentation of newborn brain MRI using wavelet filter banks, International Journal of Neuroscience, 130:5, 499-514.

[23] B. Surányi, L. Kovacs and L. Szilagyi, "Segmentation of Brain Tissues from Infant MRI Records Using Machine Learning Techniques," 2021 IEEE 19th World Symposium on Applied Machine Intelligence and Informatics (SAMI), 2021, pp. 000455-000460.

[24] Sadegh Pasban,Sajad Mohamadzadeh,Javad Zeraatkar-Moghaddam,Amir Keivan Shafiei,Infant brain segmentation based on a combination of VGG-16 and U-Net deep neural networks ,IET image process. 2020;14(17):4756-65, DOI: 10.1049/iet-ipr.2020.0469.

[25] Zhou, H., Zhang, Y., Huang, D., Li, L. (2013). Semi-supervised Learning with Transfer Learning. In: Sun, M., Zhang, M., Lin, D., Wang, H. (eds) Chinese Computational Linguistics and Natural Language Processing Based on Naturally Annotated Big Data. NLP-NABD CCL 2013 2013. Lecture Notes in Computer Science (), vol 8202. Springer, Berlin, Heidelberg. 11.

[26] Tushar H. Jaware and K. B. Khanchandani and Durgeshwari Kalal,An atlas-free newborn brain image segmentation and classification scheme based on SOM-DCNN with sparse auto encoder,Computer Methods in Biomechanics and Biomedical Engineering: Imaging \& Visualization, vol 8, pages 49-64, 2020, Taylor & Francis.

[27] Anbeek, P., Vincken, K., Groenendaal, F. et al. Probabilistic Brain Tissue Segmentation in Neonatal Magnetic Resonance Imaging. Pediatr Res 63, 158–163 (2008).

[28] [28]Beare RJ, Chen J, Kelly CE, Alexopoulos D, Smyser CD, Rogers CE, Loh WY, Matthews LG, Cheong JLY, Spittle AJ, Anderson PJ, Doyle LW, Inder TE, Seal ML and Thompson DK (2016) Neonatal Brain Tissue Classification with Morphological Adaptation and Unified Segmentation. Front. Neuroinform. 10:12, 2013.

[29] [29]Ivana Isgum, Manon J.N.L. Benders, Brian Avants, M. Jorge Cardoso, Serena J. Counsell, Elda Fischi Gomez, Laura Gui, Petra S. Hűppi, Karina J. Kersbergen, Antonios Makropoulos, Andrew Melbourne, Pim Moeskops, Christian P. Mol, Maria Kuklisova-Murgasova, Daniel Rueckert, Julia A. Schnabel, Vedran Srhoj-Egekher, Jue Wu, Siying Wang, Linda S. de Vries, Max A. Viergever, Evaluation of automatic neonatal brain segmentation algorithms: The NeoBrainS12 challenge,Medical Image Analysis,Volume 20, Issue 1,2015,Pages 135-151.

[30] [30]Ding Y, Acosta R, Enguix V, Suffren S, Ortmann J, Luck D, Dolz J and Lodygensky GA (2020) Using Deep Convolutional Neural Networks for Neonatal Brain Image Segmentation. Front. Neurosci. 14:207.

[31] A. McAllister, J. Leach, H. West, B. Jones, B. Zhang and S. Serai, “Quantitative Synthetic MRI in Children: Normative Intracranial Tissue Segmentation Values during Development”,American Journal of Neuroradiology December 2017, 38 (12) 2364-2372.

[32] D. Nie, L. Wang, Y. Gao and D. Shen, "Fully convolutional networks for multi-modality isointense infant brain image segmentation," 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI), 2016, pp. 1342-1345.

[33] Feng Shi, Yong Fan, Songyuan Tang, John H. Gilmore, Weili Lin, Dinggang Shen, Neonatal brain image segmentation in longitudinal MRI studies,NeuroImage,Volume 49, Issue 1,2010,Pages 391-400.

[34] Jose Dolz, Christian Desrosiers, Li Wang, Jing Yuan, Dinggang Shen, Ismail Ben Ayed, Deep CNN ensembles and suggestive annotations for infant brain MRI segmentation,Computerized Medical Imaging and Graphics,Volume 79,2020.

[35] Virupakshappa, Amarapur, B. Cognition-based MRI brain tumor segmentation technique using modified level set method. Cogn Tech Work 21, 357–369 (2019).

[36] Ali Isin Cem Direkoglu, Melike sah,Review of MRI-based Brain Tumor Image Segmentation Using Deep Learning Methods,Procedia Computer Science, Volume 102, 2016, Pages 317-324.

[37] Xiangjian Chen,Di Li,Xun Wang,Xibei Yang,Hongmei Li ‘Rough intuitionistic type-2 fuzzy c-meansclustering algorithm for MR image segmentation’, IET Image Process., 2018,13, (4), pp. 607–614.

[38] Sezavar, A., Farsi, H., Mohamadzadeh, S. ‘A modified grasshopperoptimization algorithm combined with CNN for content based imageretrieval’, Int. J. Eng., 2019, 32, (7), pp. 924–930.

[39] Ostertag, C., Beurton-Aimar, M., Urruty, T.: ‘3D-SiameseNet to analyze brainMRI’. 10th International Conference on Pattern Recognition Systems (ICPRS-2019), Tours, France, 2019, pp. 18–23.

[40] M. Huang, W. Yang, Y. Wu, J. Jiang, W. Chen and Q. Feng, "Brain Tumor Segmentation Based on Local Independent Projection-Based Classification," in IEEE Transactions on Biomedical Engineering, vol. 61, no. 10, pp. 2633-2645, Oct. 2014.