Early Brain Tumour Detection Using Residual Network and Random Forest

Dr. S. Satheesh[1], Dr. P. Ashok Babu[2]

[1]*Professor, Department of ECE, RISE Krishna Sai Prakasam Group of Institutions, Ongole, Andhra Pradesh, India.*

[2]*Professor and Head, Department of ECE, Institute of Aeronautical Engineering, Dundigal, Hyderabad, Telangana, India.*

Abstract: In order to segment a brain tumor, it is necessary to distinguish between distinct tumor tissues such as active cells, necrotic core, and edema, and normal brain tissues such as white matter and grey matter (GM), as well as cerebrospinal fluid (CSF). Magnetic Resonance Imaging (MRI) based brain tumor segmentation studies have gained increasing interest in recent years because they are non-invasive and provide strong, soft tissue contrast. In addition, innovative methods of brain tumor segmentation using computer-aided methodologies have become more mature over almost two decades, and they are getting closer to being used in normal clinical settings. This paper aims to provide a comprehensive overview of brain tumour segmentation approaches using magnetic resonance imaging (MRI). The first section provides a basic introduction to brain tumours and imaging methods for brain tumours. In addition, the paper proposed a convolution-based optimization method. With the help of Random forest techniques, this proposed method improves segmentation and classification parameter

Keywords: Brain Tumor, Classification, Random Forest, Residual CNN.

I. INTRODUCTION

Neuroimaging applications such as surgery, surface reconstruction, and image registration need brain area segmentation [1] [3]. All known approaches rely on registration and image geometry. If this fails, the chances of success are slim. Convolutional Neural Network (CNN) is utilised to prevent this. For non-geometric brain extraction. CNN studied the brain's connections and form. MR imaging, CT imaging, digital mammography, and other modalities have been used to diagnose medical procedures accurately [10] [15]. These may offer extensive anatomical information. As a result, diagnostic imaging became an important tool in diagnosis and treatment planning. This is the initial stage in any neuroimaging application like tissue segmentation and volume computation. Because of the intricate borders and poor contrast, automatic skull removal takes a long time. Scientists create numerous approaches.

Deep learning (or deep structured learning) is a machine learning algorithm. Supervised or unsupervised data learning from the input image [4] [18]. Traditional machine learning techniques for segmenting normal (e.g., white matter and grey matter) and diseased brain tissues have been developed (e.g. Brain tumours). This division needs rigorous engineering and particular knowledge to create. Traditional machine learning methods also lack generalisation [2]. Despite a significant effort from the medical imaging research community, automated segmentation of the brain structures and detection of the abnormalities remain an unsolved problem due to normal anatomical variations in brain morphology, variations in acquisition settings and MRI scanners, image acquisition imperfections, and variations in the appearance of pathology. Deep learning, a novel machine learning approach that avoids the constraints of standard machine learning algorithms may help identify new valuable imaging characteristics for quantitative brain research [17]. This includes computer-aided detection of breast lesions, computer-aided diagnosis of breast lesions and pulmonary nodules, and histological diagnosis.

1.1.1 Image Segmentation

Images are segmented into regions or categories representing different things or sections of objects. Each pixel in an image belongs to one of these categories. • Pixels in the same category have comparable greyscale values and form a contiguous zone; • Pixels in separate categories have differing values. Semantically meaningful, homogenous, non-overlapping patches have comparable qualities such as intensity, depth, colour, or texture [10] [13]. The segmentation output is either an image of labels identifying each homogenous area or a collection of contours that characterise the region's borders. White matter (WM), grey matter (GM), and cerebrospinal fluid (CSF) are the three basic tissue types in brain MRI (CSF). The segmentation findings are then utilised for anatomical structure analysis, pathological area analysis, surgical planning, and visualisation [18] [19].

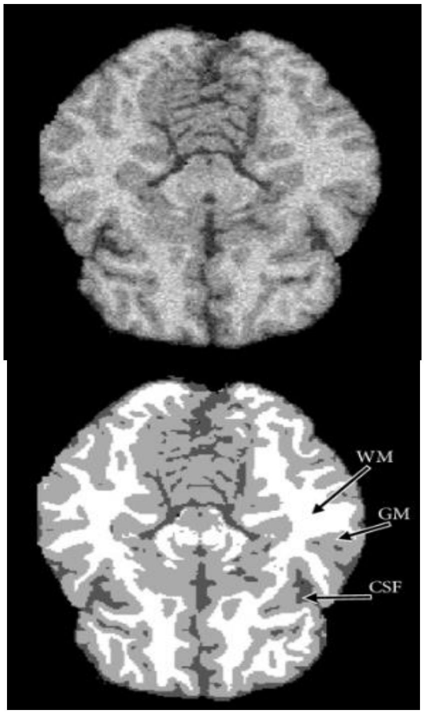

Figure 1: Brain Region segmentation with (a) real MR image (b) segmentation image with GM, CSF, and WM

Image segmentation can use 2D images, 2D image sequences, or 3D volumetric images. The majority of image segmentation research has been done in 2D. However, when dealing with 3D data (for example, MRI images), each image "slice" is generally segmented independently.

It is sometimes necessary to use post-processing to combine fragmented 2D slices into a 3D volume or a continuous surface. Furthermore, removing critical anatomical information in 3D space may result in inconsistent and non-smooth segmentation.

For more accurate volumetric image segmentation, 3D segmentation algorithms are required. The processing components, pixels/voxels, and 2D or 3D neighbourhoods are the primary differences between 2D and 3D image segmentation. However, 2D image segmentation algorithms can be extended to 3D space [2] [15].

1.2 Deep Learning

Deep learning extracts information from raw images by using multiple layers (typically more than five) of neural networks. As opposed to hand-crafted feature extraction in standard machine learning algorithms, self-learning algorithms can extract a complex hierarchy of features from images. As a result, big data training produces excellent results and generalizability.

Modern deep learning methods have been made possible by rapid advances in GPU computing power [13]. This enables deep learning algorithms to learn from millions of images while remaining resistant to image variations. As a result, deep learning algorithms have been developed for various applications, including image object identification and segmentation, voice recognition, and disease genotype/phenotype detection and classification. Techniques such as stacked auto-encoders, deep Boltzmann machines, convolutional neural networks, and others fall into this category.

Most image segmentation and categorization use CNNs. Deep CNNs [1] produced outstanding results in the ImageNet competition in 2012. Applied to a dataset of around a million images that contained 1000 distinct classes, CNNs almost decreased the error rates of the previously best computational algorithms [9]. Some systems have over 100 layers, resulting in millions of weights and billions of connections between neurons. Convolution, pooling, activation, and classification layers are typical CNN layers (fully connected). In this layer, a kernel is convolved over the input image. The pooling layer uses the maximum or average of the chosen neighbourhood to down sample the output of previous convolutional layers. Activation functions like Rectified Linear Unit (ReLU) and Leaky ReLU are widely employed.[10] [3].

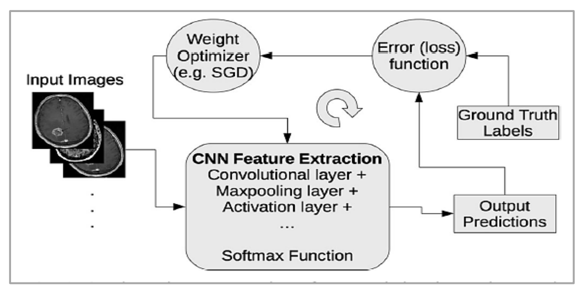

Figure 2: Basic Architecture

II. RELATED WORK

Siqi Bao et al. [1] developed a unique strategy for brain MR image segmentation that has been used deep learning methods to achieve preliminary labelling and graphical models to generate the final output. The MS-CNN architecture captures discriminative information for each sub-cortical structure and generates a label probability map for the target image.

Using deep learning-based segmentation for quantitative brain MRI, Zeynettin Akkus et al. [3] intend to present an overview. First, we'll look at existing deep learning architectures for segmenting brain regions and lesions. Then we review and examine deep learning's performance, speed, and characteristics. Finally, we examine the existing condition and forecast future changes and trends.

Mohammad Havaei et al. used Deep Neural Networks (DNNs), the suggested networks that target glioblastomas (low and high grade) shown on MR. These tumours may occur anywhere in the brain and have any form, size, or contrast. For these reasons, we are investigating a machine learning solution based on a flexible, high-capacity DNN.

As an alternative to surgical biopsies and histological examination, convolutional neural networks (CNN) were used by Zeynettin Akkus et al. [5].

On the other hand, Tom Brosch et al. [6] suggested a unique segmentation strategy based on deep 3D convolutional encoder networks with shortcut connections. This model is a convolutional neural network with two coupled pathways: a de-convolutional route that predicts the final voxel segmentation.

Automatic segmentation using Convolutional Neural Networks (CNN) was suggested by Sérgio Pereira et al. [7]. Small kernels allow for deeper architectures and reduce overfitting by reducing the number of weights in the network. Although not prevalent in CNN-based segmentation approaches, intensity normalisation and data augmentation were successful for brain tumour segmentation in MRI images.

To identify CMBs from MR Images, Qi Dou et al. presented a 3D convolutional neural network (CNN). Instead of using low-level descriptors or 2D CNNs, our technique utilises spatial contextual information in MR volumes to extract more representative high-level features for CMBs, resulting in improved detection accuracy.

III. PROPOSED FRAMEWORK

a. Convolution

Considering a network with $\tilde{L} \geq 1$. Among $\tilde{L}$ layers, $\tilde{L} - 1$ represent hidden type of layers. Let y_o represent the network input. For each of the layer $\tilde{l} \in \{1, 2, \ldots, \tilde{L}\}$ set $a_{\tilde{l}} = \omega_{\tilde{l}} s\,(a_{\tilde{l}-1})$ where s presents a vector-based function, $s(a_0) = x_0$. The layers of consecutive nature are interlinked. Let $f(\omega, x_0)$ and $\omega = (\omega_{\tilde{l}})_{\tilde{l}}$ be the network output at end of $\tilde{L}^{\text{th}}$ layers.

Local gradient based back propagated error: Each of the layer $\tilde{l}$ involves various units. The local gradient based back propagated error is usually defined by $(El)_{a_i}$as the partial derivative at i$^{\text{th}}$ unit: The use of rule based on classical chain results in:

$$(El)_{a_i} = (El)_{a_j}.(a_j)_{wij}$$

Linear Networks: We usually refer to the network of linear form when there is "s" type of mapping which identifies the function; s (a) = a: In such type of case, the $f(\omega, x_0)$ output function represents a weight-based polynomial function.

Maxout: This layer represents a simple layer where the activation-based function is the maxima of inputs.

Maxpooling: It is usually done by putting into use of a maximized filter to sub regions (non-overlapping) of the primary representation as shown in figure 4.2 below.

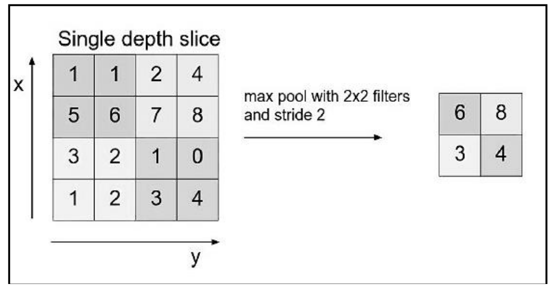

Figure 3: Max pool operation example

A unit of max-pooling 'j' outputs the maxima of all the unit outputs from where it accepts the inputs. Further to the process of max pooling, the units of pooling can perform various other type of functions like L2-norm pooling or even the process of average pooling.

Rectifiers: This represents a neuron layer that is applies the activation function of non-saturating form $\mathrm{s(a)} = \max(0;\, a)$: The other type of functions are mainly used for increasing the nonlinearity, for instance, the saturating form of hyperbolic tangent $\mathrm{s(a)} = \tanh(a)$; $\mathrm{s(a)} = \mathrm{j}\tanh(\mathrm{a})\mathrm{j}$, and $\mathrm{s(a)} = (1 + e^{-\alpha})^{-1}$as the sigmoid function: The RLU i.e. Rectified Linear Units are mainly used in various kind of implementations.

Dropout: The technique of dropout helps in improving the neural networks and basically aims to mitigate or reduce the overfitting problem. It mainly comprises of dropping out all the units (visible and hidden) in the methodology of neural networks. With this technology, it usually ignores all the operations of that specific units, along with its outgoing and incoming links or connections.

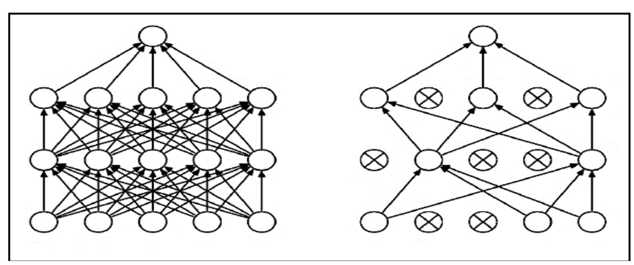

Figure 4: Left figure: A standardized neural network (NN) with two hidden layers. Right figure: An instance of a produced

thinned net by putting into use of a dropout on the left of the network. The units that are of crossed form has been dropped

Dropconnect: It represents dropout refinement where instead of units, the links are dropped during the period of training.

Convolution layers: In a convolutional layer, the units of convolutional layer shares weight through a discrete type of convolution.

b. Learning the Network

The prediction-based error is evaluated using the "loss" function, which aids in estimating the distance from the network based on predicted label levels. By adjusting the system weights, this mistake or distance propagates back into the network. Back-propagation is a technique that uses gradient descent to update the network weights. The method of updating network weights is generally dependent on the error made by the network.

The technique of Gradient descent allows updating the parameters of the gradient in the opposite direction of the objective function J () with respect to the system-based parameters. The learning rate determines the step size required to attain a local minima.

IV. PROPOSED METHODOLOGY

A new model has been proposed in the following steps:

i. First, upload brain MR Images.
ii. The image was denoised and pre-processed in this step.
iii. Next, we'll look for a group that has the same geographic location.
iv. Apply the convolution technique in the fourth step.
v. After Residual Convolution, extract and organise the low-level features.
vi. To go on to step 6, you must first ensure that the output is optimal.
vii. Find the non-overlapping features and random forest, then analyse precision, recall, and Accuracy of the random forests.

Proposed methodology Flowchart: This section contains the proposed methodology based on the steps outlined in the previous section.

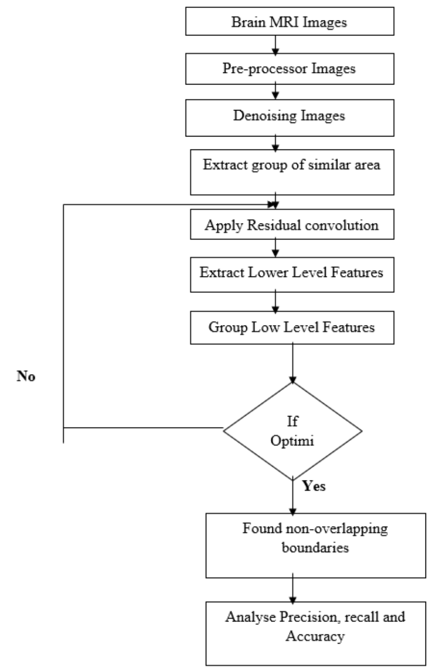

Figure5: proposed flow chart

V. RESULTS

The proposed and present strategies are compared in Table 1 using performance metrics such as precision, recall, and accuracy. It depicts how uncertainty in a system's output can be distributed and allocated to various sources of uncertainty in the system's inputs and how this might be done.

Table 1: Comparison of Performance metrics between existing and proposed approach

Approaches	Accuracy	Precision	Recall
CNN	90.12	91.12	90.12
Residual Network	93.132	92.12	91.22
Residual-RF	95.14	96.12	98.34

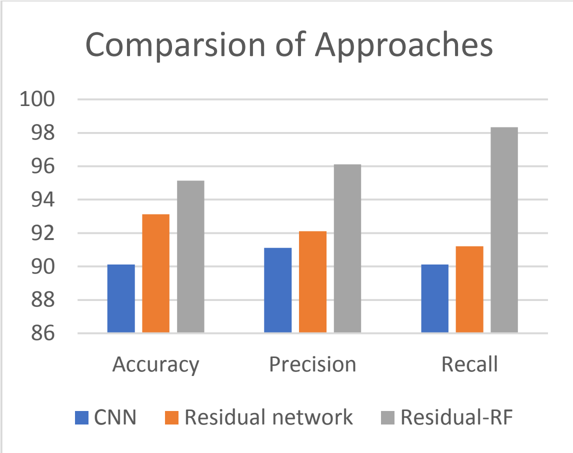

Figure 6: Comparison of Performance metrics between the existing and proposed approaches

VI. CONCLUSION

Brain Tumor segmentation is considered a challenging operation because of the diversity of Tumor forms and the difficulty of establishing tumors' location, size, and texture in magnetic resonance imaging (MRI). Tumor segmentation by hand is a time-consuming procedure that is prone to human error.

This paper proposes an automated method for finding cancer slices in volumetric MRI brain scans and segmenting the Tumor across all image slices, which can be used in conjunction with other investigations.

In the pre-processing step, a set of algorithms is used to clean and standardize the data that has been collected. Brain Tumor segmentation algorithms have achieved good results in medical image analysis; nonetheless, there is a substantial gap between them and practical applications. In the suggested technique, increase feature mapping of segmented brain images, which would result in improved categorization.

VII. REFERENCES

[1] Bao, S., & Chung, A. C. (2018). Multi-scale structured CNN with label consistency for brain MR image segmentation. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, *6*(1), 113-117.
[2] Kamnitsas, K., Ledig, C., Newcombe, V. F., Simpson, J. P., Kane, A. D., Menon, D. K., & Glocker, B. (2017). Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. *Medical image analysis*, *36*, 61-78.
[3] Akkus, Z., Galimzianova, A., Hoogi, A., Rubin, D. L., & Erickson, B. J. (2017). Deep learning for brain MRI segmentation: state of the art and future directions. *Journal of digital imaging*, *30*(4), 449-459.
[4] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., & Larochelle, H. (2017). Brain tumour segmentation with deep neural networks. *Medical image analysis*, *35*, 18-31.
[5] Akkus, Z., Ali, I., Sedlář, J., Kline, T. L., Agrawal, J. P., & Parney, I. F. Predicting 1p19q Chromosomal Deletion of Low-Grade Gliomas from MR Images Using Deep Learning.(2016).
[6] Brosch, T., Tang, L. Y., Yoo, Y., Li, D. K., Traboulsee, A., & Tam, R. (2016). Deep 3D convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation. *IEEE transactions on medical imaging*, *35*(5), 1229-1239.
[7] Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumour segmentation using convolutional neural networks in MRI images. *IEEE transactions on medical imaging*, *35*(5), 1240-1251.
[8] Dou, Q., Chen, H., Yu, L., Zhao, L., Qin, J., Wang, D., & Heng, P. A. (2016). Automatic detection of cerebral microbleeds from MR images via 3D convolutional neural networks. *IEEE transactions on medical imaging*, *35*(5), 1182-1195.
[9] Havaei, M., Guizard, N., Larochelle, H., & Jodoin, P. M. (2016). Deep learning trends for focal brain pathology segmentation in MRI. In *Machine Learning for Health Informatics* (pp. 125-148). Springer, Cham.
[10]. Moeskops, P., Viergever, M. A., Mendrik, A. M., de Vries, L. S., Benders, M. J., & Išgum, I. (2016). Automatic segmentation of MR brain images with a convolutional neural network. *IEEE transactions on medical imaging*, *35*(5), 1252-1261.
[11] Cheng, J. Z., Ni, D., Chou, Y. H., Qin, J., Tiu, C. M., Chang, Y. C., & Chen, C. M. (2016). Computer-aided diagnosis with deep learning architecture: applications to breast lesions in US images and pulmonary nodules in CT scans. *Scientific reports*, *6*, 24454.
[12] Litjens, G., Sánchez, C. I., Timofeeva, N., Hermsen, M., Nagtegaal, I., Kovacs, I., & Van Der Laak, J. (2016). Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis. *Scientific reports*, *6*, 26286.
[13] Galimzianova, A., Pernuš, F., Likar, B., & Špiclin, Ž. (2016). Stratified mixture modelling for segmentation of white-matter lesions in brain MR images. *NeuroImage*, *124*, 1031-1043.
[14] Nie, D., Wang, L., Gao, Y., & Sken, D. (2016, April). Fully convolutional networks for multi-modality isointense infant brain image segmentation. In *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)* (pp. 1342-1345). IEEE.
[15] Tomas-Fernandez, X., & Warfield, S. K. (2015). A model of population and subject (MOPS) intensities with application

to multiple sclerosis lesion segmentation. *IEEE transactions on medical imaging*, *34*(6), 1349-1361.

[16] Zhang, W., Li, R., Deng, H., Wang, L., Lin, W., Ji, S., & Shen, D. (2015). Deep convolutional neural networks for multi-modality isointense infant brain image segmentation. *NeuroImage*, *108*, 214-224.

[17] Wang, L., Gao, Y., Shi, F., Li, G., Gilmore, J. H., Lin, W., & Shen, D. (2015). LINKS: Learning-based multi-source IntegratioN frameworK for Segmentation of infant brain images. *NeuroImage*, *108*, 160-172.

[18] Maier, O., Schröder, C., Forkert, N. D., Martinetz, T., & Handels, H. (2015). Classifiers for ischemic stroke lesion segmentation: a comparison study. *PloS one*, *10*(12), e0145118.

[19] Zhao, L., & Jia, K. (2015, September). Deep feature learning with discrimination mechanism for brain tumour segmentation and diagnosis. In *2015 International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP)* (pp. 306-309). IEEE.