A Review on Stroke Lesion Analysis in MRI Datasets

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Abstract. Stroke is one of the major causes of disability in the world. The various disabilities due to stroke includes intellectual functioning damage locomotory dysfunction, visual and hearing impairment, disfigurement etc., This occurs due to occlusion or inhibition of blood supply to the brain which is known as Ischemic stroke, whereas rupturing of blood vessels to the brain causes hemorrhagic stroke. Imaging techniques such as CT and MRI have played a huge role in the visualization of stroke lesions. Segmentation of the salvageable tissue and its outcome of how it affects a person's lifestyle is the key focus of research as automated model is highly recommended to reduce the time and increase the accuracy in the prediction of stroke lesion in comparison to manual intervention.

Keywords. Stroke lesions, Image Modalities-CT, MRI, Segmentation, Convolutional NeuralNetwork.

1. Introduction

Cerebro vascular accident (CVA) is the major cause of disability or death across the world. CVA occurs due to occlusion of blood vessel due to atherosclerosis or occurrence of embolus in the blood vessels causes ischemic stroke[1]. High pressure or weak blood vessels rupture causing hemorrhagic stroke where the blood is not supplied to the region beyond the rupture. Necrosis of the brain tissue due to lack of blood flow causes temporary or permanent damage to the person[2]. Treatment for stroke involves identifying the penumbra (potentially recoverable) and core (irrecoverable) regions of the lesion and restoring the blood flow to the former where flow of blood is restricted[3]. Early intervention and accurate detection can cause relatively less damage based on the functional outcome after stroke[4]. Non-Invasive modalities like magnetic resonance imaging (MRI) and computerized tomography (CT) are used in the detection of brain lesions. Change in the water molecules of the brain due to the effect of magnetic field produces an increased signal in MRI and reduced signal in CT which helps in the detection of stroke. Manual intervention in identifying the stroke affected area is a cumbersome and tedious task. Thus, various computer aided techniques have been developed in the recent years to support the effective diagnosis of brain tissue damages.

Brain CT provides detailed information along the horizontal or axial view of the head in comparison to X-ray. CT of the brain is performed to assess the injuries,

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inter-cranial bleeding, lesions and structural anomalies. Radiation exposure is the main disadvantage of CT as the exposure limit must be consulted with the physician. Similarly, the contrast medium used could cause allergic reactions[5]. MR Imaging of the brain uses magnetic and radio waves to provide detailed structure of the brain. MRI is safer than CT as it does not use radiation [6]. The radio waves manipulate the position of the atoms which is send to the system for producing images. It provides a clear vision of the brain in comparison to CT, X- ray or ultrasound[7]. CT scans are widely used as they are less expensive. However, MRIs produce a detailed image in contrast to CT. Soft tissues, Ligaments and internal organs produce a detailed image in MRI than CT[8].

Image segmentation of the brain has opened new horizons in studying the lesions of the brain for medical diagnostics. Region of Interest (ROI) is obtained through precise segmentation which is a complex and tedious task if performed manually. This paper presents a survey on stroke lesion segmentation and discusses the validation metrics such as accuracy, precision, sensitivity and dice coefficient. The general architecture for stroke lesion analysis system is presented in fig 1.

2. Methods and Techniques

Chen et al.,[9] proposed a method of identifying the white matter hyperintensity of the brain as it is closely associated with stroke, dementia and cognitive impairment. Iterative linearly constrained minimum variance (ILCMV) is a classification method which iteratively captures the spatial information through LCMV which is used to effectively used in classifying both normal and white matter of the brain by combining both spectral and spatial information to detect the white matter hyper intensity (WMH). This method reduces the time of operation in identifying the classes in the brain using different filters such as gaussian, gabor, guided and bilateral filter (BF). Gaussian filter combined with ILCMV showed an accuracy around 95% along with dice similarity coefficient (DSC) of 0.936 and above.

Figure 1., Architecture of general stroke lesion analysis system

Sergio et al., [10] used a method of feature recombination and recalibration where number of feature maps are increased linearly which allows the information to be

mixed efficiently which is called as spatial adaptive squeeze and excite segmentation (SegSE). The recombination involves mixing the features linearly whereas recalibration is used to obtain the relationship between the features and suppress the less relevant ones. FCN is utilized for the segmentation of lesions. The squeeze operation involves suppressing the feature maps along with ReLu activation which is further recalibrated using excitation approach. This approach when evaluated on ISLES 2017 dataset showed an improved dice coefficient score of 0.34 and sensitivity of 0.55 which was higher than the other methods used in evaluation of lesion prediction.

Rongzhao et al., [11] proposed a 3D fully convolutional and densely connected convolution network for automatic and accurate segmentation of ischemic stroke. These densenets uses 20 layers of convolution which allows input from the previous layers to be included in the next layer. Auxillary classification pathway is used to recover the lost images due to down sampling operation. Dice function is used to rectify the class imbalance problems. Skip connections in the network is overcome by deep residual learning. A densenet consists of dense unit, growth rate and dense block. The dense unit reduces the resolution and number of features which causes a large variation in lesion appearance. Introduction of auxiliary pathway over dense unit increases the prediction volume. The automatic segmentation leads to unwanted rejection of samples that are actually lesions. True lesions along the edge can be missed. The DSC of 77.14% with lesion precision of 89% is achieved using this model.

Wang et al., [12] utilized a 3D cross hemisphere neighbourhood difference convnet, a CNN methodology for segmentation which utilizes patch-based approach in 3D space. The symmetry of the brain is considered to identify the lesion region by finding the similarity between the images and the cross-hemisphere neighbourhood difference provides robustness to the symmetry. The Dice score of 80 % was achieved using this method.

Vupputuri et al.,[13] proposed a superpixel based segmentation on axial and coronal MR images. Superpixels based clustering are used to improve the speed and accuracy of the lesion segmentation. Hierarchical region splitting method is used to perform pre-processing and the output image is normalized using Z-score. Sobel operator is used to derive the vertical edges and patch wise intensity and region patch-wise intensity is compared to determine the hemisphere with lesions. A simple linear iterative clustering method is used on the hemisphere of the brain where the lesion is present which is a superpixel based segmentation. Agglomerative clustering is used to group the lesions together. The clustering method causes over and under estimation of injury. Multi modal and multi view segmentation was not performed using this method. MICCAI challenge dataset demonstrated higher performance with dice similarity score of 81.14%, average sensitivity of 82.32% and specificity of 93%.

Sathish et al., [14] illustrated an adversarial learning methodology in deep learning for the semantic segmentation of the brain. Fully automated Convolutional neural network is used to estimate the core and penumbra using sequence maps in MRI. Segmentation includes an encoder-decoder similar to VGG11[15] was used for the large-scale image classification. Discriminator uses a batch normalization and

leaky ReLU activation to determine the non-linearity. Sigmoid activation was also used in the layers of CNN which determines the cross-entropy loss and turing test discriminator identifies the penumbra of the lesion. Diffusion-Weighted Imaging (DWI), Time to Peak (TTP) and Time to peak of the impulse response (Tmax) information were trained and 3-fold cross validation was performed. Over and under segmentation was considerably reduced. Unified Diffusion and perfusion map the input for deep learning-based feature segmentation to produce accuracy. Limited availability of diffusion and perfusion images causes overfitting of training data. This method was evaluated on ISLES 2015 dataset to obtain a dice score of 0.82 and 0.73 for segmentation of penumbra and core.

Khademi et al., [16] discussed about the white matter lesion segmentation for FLAIR MRI. Partial volume averaging (PVA) is used to compute the volume of the lesions. This generates an image intensity proportional to the tissue which helps in determining the edge information. Fuzzy edge technique was used to group significant and suppress the rest. Thus, normalizing the edge information. Intensity and edge measures were used to denoise the fuzzy edge. Single modality and model free approach was used for classification which caused high correlation to segmentation by experts. PVA performs poor due to bright CSF in ventricles and assigning low α to small lesions. The method showed an accuracy above 98% in segmenting WML, brain and CSF.

Akshat et al.,[17] proposed a Multisequence network (MSNet) architecture to determine the lesions in the MRI Image. MSNet, a deep neural network combines multi sequence images to differentiate between core and penumbra. The drop out layer is combined with the convolutional layer output to decrease misclassification. MSNet is used to decrease the over and under estimation of lesions in the MRI sequence. Pixel by pixel comparison is used to decrease the load. Core and penumbra segmentation showed a better performance in core in comparison to penumbra when tested on ISLES 2015 dataset with DSC of 0.68, sensitivity of 0.805 and specificity of 0.99.

Yanran et al., [18] proposed a deep lesion symmetry convNet for chronic lesion segmentation using MRI. SymROBEX algorithm was used to perform skull stripping which is based on random forest. Histogram equalizer was then applied to provide better contrast. The network construction was mapping of voxels to TI modal. Post processing includes smoothing of lesion images. The Dice similarity coefficient using bilateral voxel improved the performance from 0.63 to 0.78 as compared to unilateral voxel descriptor.

Asit et al., [19] proposed an expectation- maximization (EM) algorithm which was further processed using fractional order Darwinian particle swarm optimization (FODPSO) to increase the accuracy. Maximum likelihood is computed probabilistically on all the features in an unsupervised manner. The expectation step is to obtain the lost data whereas the maximization step determines the best fit. FODPSO is an optimization method used to control the convergence. GLCM method is used to extract the features of the ROI. Random Forest classifier and decision tree are further used to classify the image. RF classifier provides an accuracy of 93.4% in determining the class labels. 3D volumetric details of the ROI were not used for analysis.

Keerthana et al., [20] proposed segmentation of stroke based on Fuzzy C-Means method. Fuzzy C-means clustering used for clustering image objects is an unsupervised method used in various fields effectively. Various data point distances are analysed between each pixel and cluster center. The method minimizes the energy using Lagrange multiplier which performs the needed optimization. The segmented portion is used to extract the region of stroke based on edge detection and the size provided the needed details for decision making.

Haocheng et al., [21] combined both CNN and hand-crafted features for the effective segmentation of the stroke images. A Fully Convolutional neural network is used classification with one down sampling along with three up sampling. Intensity, hemispheric intensity between the pixels, first order statistics of volume along with maximum response filters are used as and crafted features which is further applied to classifiers for effective detection stroke.

Karthik et al., [22] combined watershed approach for segmentation of ROI along with discrete curvelet transformation for feature extraction. Segmentation approach limits the neighbourhood drainage as it utilizes drop of water principle which moves from maxima to local minima. Further, discrete curvature transform discretizes the converted gray image from which the curvature coefficients are determined which helps in analysing the mean, variance, standard deviation, skew and kurtosis for analysing the features for its classification using SVM. This method achieved 99.1 % accuracy for 45 clinical datasets.

Liang et al., [23] proposed a method to automatically segment the stroke lesions along with minimizing the number of false positives. The proposed model contains two framework which includes ensemble adapted DeconvNets (EDD Net) and Multiscale Convolutional Label Evaluation Net (MUSCLE Net). The EDD Net achieves an optimal segmentation at all levels and MUSCLE net removes the number of false positives. EDD Net uses the image patches to identify the lesions using DeconvNets which utilizes convolution and pooling layers along with deconvolution and unpooling layers in order to create segmentation probability map. The smaller lesions are then provided to the MUSCLE Net to differentiate the true and false positives. This method relatively reduced the number of false positives and provided 0.67 Dice coefficient and the lesion detection rate is 0.94.

Kamnitsas et al., [24] proposed a 3D convolutional neural network for lesion segmentation. This methodology includes CNN includes 11 layers which is sampled in parallel processing of input images through convolutional pathways. The sub-sampled input patch is obtained from the original image thus providing a large around the image to be processed. Time to analyse the image has been significantly improved. A dice score of 64% was achieved when tested on ISLES 2015 dataset.

Shubham et al., [25] proposed a patch-based approach with multi scale convolutional layers are used to segment the MRI images as the region containing lesions are less in comparison to the region associated with lesions. The local and global features are acquired effectively from different paths. The binary accuracy of this method is 96% with a dice score of 0.81.

Zhiyang et al., [26] proposed a 2D sliced based segmentation on multi spectral MRI that includes diffusion weighted image, apparent diffusion coefficient and T2-weighted image using residual convolutional network (Res-FCN). Input

patches are used to evaluate the lesions which is extracted by using sliding window scheme. The features are extracted from the Res block through convolutional layers. The number of false negatives were decreased on evaluation on the testing data due to high accuracy in segmentation with a mean dice coefficient of 0.645.

Albert et al., [27] proposed segmentation on multi modal MRI using 3D U-net and Res-Net architecture. The residual block with 2 convolution layers is used for down sampling. The input images are analysed as patches to overcome the class imbalance problem due to a contrast variation in healthy and lesion tissues. A random offset value is provided to the lesion tissues to retain them in the final extraction. The method provided better sensitivity with lower Hausdorff distance. This method achieved a DSC of 0.84 and sensitivity of 0.89.

Jose et al., [28] proposed a U-Net based architecture for segmentation tasks. The encoding path is split into N- streams for different image modality along with hyper dense connections to improve the information flow with deep supervision along the reduction of over fitting on small training sets. InceptionNet is employed that includes different kernel sizes for estimation of lesions which improved the dice similarity coefficient to 0.635 and considerable reduction in modified Hausdorff distance to 18.64 mm.

Guerrero et al., [29] proposed a Fully convolution CNN network called uResNet that contains an analysis path to determine the features and synthesis path combines these features with class likelihood for segmentation. This method uses single path to extract the features of the image patch. The Dice score obtained provides a near perfect result in accordance to lesion prediction algorithm (LPA) and Deepmedic. UResnet is also capable of distinguishing different types of lesions effectively. The stroke dice score increased to 40 % with WMH to 70%.

Subbanna et al., [30] proposed a Bayesian technique to estimate the lesions using the gabor textures which were extracted from the FLAIR image intensities. The Bayesian classification distinguishes between the lesion and non-lesion voxels which is provided as an input customized Markov Random Fields (MRF). The MRF utilizes both the intensities of the voxel along with the intensity of the neighbourhood pixels in order to preserve the boundary of the lesions. This method qualitatively identifies and segments all the lesions with higher accuracy and average dice coefficient of 0.582 using multi- modal MRI datasets

Anjali et al., [31] proposed a random forest method for segmenting the stroke lesions. Histogram based thresholding which is a pixel level image segmentation to segment the region of interest. Random forest reduces the computational cost as the number of features for splitting is reduced. Segmentation accuracy of 3D MRI is increased with average overlap accuracy measuring 0.67 and average hausdorff distance 28.09 mm.

Oskar et al., [32] proposed a fully automated method for segmentation of stroke using extra trees. Extra tree forest are ensemble classifiers which uses a random threshold value for each feature. This method is useful in training uncertain data and is robust to noise. Evaluation on clinical dataset provides dice coefficient to 0.65. A detailed summary is represented in Table 1.

3. Conclusion

Various automatic and semi-automatic based methodologies used in segmentation of stroke were discussed. All the techniques discussed above show relatively high

satisfactory results but further analysis is needed to increase the accuracy, computational speed and precision with the significant decrease in manual intervention. Most of the methods used ISLES dataset for calculation and hence further studies can be carried with clinical dataset with considerably higher MRI images.

Table 1. Methods used in stroke lesion analysis.

S.No	Referen ce Paper No.	Dataset Used	Methodology	Performance Measure
1.	[9]	BrainWeb and Clinical dataset	ILCMV with Gaussian filters	Accuracy -95% Dice score -0.936
2.	[10]	ISLES 2017	spatial adaptive squeeze and excite segmentation (SegSE)	Dice score-0.34 Sensitivity-0.55
3.	[11]	ISLES2015-SSIS data set	3D FCN	Dice score -0.77
4.	[12]	Clinical Dataset	3D Cross hemisphere convnet	Dice score-0.80
5.	[13]	MICCAI	Superpixel based segmentation	Dice Score-0.81 Sensitivity-82.32% Specificity-93%
6.	[14]	ISLES 2015	adversarial learning methodology using FCN	Dice score-0.82 (penumbra)
7.	[16]	Clinical Dataset	Partial Volume Averaging	Accuracy -98%
8.	[17]	ISLES 2015	MSNet	Dice score-0.68 Sensitivity-0.805 Specificity-0.99
9.	[18]	Clinical dataset	ConvNet + symROBEX	Dice score -0.63 to 0.78
10.	[19]	Clinical dataset	EM Algorithm +FODPSO +GLCM	Accuracy- 93.4%
11.	[22]	Clinical Dataset	Watershed method+ discrete curvelet transformation	Accuracy- 99.1%
12.	[23]	Clinical Dataset	EDD Net + MUSCLE Net	Dice score - 0.67
13.	[24]	ISLES 2015	3D CNN	Dice score - 0.64
14.	[26]	Clinical Dataset	Res-FCN	Dice score-0.645
15.	[27]	ISLES 2015	3D U-net +Res Net	Dice score -0.84 Sensitivity-0.89
16.	[28]	ISLES	U-Net + InceptionNet	Dice score - 0.635
17.	[29]	Clinical Dataset	UResNet	Dice score - 0.70
18.	[30]	Clinical Dataset	Bayesian Technique + Markov Random Fields	Dice Score -0.582
19.	[32]	Clinical Dataset	Ensemble Classifiers	Dice Score -0.65

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