Survey on Methods Used For Detection and Classification of Brain Hemorrhages

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Abstract - *The main aim of this work is to identify acute intracranial hemorrhage and its subtypes by using artificial neural networks. Brain hemorrhage is a type of stroke which is caused due to the rupturing of blood vessels and bleeding inside the brain. The research on the automatic detection and classification of brain hemorrhage is going on for past two decades. Watershed algorithm and deep learning methods are currently being used for the same.*

***Key Words*: CNN, Hemorrhage, CT scan, Deep learning, Feature Extraction, Dataset.**

1. INTRODUCTION

Brain hemorrhage is a type of stroke which is caused due to rupturing of blood vessels inside the brain. This may increase the pressure in the brain tissues, as well as reduce the blood flow to the tissues and also kill the brain cells. Brain hemorrhage is classified into four types namely:-

Epidural hematoma:

Condition that is caused due to a type of bleeding that occurs between the outer membrane covering the brain (dura mater) and the skull.

Subdural hematoma:

Condition that is caused due to a type of bleeding in which a collection of blood - usually associated with a traumatic brain injury - gathers between the inner layer of the dura mater and the arachnoids mater of the meninges surrounding the brain.

Subarachnoid hematoma:

Condition that is caused due to a type of bleeding that occurs between the arachnoid membrane and pia mater surrounding the brain.

Intracerebral hematoma:

Condition that is caused due to a type of bleeding that occurs within the brain tissue or underneath the skull, pressing on the brain.

2. LITERATURE SURVEY

Mayank and his team have proposed an algorithm that utilizes contra-lateral symmetry for the detection of stroke affected parts in a given CT volume. The approach suggested is a unified one that can detect and classify any kind of stroke. However, the result of testing 347 slices shows that it fails when both the hemispheres suffer from same type of stroke symmetrically. The fact that strokes are usually spatially continuous has been utilized to reduce the false positives for any normal scan. The work also suggested that histograms recording the spatial information can be used to detect and segment the strokes that occur symmetrically in both hemispheres [1].

Phong and his team proposed an approach for diagnosing brain hemorrhages, mainly using the three types of CNN - LeNet, GoogLeNet, and Inception-ResNet. The training phase initially consisted of training the last fully connected layers of GoogLeNet and Inception-ResNet and all the layers of LeNet.A dataset consisting of 100 cases was collected from 115 Hospital located at Vietnam. The result shows that LeNet, GoogLeNet, and Inception-ResNet got an accuracy of 0.997, 0.982 and 0.992. The conclusion was that LeNet is a more time-consuming model than the other two. The combination of deep learning techniques and HPC systems can be used to deal with some medical problems like brain hemorrhage. The major setback is caused due to the lack of medical images [2].

Balasooriya and Perera's research aimed to develop and evaluate an intelligent and accurate system through which one can tell whether a hemorrhage is present and specify the type by feeding brain CT images and by using methods like C means and Watershed Algorithm along with neural network. This enables users like radiologists or doctors as well as medical students to diagnose if one exists. The system's implementation is divided into three sections- 1. Pre-process Image, 2. Segment the Image and Extract Features for ANN, 3. Train the System. Future enhancements involve improvising the system so that it can be supported for brain tumors and cancers as well [3].

Majumdar and his team proposed an approach that identified unenhanced head CT scans of the brain as well as normal ones that demonstrated no evidence of intracranial hemorrhage. A total of 134 CT scans images were used. Of these, 88 of the images had at least one hemorrhage and the rest were normal. The images were divided into three sets- training set, validation set, and test set. Here a U-Net model, which is a modified version, is used along with techniques related to data augmentation specific to CT. The network architecture used comprises of 9 convolutional blocks and it operates on slices which are 2-dimensional [4].

Al-Ayyoub and his team proposed a method where the issue of detecting brain hemorrhages and classifying them using CT scans is considered. The approach is mainly of two parts. First is the image processing part and second is classification and testing part. The focus is on segmentation using Otsu's method where the hemorrhage region is extracted from the image. MATLAB code was written for carrying out image processing, features extraction and segmentation. In the classification part, the image is classified according to the features of the ROI (region of interest). Here the Weka tool is used for the classification. For testing and evaluation part, the 10-fold cross-validation method was used [5].

Sudha and her team proposed a new fuzzy rule-based method for segmenting hemorrhages, mainly for compression. Features taken for fuzzification are: 1. *Intensity (INT), Mean difference (MD), Mode difference (MOD)*. Not all types of hemorrhage images were taken but only specific types like ICH (intracerebral haemorrhage) and IVH (intraventricular hemorrhage) were taken for experimentation [6].

Chang and his team proposed a method which evaluates a CNN that is optimized for the detection of intraparenchymal, epidural/subdural, and subarachnoid hemorrhages on non-contrast CT. The quantification of intraparenchymal, epidural/subdural, and subarachnoid haemorrhages is also done. The mask R-CNN architecture is used in this study. A 5-fold cross-validation technique was used for the evaluation of initial training samples [7].

Sumijan and his team proposed a method where images of CT-scan are used to determine the area of the brain bleeding and to detect and extract the brain bleeding, so that the volume of the brain bleeding can be calculated. All this is done by hybrid thresholding method. The research consists of 5 stages namely: 1. cropping the area, 2.Detecting the areas of the brain, 3. Extraction of areas of the brain, 4. calculating the area per slices, 5. calculating the volume of the brain bleeding area. Extensive counting algorithm is used to calculate the area of the brain bleeding per slice and volume [8].

Davis & Devane proposed a method where certain pre-processing operations are done on the CT image of the brain. The next step is segmenting the image. This is done with the help of Watershed algorithm. The segmentation of the images using watershed algorithm smoothens the CT image. Using watershed lines the distinct regions in the system are classified. The segmented image is then given as input to GLCM (Grey Level Co-occurrence Matrix) wherein various features are extracted. These extracted features are in turn given as input to the ANN, for classification, and the model is trained. Here, feed forward along with back propagation network is used and due to this the accuracy is more. The results show that the proposed method is best suitable for ICH and SDH type of hemorrhages [9].

Ahmed and team proposed a method which explored deep learning methods and feature learning using MRI data of brain tumors to predict survival time .The data is pre-processed by creating a region of interest (ROI) that contained the tumor. The CNN is pre-trained and is called the Fast (CNN-F) architecture. CNN-F consists of 8 learnable layers, in which 5 are convolutional, the rest 3 being fully connected. CNN-F was chosen because of its fast processing. The CNN was fine tuned with a stochastic gradient descent with learning rate that was set less than the initial learning rate, thus improving the accuracy. This system uses MatConvNet, Random Forest classifier, and CNN as the main technique [10].

Huang and his team proposed an approach where grading of brain tumor using multiphase MRI brain images is done and comparing the results with many other configurations of deep learning frameworks and Neural Networks. The grading performance is presented, on the testing data, by measuring the sensitivity and specificity. Results showed a max improvement of about 18% on grading performance of CNN based on specificity and sensitivity when compared with NN. The visualizations of kernels and also the output results on different layers showed that both produce similar results leading to same grading result. It also shows that more complex CNN structure might not work accurately to get the results of simple structured CNNs. The main drawback is that the training samples are relatively small [11].

3. TABULATION

Ref no	Paper Title	Methods used	Drawbacks
1	A method for automatic detection and classification of stroke from brain CT images	Image enhancement, Wiener filtering, histogram comparison	fails if a same type of stroke has occurred symmetrically in both hemispheres
2	Brain Hemorrhage Diagnosis by Using Deep Learning	Types of CNN's like LeNet, Google Net, and Inception-ResNet	High power consumption, small dataset
3	Intelligent Brain Hemorrhage Diagnosis System	Fuzzy C means, Watershed Algorithm, neural network.	Couldn't achieve the recognition of EDH and

			SAH, over-fitting
4	Detecting Intracranial Hemorrhage with Deep Learning	U-Net model (modified version), data augmentation techniques	subarachnoid hemorrhages were difficult to detect
5	Automatic Detection and Classification of Brain Hemorrhages	Otsu's method, MATLAB code, Weka tool	Computational complexity
6	Fuzzy rule-based segmentation of CT brain images of hemorrhage for compression	Fuzzy-clustering where features like intensity, mean difference, mode difference are taken	Only a specific type of hemorrhage are detected like ICH and IVH
7	Hybrid 3D/2D Convolutional Neural Network for Hemorrhage Evaluation on Head CT	mask R-CNN (ROI-based CNN)	susceptible to adversarial noise
8	Detection and extraction of brain hemorrhage on the CT-scan image using hybrid thresholding method	Hybrid Image Thresholding Method	Computational burden
9	Diagnosis & Classification of Brain Haemorrhage	Watershed algorithm, Grey Level Co-occurrence Matrix (GLCM), ANN	High computation power
10	Fine-tuning convolutional deep features for MRI based brain tumor classification	MatConvNet, Random Forest classifier, CNN-F	limited training data
11	Brain Tumor Grading Based on Neural Networks and Convolutional Neural Networks	CNN (unsupervised deep-learning model)	Training samples are relatively small.

4. CONCLUSION

Brain hemorrhages can be detected by CT scan, MRI, etc by the health professionals. Even though there are various techniques for automatically detecting the hemorrhage, but they require high image segmentation, accuracy, noise removal. The study highlights the various techniques and methods used to detect hemorrhages in brain effectively and to classify the type of hemorrhage present. As observed, there is a cut-off between accuracy and the computational complexity and a smaller set of training samples is taken for training the model. Hence by using CNN, which is advanced, the above problems can be minimized to an extent and working with a larger set of images will guarantee a better, accurate and an efficient result.

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