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DETECTION OF HEAMORRHAGE IN BRAIN USING DEEP LEARNING

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Abstract- *Cerebrovascular diseases are the third cause of death in the world after cancer and heart diseases. Brain heamorrhage is one of the most common cerebral vascular diseases. Brain heamorrhage is caused by the bursting of brain artery leading to bleeding and can have a fatal impact on brain function and its performance. For diagnosis of heamorrhage medical experts suggest either MRI or CT .CT images are used in greater ratio due to its ease of use, price constraints and high speed. The identification of cerebral heamorrhage is not known immediately. Therefore we need a certain method that can segment the CT scan image quickly and automated. The goal is to obtain the segmentation of brain part that is affected with heamorrhage quickly and accurately using the method of Deep Learning. So patients with cerebral heamorrhage can immediately obtain the medical treatment in accordance with the needs.*

Keywords: **Brain heamorrhage, CT images, deep learning**

1. INTRODUCTION

The brain is one of the largest and most complex organs in the human body. It is made up of more than 100 billion nerves that communicate in trillions of connections called synapses. The brain integrates sensory information and direct motor responses. It also helps the people to think, feel, and emote. Thus brain is called the Centre of Learning which gives commands to all other organs in the body. There are many situations where the brain gets affected, infected, injured so that their normal activity gets collapsed. One of those situations is the development of heamorrhage. Brain heamorrhage is a serious category of head injury that can have a fatal impact on brain function and performance. Brain heamorrhage can be diagnosed by two kinds of imaging modality: Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). After going through many of the literatures and checking with medical experts CT images are chosen in this work. CT images are known to have many advantages over MRI such as: wider availability, lower cost and higher speed. Moreover, CT scanner might be favored over MRI scanner due to patient-related issues such as the patient being too large to fit in the MRI scanner, claustrophobic, has metallic or electrical implants or is unable to remain motionless for the duration of examination due to age, pain or medical conditions . Finally, the quality of CT images is high enough to accurately diagnose brain heamorrhage.

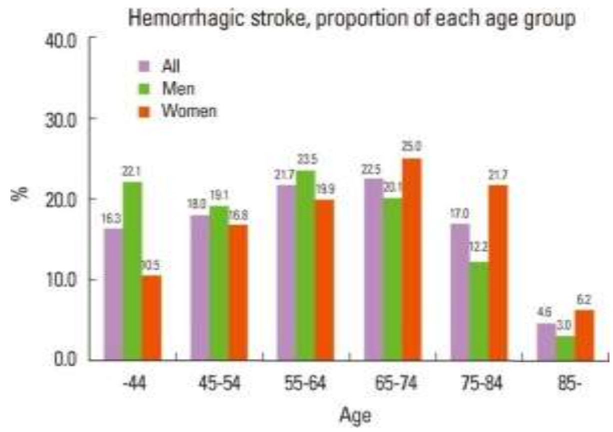


Fig 1 Survey reports of people affected with heamorrhage globally

2. RELATED WORK

There were many approaches related to detection of heamorrhage. [1] Alexandra Lauric and Sarah Frisken proposed soft segmentation methods like Bayesian classification, Fuzzy c-Means, and Expectation Maximization is applied on CT brain images and they have compared all these methods to produce a best accuracy. The first method used a Bayes rule to predict that a given pixel belongs to a particular class by using a conditional probability. The second segmentation alternates between partitioning the pixels into clusters and updating the parameters of each cluster. Like many clustering algorithms, FCM favors large clusters and, as a result, pixels belonging to small clusters are often misclassified. To compensate the misclassification, they used the Population-Diameter Independent (PDI) algorithm, which was introduced in [2] as a variation of FCM. The PDI algorithm uses cluster weights to balance the influence of large clusters. The third segmentation method partitions pixels into clusters by determining the maximum likelihood parameters of a mixture of known distributions. All three methods perform segmentation by constructing statistical models but they have both strengths and limitations. Bayesian classification is simple, fast and robust, but it requires training and is sensitive to the accuracy of training data. FCM is an efficient, self-organizing clustering algorithm which does not require training. However, unlike the Bayesian classifier, FCM does not explicitly incorporate prior knowledge. Expectation Maximization combines the strengths of both algorithms, it is based on Bayes rule, so it incorporates prior knowledge, but it is an unsupervised segmentation method, so it does not require any training. [3]The authors used a aforementioned approach like image preprocessing, image segmentation, feature extraction, and classification to detect whether a brain heamorrhage exists or not in a Computed Tomography (CT) scans of the brain which is a binary classification. Moreover, the type of the heamorrhage is identified which is a multi classification .The accuracy is 92% for the binary classification and this can be improved with large number of datasets and better feature extraction algorithm .[4] In this article the authors used a watershed segmentation and Multi Layer Perceptron to find the presence of heamorrhage. Features are extracted using watershed segmentation and Gabor filter. The extracted features are classified using Multilayer Perceptron (MLP). Finally images are classified as stroke and non-stroke images.[5,8] The author's goal is to segment the part of brain bleeding more quickly and accurately. The preprocessing of CT scan image starts from color filtering, erosion and dilation methods to eliminate the noise contained in the image. Then they performed the watershed and cropping segmentation to separate the skull bones of the CT image. Median filter is used to improve the image quality. Then the image is again segmented using the threshold method to separate the image of cerebral heamorrhage as the observed object. At last the calculation of area and volume percentage of bleeding in the brain is performed. From this approach the calculation of brain area has an average error of 1.13% and the calculation of the bleeding area has an average error of 11.17%. This system can be improved with the incorporation of better feature extraction and pre-processing methods to improve the accuracy rate.[6,7] Detect and classifies stroke in skull CT images through analysis of brain tissue densities. Featuring techniques such as gray level co-occurrence matrix, local binary patterns, central, statistical, Hu's, Zernike's moments were used.[11]The author focused on detecting the correct location and type of the heamorrhage in MRI Brain image. To segment the hemorrhagic region, structure specific Multi level Set evolution algorithm is implemented. To extract sharpened tetra features an enhanced Local tetra pattern based feature extraction algorithm and the features are optimized by applying an enhanced Grey Wolf Optimization algorithm. Finally, a Relevance Vector Machine based Classifier is implemented to classify the types of the heamorrhages.

3. WHY DEEP LEARNING?

Automated image analysis is a tool based on machine learning algorithms .Machine learning are the key enablers to improve the quality of image diagnosis and helps in interpretation by facilitating through efficient identification. Machine learning includes simple Neural Network, Deep Learning, Artificial neural networks which are structurally and conceptually inspired by human biological nervous system. Deep learning is the one extensively applied technique that provides state of accuracy. It is the most effective and supervised machine learning approach that uses deep neural network model(DNN) which is different from the simple neural network. DNN shows a larger approximation to human brain as compared to simple neural network.

4. STRUCTURE OF DEEP NEURAL NETWORK

The basic computational unit in a simple neural network is the neuron which takes multiple signals as inputs, combines them linearly using weights, and then passes the combined signals through nonlinear operations to generate output signals. Perceptron is one of the earliest neural network methods. It consists of input layer that is directly connected to output layer and was good to classify linearly separable patterns. To solve more complex pattern, neural network was introduced that has a layered architecture i.e., input layer, output layer and one or more hidden layers.

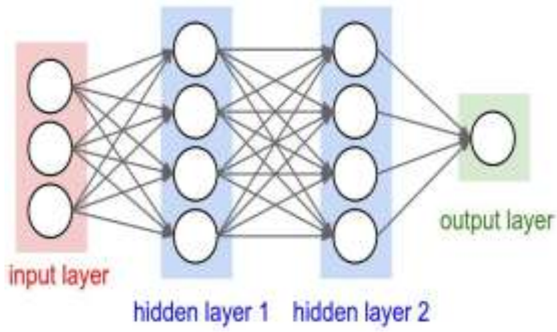


Fig 2 The structure of deep neural network

Deep Neural network consist of interconnected neurons that sums up the input data and apply the activation function to the summed data and finally provides the output that might be propagated to the next layer. Thus adding more hidden layer allows to deal with complex as hidden layer capture nonlinear relationship. Deep learning will not only help to select and extract features but also construct new ones, furthermore, it does not only diagnose the disease but also measures predictive target and provides actionable prediction models to help physician efficiently.

5. VARIOUS ALGORITHMS OF DEEP LEARNING

Various types of deep learning algorithms which are in use are Convolutional neural networks (CNN), Deep belief network (DBN), Deep auto encoder (DA), Deep Boltzmann machine (DBM), Deep conventional extreme machine learning (DC-ELM), Recurrent neural network (RNN). Deep learning based algorithms showed promising performance as well speed in different domains like speech recognition, text recognition, lips reading, computer-aided diagnosis, face recognition, drug discovery.

6. PROPOSED METHOD

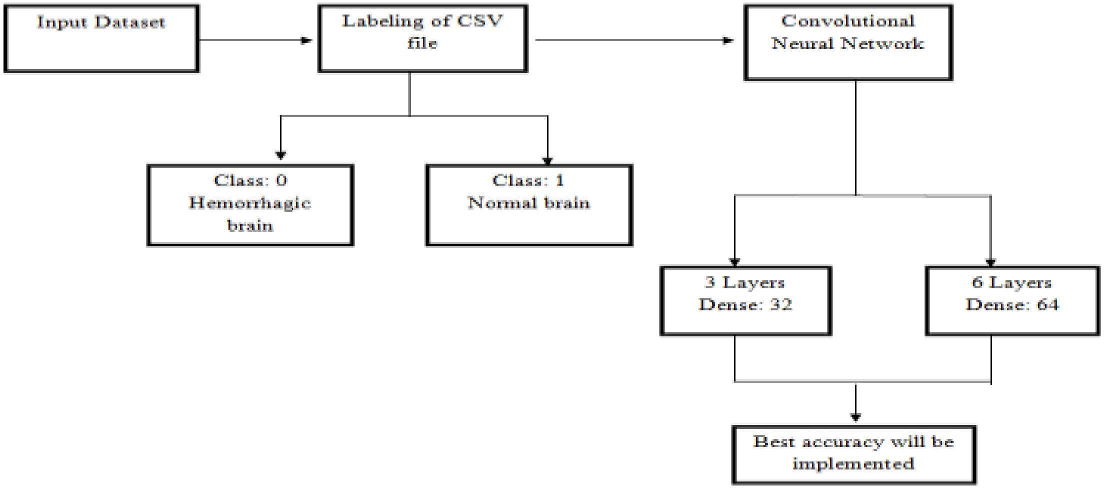


Fig 3 Block diagram

Among the above mentioned algorithms CNN model is widely used in digital imaging processing because it reduces input image size without any loss of information and it also helps to improve the computational speed. CNN consists of several steps they are Input Layer, Hidden Layer, Activation Function, Max pooling Layer, Dense layer and Drop out Layer. CNN works under Sequential process which means Hidden layer output will be input to Activation function, output of Activation function will be input to next layer.. The count of images are 100 normal and 100 abnormal (heamorrhage affected brain) images. Among them the first 90 normal and abnormal brain images is used for training and the remaining 10 normal and abnormal images is used for testing which are in the ratio of 8:2.

TABLE 1 the training and testing dataset

Type of image	Training	Testing
Normal brain	90	10
Abnormal brain	90	10
Total	180	20

Priorly images of Haemorrhagic Brain and Normal Brain are labelled in separate CSV file for dependent variable where normal brain is labelled as ‘0’ and hemorrhagic brain is labelled as ‘1’.we add 3 Layers with the dense of 32, and 6 layers with the dense of 64 to compare the accuracy with a kernel size of 3*3 and strides 2 ,and Relu as a Activation Function to get maximum possibility of a positive integer. Convolutional layer will continue for 32, 64,512 to prevent the loss of information and finally a web development model is created to test the results.

Algorithm 1 for The Convolution model

1. **model.add(Conv2D(32,kernel_size=3,strides=2,padding='same'activation='relu', input_shape=input_shape))**
2. **model.add(MaxPooling2D(pool_size=2))**
3. **model.add(Conv2D(32, kernel_size=3, strides=2, padding='same', activation='relu'))**
4. **model.add(MaxPooling2D(pool_size=2))**
5. **model.add(Conv2D(64, kernel_size=3, strides=2, padding='same', activation='relu'))**
6. **model.add(GlobalAveragePooling2D())**
7. **model.add(Dropout(0.4)) model.add(Dense(64, activation='relu'))**
8. **model.add(Dropout(0.4))**
9. **model.add(Dense(1,activation='sigmoid’))**
10. **return model**

7. RESULTS

Input image will be uploaded, back-end process takes the input and predict with trained model. Depending upon the threshold value Haemorrhage and Normal Brain will be identified and displayed.

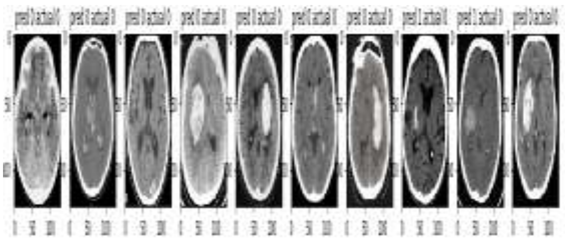


Fig 5 the brain with heamorrhage

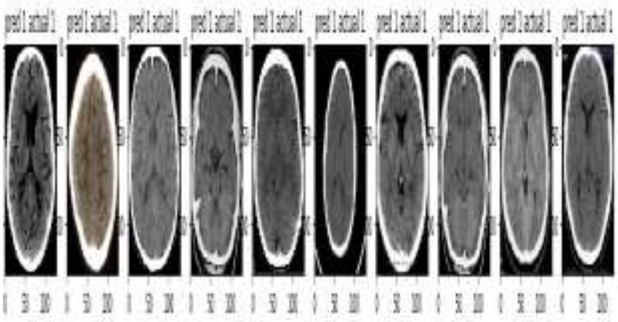
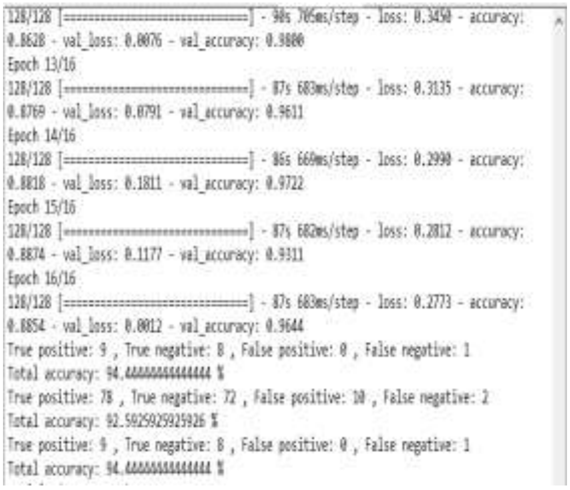


Fig 6 the normal brain predicted



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128/128 [==============================] - 90s 705ms/step - loss: 0.3450 - accuracy:
0.8628 - val_loss: 0.0076 - val_accuracy: 0.9800
Epoch 13/16
128/128 [==============================] - 87s 683ms/step - loss: 0.3135 - accuracy:
0.8769 - val_loss: 0.0791 - val_accuracy: 0.9611
Epoch 14/16
128/128 [==============================] - 86s 669ms/step - loss: 0.2990 - accuracy:
0.8818 - val_loss: 0.1811 - val_accuracy: 0.9722
Epoch 15/16
128/128 [==============================] - 87s 682ms/step - loss: 0.2812 - accuracy:
0.8874 - val_loss: 0.1177 - val_accuracy: 0.9311
Epoch 16/16
128/128 [==============================] - 87s 683ms/step - loss: 0.2773 - accuracy:
0.8854 - val_loss: 0.0012 - val_accuracy: 0.9644
True positive: 9 , True negative: 8 , False positive: 0 , False negative: 1
Total accuracy: 94.44444444444444 %
True positive: 78 , True negative: 72 , False positive: 10 , False negative: 2
Total accuracy: 92.5925925925926 %
True positive: 9 , True negative: 8 , False positive: 0 , False negative: 1
Total accuracy: 94.44444444444444 %
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Fig 7 Number of Epochs and the accuracy resulted

With this method the heamorrhage in brain can be predicted with the accuracy of 94.4% in the web development of python. Additionally, we can use his method to predict the types of heamorrhage and to find the area of heamorrhage in brain to grab a better performance.

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