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An Automated System of Brain Hemorrhage Detection using Deep Learning

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***Abstract* – In our human body, brain is one of the most complex organs that works with billions of cells. A brain hemorrhage is a type of stroke that is caused due to bleeding which occurs due to the result of ruptured artery Medical imaging is used to create a visual representation of the organs and tissues in the body. Either MRI or CT scans for the purpose of diagnosis are suggested by medical experts. The proposed system will employ CT images as they pass X-ray beams in an arc and this enables to take several pictures. The proposed system classifies the CT image of brain is affected or not image using Deep Convolutional Neural Network.**

***Keywords*– brain, hemorrhage, convolution neural networks.**

I. INTRODUCTION

Medical imaging is the practice of developing the pictorial representations of the inner constituents of human body along with certain functions of the organs or tissues constituting its own physiology. This is critically important for early diagnosis and treatment. There are various types of images obtained by several methodologies such as Magnetic Resonant Imaging (MRI), Computed Tomography (CT) are processed for medical assistance and treatment. The objective of research mentioned in this system is to detect the presence of hemorrhage using deep convolutional network. CT is an extensively used technique which facilitates the diagnosis and prognosis of brain hemorrhage in many neurological diseases and conditions.

1. Deep Learning

Deep learning (also known as deep structured learning or differential programming) is part of an artificial intelligence which comes under machine learning. Deep Learning can be broadly classified as supervised, semi-supervised or unsupervised. When compared to machine learning, deep learning contains many formulas and it can be easily predicted and more number of datasets can be given.

Deep learning has several types of architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, speech recognition, processing of language, audio/video and voice recognition, filtering process of network, automatic machine translation, bioinformatics, design of drug, medical image analysis, material inspection and programs on board games, where they have produced far better results being comparable and in some cases when compared to human expert performance.

2. Convolutional neural network

Convolutional neural networks (CNN), comes under one as one of the most used algorithm of deep neural networks, most commonly applied to analyse visual images. They are also termed as shift invariant or space invariant artificial neural networks, based on their shared-weights architecture and translation invariance characteristics. They have large amount of applications in the field of recognition of image and video, recommender systems, classification of pictures, medical image analysis, natural language processing, and financial time series. CNNs are regularizing versions of multilayer perceptrons. Multilayer perceptrons generally mean fully connected networks, that is, each and every neuron in one layer is connected to all neurons in the next layer. The "fully-connected" of these networks makes them prone to data overfitting. There are typical ways of regularization include addition of some form of magnitude measurement of weights to the loss function. CNNs have many ways to approach towards regularization, taking advantage of the hierarchical pattern in data and assembling of complex patterns by using convolutional networks are being inspired by biological processes that provide the connectivity pattern between neurons resembling the organization of the animal visual cortex. Individual cortical neurons often respond to stimuli only in a restricted region of the visual field known as the receptive field. Overlapping of different neurons takes place partially in a specific area of the receptive field in order to visual the images.

CNNs uses only little amount of pre-processing compared to other image classification algorithms. This means that the network has the provision to learn about the filters that were handled in the traditional methods.

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This independence from prior knowledge and human effort in feature design is a major advantage smaller and simpler patterns. Therefore, on the connected and complexity scale, CNNs are on the lower extreme. The name “convolutional neural network” indicates that the network by default indicates a mathematical operation called convolution. Convolution is a special kind of linear operation. Convolutional networks are neural networks which use convolution in place of general matrix multiplication in at least one of their layers.

II. DESIGN

A convolutional neural network is made up of an input layer, an output layer, in addition to multiple hidden layers. The hidden layers of a CNN usually carries with it a series of convolutional layers that convolute with a multiplication or different real. The activation operation is often a RELU layer, and is afterwards followed by further convolutions like pooling layers, absolutely connected layers and standardization layers, named as hidden layers as a result of their inputs and outputs are cloaked by the activation operation and final convolution.
Though the layers square measure conversationally named as convolutions, this is often solely by convention. Mathematically, it’s technically a slippy real or cross-correlation. This has significance for the indices within the matrix, therein that it affects however weight is set at a particular index purpose.

1. Convolution

When programming a CNN, the input may be a tensor with form (number of images) x (image width) x (image height) x (image depth). Then when passing through a convolutional layer, the image becomes abstracted to a feature map, with form (number of images) x (feature map width) x (feature map height) x (feature map channels). A convolutional layer at intervals a neural network ought to have the subsequent attributes:

- Convolutional kernels outlined by a breadth and height (hyper-parameters).
- The total number of input channels and output channels (hyper-parameter).
- The depth of the Convolution filter (the input channels) should be adequate to the amount channels (depth) of the input feature map.

Convolutional layers deform the input and pass its result to the succeeding layer. This can be like the response of a nerve cell within the cortical area to a selected stimulant. Each convolutional nerve cell processes information just for its receptive field. Though totally connected feedforward neural networks will be wont to learn options moreover as classify information, it is not sensible to use this design to pictures. A really high range of neurons would be necessary, even during a shallow (opposite of deep) design, thanks to the terribly giant input sizes related to pictures, wherever every picture element is an appropriate variable. For example, a totally connected layer for a (small) picture of dimensions 100 x 100 has 10,000 weights for each nerve cell in the second layer. The convolution function gets a solution to this problem as it decreases the number of free parameters, permitting the network to be denser with lesser parameters. For example, despite of the picture size, tiling regions of dimension 5 x 5, each one with the same shared weights, needs only 25 learnable parameters. In this manner, it firmly decides the vanishing or shattering gradients problem in training traditional multi-layered neural networks with several layers by the use of back propagation.

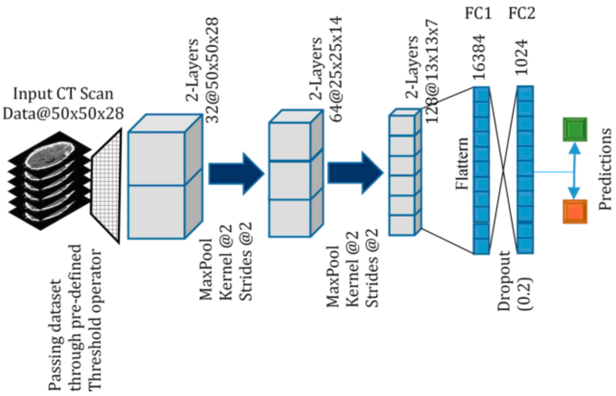

Fig.1. Convolutional Layering.

2. ReLU layer

ReLU is the abbreviated form of rectified linear unit, which applies the non-saturating activation function . It successfully eliminates negative values from an activation map by setting their value to zero. It rises the nonlinear properties of the decision function and of the overall network without causing effects to the receptive fields of the convolution layer. Other functions are also used to rise the nonlinearity, for example the saturating hyperbolic tangent , , and the sigmoid function . ReLU is always preferred to other functions since it undertakes the training of the neural network many times faster without giving an important penalty to generalization accuracy.

3. Pooling

Convolutional networks might embody native or global pooling layers to contour the underlying computation. Pooling layers scale back the scale of the information by combining the outputs of nerve cell (neurons) clusters at one layer into one nerve (single neuron) within the next layer. Local pooling combines minute clusters, typically 2 x 2. Global pooling acts on all the nerve cell of the convolutional layer. Additionally, pooling might work out a max or a mean. Max pooling uses the maximum value from every of a cluster of neurons at the prior layer. Average pooling uses the average value from each of a cluster of neurons at the previous layer. The pooling layer functions individually on every depth slice of the input and resizes it spatially. The regular form mostly used is a

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pooling layer with filters of size 2×2 applied with a stride containing 2 downsamples at every depth slice in the input by 2 along both the breadth and height, discarding 75% of the activations:

In this case, every max operations are over 4 numbers. The depth dimensions retain as the same.

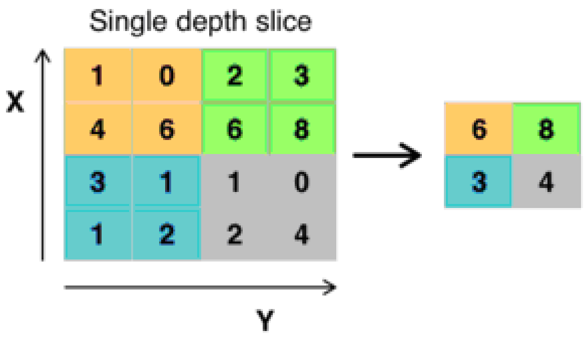

Fig.2. Max pooling with a 2x2 filter and stride = 2

4. Fully connected
Fully connected layers connect each and every neuron in one layer to every neuron in another layer. It works on the principle the same as the traditional multi-layer perceptron neural network (MLP). The matrix which is flatter goes through a fully connected layer for classification of images.

5. Receptive field
In neural networks, every neuron takes the input from different number of locations in the previous layer. In a layer which is connected fully, each neuron gets the input from each element of the previous layer. In a convolutional layer, neurons takes the input from only an allotted subarea of the previous layer. Typically the subarea can be of a square shape (e.g., size 5 by 5). The location where input is given of a neuron is called its receptive field. So, the layer in which it is connected fully, the receptive field is the entire previous layer. In a convolutional layer, the receptive area is smaller than that of the entire previous layer.

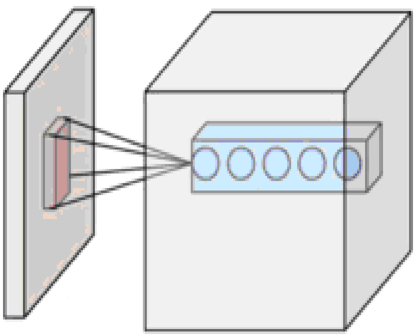

Fig.3. Neurons of a convolutional layer, connected to their receptive field.

6. Weights
Each neuron in a neural network produces an output value by providing a specific function to the input values coming from the receptive field in the previous layer. The function that is applied to the input values is obtained by a vector of weights and a bias (typically real numbers). Learning, in a neural network, progresses by making periodic changes to these biases and weights. The vector of weights and the bias are termed as filters and represent particular features of the input (e.g., a particular shape). A distinguishing feature of CNNs is that many neurons mostly share the same filter. This helps in reducing memory footprint because a single bias and a single vector of weights are used all over the receptive fields sharing that filter, as opposed to every receptive field having its own bias and vector weighting.

7. Dropout
Because a layer which is fully connected occupies most of the parameters, it is advised to overfitting. The popular method to reduce overfitting is dropout.

III. METHODOLOGY

The proposed technique has the following steps
Step1: Data Collection
The Dataset contains 50% of normal head CT slices and 50% of other with hemorrhage out of 200 images. There is no distinction between the kinds of hemorrhage. Each slice comes from a different person. The main idea of our project is to develop ways to predict imaging findings even in a context of little data.

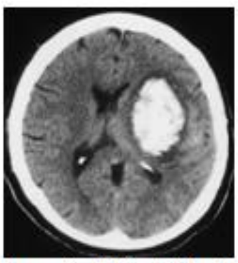

Figure 4: Affected brain

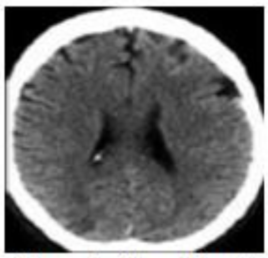

Figure 5: Normal brain

Step2: Data Preparation
To proceed further, Data Preparation is a must. Hemorrhage affects Brain and Normal Brain CT images are labelled in separate CSV file for dependent variable.

Step3: Split dataset into Training and Test Set
The Dataset contains totally 200 images. The normal Brain CT images are in the count of 100 and the Hemorrhage affected CT images are in the count of 100.The images are splitted in the ratio of 8:2. From this, 90 images are from Normal Brain and 90 images are from Hemorrhage affected brain, totally 180 images are for the training set. 10 images from Normal Brain and 10 images from Hemorrhage affected brain are for the testing set.

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	Training	Test
Normal CT Brain	90	10
Haemorrhage	90	10
Total	180	20

Step4: Build Convolutional Neural Network
Convolutional Neural Network reduces the input image size without loss of information in the image.CNN helps to improve the computational speed.CNN consist 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.In this project it is planned to add 3 Layers, two drop outs, Relu as Activation Function.

Step5: Highest Accuracy Model
The best accuracy model will be taken for web development. The combination of several trail leads to decide the best accuracy.

```
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 %
```

Fig.6. 3 Layers+Dense layer 32.

Step6: Web Development
The input image will be uploaded in a web page created.The back-end process takes the input and the output will be predicted with the trained model. Depending upon the threshold value hemorrhage affected brain and normal brain will be identified and displayed. Each image can be checked for the result individually.

- If Threshold value is Greater than 0.5 then it is a Hemorrhage affected brain.
- If Threshold value is Less than 0.5 then it is a Non-Hemorrhage affected brain.

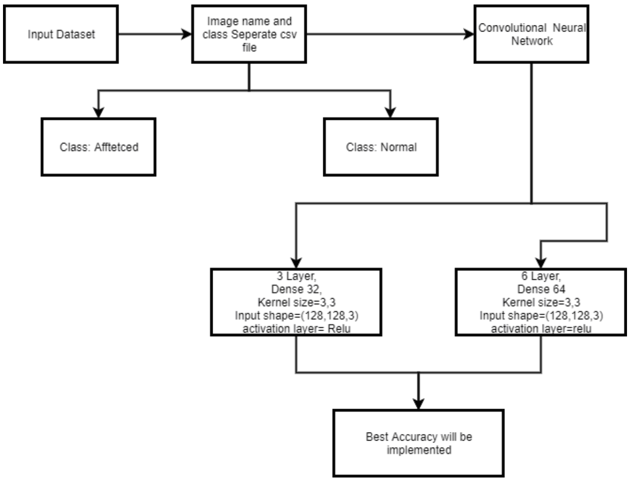
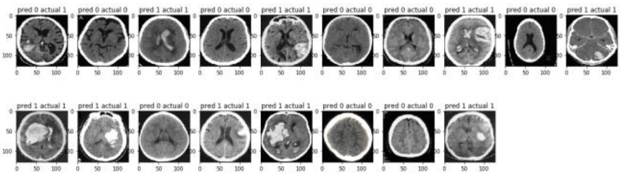
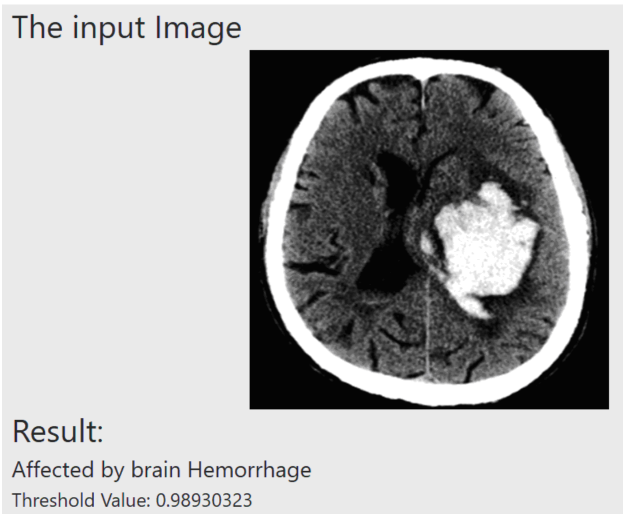


Fig.7.Block Diagram of Detection Process.

IV. RESULT



The above output is the comparison of the predicted and actual values.



V. CONCLUSION

The brain hemorrhage detection system is implemented using deep convolutional neural networks. The proposed system uses different methodologies which comes under convolutional neural network. The name “convolutional neural network” (CNN) indicates that the network employs a mathematical operation called convolution. Convolution is a specialized kind of linear operation. Convolutional Neural networks (CNN) are simple forms of neural networks which uses convolution in place of matrix multiplication in at least one of its layers. In this paper we use three hidden layers which provides a good high accuracy. The computational time has reduced by using only three convolution layers and a dense layer 32. The splitting of images for training and testing sets in a better ratio of 8:2 has given the result. The advantages of this automated brain hemorrhage detection system are ,it has high accuracy in predicting the output, it provides a clarification for the doctor's result, common people can also analyze if the brain is affected or not. The system claims to provide proper training of the model set with adequate layers of convolution inorder to obtain the desired results. It needs careful selection of images in the deep learning mechanism.

REFERENCES

[1]. Collobert, Ronan; Weston, Jason (2008-01-01). A Unified Architecture for Natural Language Processing: Deep Neural Networks with Multitask Learning. Proceedings of the 25th International Conference on Machine Learning. ICML '08. New York, NY, USA: ACM. pp. 160–167. doi: 10.1145/1390156.1390177. ISBN 978-1-60558-205-4.

[2]. Convolutional Neural Networks (LeNet) – DeepLearning 0.1 documentation". DeepLearning 0.1. LISA Lab. Retrieved 31 August 2013.

[3]. "Convolutional Neural Networks (LeNet) – DeepLearning 0.1 documentation". DeepLearning 0.1. LISA Lab. Retrieved 31 August 2013.

[4]. Platt, John; Steinkraus, Dave; Simard, Patrice Y. (August 2003). "Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis – Microsoft Research". Microsoft Research. Retrieved 2015-12-17.

[5]. Le Callet, Patrick; Christian Viard-Gaudin; Dominique Barba (2006). "A Convolutional Neural Network Approach for Objective Video Quality Assessment" (PDF). IEEE.

[6]. Amutha Devi C, Dr, S. P. Rajagopalan (2013) "Brain Stroke Classification Based On MultiLayer Perceptron Using Watershed Segmentation and Gabor Filter" in Journal of theoretical and Applied Information Technology Vol 56 No:2 pg 410 – 416

[7]. Alexandra Lauric and Sarah Frisken "Soft Segmentation of CT Brain Data" in ResearchGate

[8]. Chiun-Li Chin, Bing-Jhang Lin, Guei-Ru Wu, Tzu-Chieh Weng, Cheng-Shiun Yang, Rui-Cih Su, Yu-Jen Pan (2017) " An Automated Early Ischemic Stroke Detection System using CNN Deep Learning Algorithm" in Icast2017

[9]. Chung Ming Lo, Shabbir Syed Abdul, Yu Chuan Li (2017) "The integration of image processing and machine learning for the diagnosis of stroke in CT" in " Computer Methods and Programs in Biomedicine" Elsevier

[10].C.S.Ee, K.S.Sim, V.Teh, F.F.Ting "Estimation of Window Width Setting for CT Scan Brain Images Using Mean of Greyscale Level to Standard Deviation Ratio"

[11].Elizˆangela de S. Rebouc¸as, Alan M. Braga, R´oger Moura Sarmento,Regis C. P. Marques and Pedro P. Rebouc¸as Filho (2017) "Level set based on brain radiological densities for stroke segmentation in CT images" in 30th International symposium on Computer based Medical Systems

[12].Igor Bisio, Alessandro Fedeli, Fabio Lavagetto, Matteo Pastorino, Andrea Randazzo, Andrea Sciarrone, Emanuele Tavanti (2017) "Mobile Smart Helmet for Brain Stroke Early Detection through Neural Network based Signals Analysis" in IEEE Global Communications Conference.

[13].Zhang, Yudong, and Lenan Wu. "An MR brain images classifier via principal component analysis and kernel support vector machine." Progress in Electromagnetics Research 130 (2012): 369-388.

[14].A.Barderaetal.,''Semi automated method for brain hematoma and edema quantification using computed tomography,'' Computerized Med. Imag. Graph., vol. 33, no. 4, pp. 304–311, 2009.

[15].Rupali Mahajan , Dr. P. M. Mahajan (2016) "Survey On Diagnosis Of Brain Hemorrhage By Using Artificial Neural Network" in " International Journal of Engineering Research Online" Vol 4 Issue 4 pg 109 – 116.