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Classification on Magnetic Resonance Imaging (MRI) Brain Tumour using BPNN, SVM and CNN

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Abstract: In this works, the main objective is to detect the high grade gliomas (HGG) and low grade gliomas (LGG) from Magnetic Resonance Imaging (MRI) Brain Tumour images by applying the efficient image segmentation and classify among them. So hybrid image segmentation techniques applied in this work, first one is canny edge detection which is used to locate the boundary of the image and second is fuzzy c-mean clustering which is used to clubbed together of the similarity intensity value into clusters. Also further eight feature extracted using Intensity based Histogram and GrayLevel Co-occurrence Matrix (GLCM). Now three classifiers learning algorithm applied in this system, first one is backpropogation neural network (BPNN) which consists of multi-layer perceptrons to solve the complex problem for the given inputs. Second one is convolution neural network (CNN) are the part of neural networks which have very effective in areas such as image recognition and image classification. Third is Support vector machine (SVM) which can be used for both classification and regression challenges. Each of one is evaluated performance based on different techniques. It found that SVM and CNN gives 88% accuracy for this work.

Keywords : Gliomas, MRI, GLCM, CNN, SVM, Canny Edge Detection, BPNN

I. INTRODUCTION

Gliomas are the type of tumour that occurs in the brain and spinal cord, starting from glial cells which help to maintain neurons and functioning of the brain. Gliomas can be low grade (slow rate of growing) or high grade (fast grade of growing. Radiologist use grade of the brain tumour based on gliomas to decide which treatment a patient needs. The condition of the tumour is of vital importance for the treatment.

Brain Tumour means collections of abnormal cells present inside the brain. As we know, cells keep growing on the daily basis of balanced diet food, exercising our body, utilizing the brain at work, etc. There are two common types of cells: Normal cells and Abnormal cells. Abnormal cells further categorized into grade level of brain tumour.

So, the Normal cells are where it can control the growth of cell, i.e. it will stop reproducing when there are enough cells present in it. Abnormal cells are where it cannot take the control of growing or reproducing the cells even if it already enough cells present in it. Or in other words all cells which is not functioning or can't control the growth or reproduction of the cell or not able to communicate with the other cells to respond signals.

Brain Tumour has the effect of life threatening which lead to patient dies. So according to World Health Organization, grading system scales are used from grade I to grade IV. These grades classify benign and malignant tumour types. The grade I and II are low grade tumour (benign-type) and Grade III and IV are high grade tumour (malignant-type).

So, the malignant type is high rate of growing brain tumor which affects the brain cells and may spread to spinal cord and other parts which will tends to cure more difficulties. So it is very essential to detect (locate whether there is tumor or not), identify and classify (whether this is benign-type or malignant-type).

They primary issue is to detect the brain tumour that should be done at early stage as soon as possible, so that radiologist can take treatment action into that before it affects the other parts or make it more complicated. So, segmentation was the choice to detect the tumour by applying different techniques done by some of the researchers. So, there is still challenging.

The challenging are: Firstly, detect the brain tumour detection by applying efficient segmentation and classify among them. Since time is also the factor on the basis the cells reacting on the bodies to cause other parts, so it should give the result as soon as possible. So, second challenge is Time consuming.

II. DIFFERENT IMAGING TECHNIQUES FOR DIAGNOSING THE BRAIN

To get the detail or information inside the brain, several imaging techniques are done but few or primary imaging techniques get done which give better details for brain.

A. Computerized Tomography (CT)

A T scans generally measure the density of the tissue inside the brain. Like a conventional X-ray image, but it scans and capture the series of X-ray images of brain in every direction. After that, these series of X-ray are then reconstructed into a single image.

Advantages are its painless, fast, inexpensive, allow precise view of brain tissues and immediate diagnosis.

Disadvantages and Risk associated with this imaging techniques are radiation exposure which may lead to increase the risk in cancer patient has to lie for a long periods of time, patient has to hold his breadth during the scan, soft tissue are less visible.

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B. *Magnetic Resonance Imaging (MRI)*

MRI generally scans the detailed image of the brain by using strong magnetic field and radio waves.

Advantages are its non-invasion (non-surgical), no radiation, extreme clear and detailed images of soft tissue than any other imaging techniques, can scan whole part of the body

Disadvantages are its expensive, less contrast image, cannot distinguish between malignant tumour and benign disease.

C. Positron Emission Tomography (PET)

PET scans generally see not only the structure of the brain but functionality in inside the brain also. To trace or to check every functionality inside the brain, its put the "tiny tracers" which specially designed radioactive molecules and revealed in the 3D images in the display unit.

Advantages are its show the structure and functioning of cells or tissues inside the brain and more sensitivity.

Disadvantages are its used ionising radiation, expensive, poor resolution, less detailed, some are allergic to the tracer, limit amount of injection of radioactive.

III. RELATED WORK

N. Varuna Shree and T. N. R. Kumar (2018) [1], proposed a methodology on Digital Imaging and Communication in Medicine (DICOM) dataset which included feature extraction using Graylevel co-occurrence matrix (GLCM) and Discrete Wavelet Transform (DWT) and apply Probabilistic Neural Network (PNN) which achieved accuracy 95%.

Nilesh Bhaskarrao Bahadure et al. (2017) [2], proposed a methodology on Digital Imaging and Communication in Medicine (DICOM) dataset which included Berkeley wavelet transform (BWT) and GLCM feature extractions and apply SVM which accuracy 95.51%.

Kalid Uusman et al (2017) [3] proposed over MICCAI BratS dataset with feature extraction are intensity, intensity difference, local neighbourhood and wavelet texture and Random forest classifier.

A. Harishavardhan et al (2017) [4], proposed the comparative analysis on three different feature extraction techniques i.e. Intensity histogram features, GLCM, Graylevel-run matrix (GLRLM) and SVM classifier which achieved accuracy 92%.

J.selvakumar et al (2012) [5], proposed the image segmentation techniques ,i.e, K-mean clustering and Fuzzy-c-mean clustering and after calculated the area of region. The more the area, it will be in critical position.

Hwan-ho Cho et al (2017) [6], proposed the methodology over MICCAI BratS which included 45 radiomics features extractions and out of these, feature selections performed for only importance ones, Logistic regression classifier which achieved accuracy 89%.

IV. PROPOSED ARCHECTURE

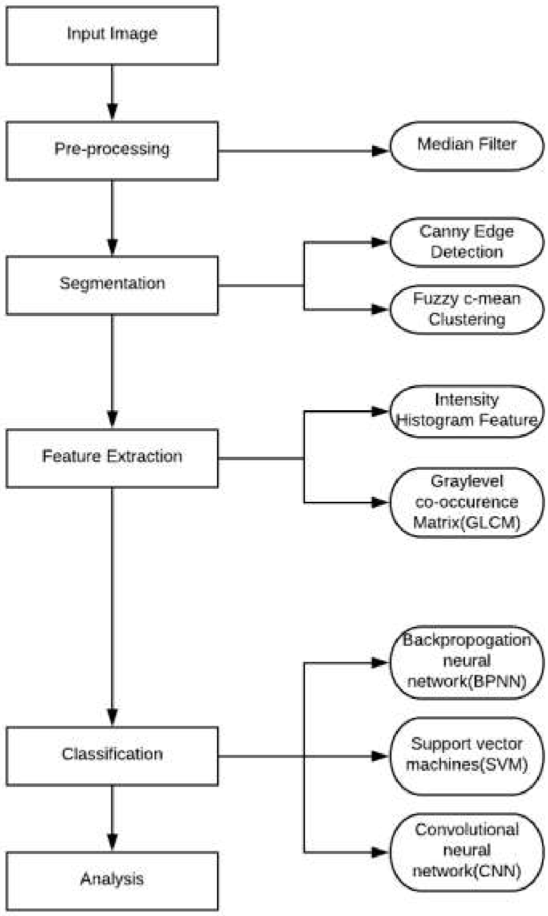

Fig 1. Flowchart proposed architecture

V. METHODOLOGY

A. Median Filtering

It is an image filtering technique which is used to remove the noise or unwanted pixel in the image. Among the other image filtering techniques, median filter [7] perform better for this application. Below show the examples:-

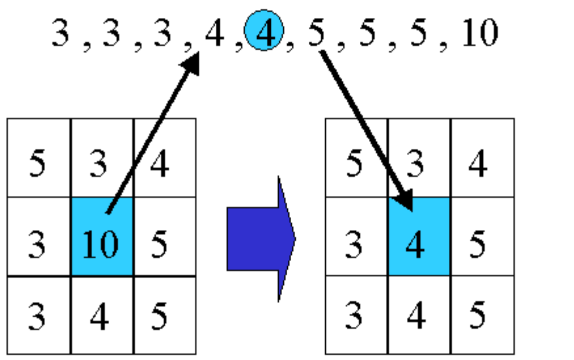

Fig 2. Visualizing way of calculating median filter

If we apply same procedure to the images, we get output as below (it kinds of little blur image):

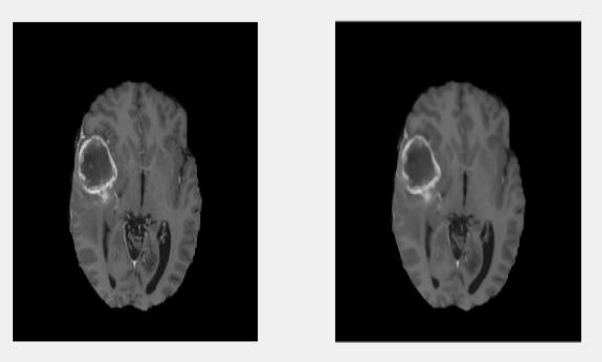

Fig 3. Output image after applying Median Filter

B. Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (or set of pixels also known as sub-pixels). The reason to apply this technique is to simplify or change the representation of an image into something that is more meaningful and easier to analysis. So there two techniques applied in this work.

i. Canny Edge Detection

It is a type of image segmentation which is boundary based techniques which used to find the boundary or edges of an image [8]. The reason to apply this technique because this will give the localization of the tumour into the bound region. The following steps are:

1. Smoothing the image which is already applied in Image filtering steps.
2. Calculate the intensity gradient to find the edge strength with Sobel operation on vertical and horizontal direction.

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} A$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ -1 & +2 & +1 \end{bmatrix} A$$

where A is an image, Gx and Gy are the horizontal and vertical direction of Sobel operator.

3. Calculate magnitude of gradient (edge strength) at each point can be calculated as $G = \sqrt{G_x^2 + G_y^2}$ and orientation can be found as $tan^{-1}(\frac{G_x}{G_y})$
4. Non-maximum suppression which to make blur edge into edge sharp.

$$M(x,y) = \begin{cases} M(x,y), if\ M(x,y) > M(x',y')\ and\ M(x,y) > M(x'',y'') \\ 0,\ Otherwise \end{cases}$$

5. Hysteresis Thresholding: It is as which may contain false edge point.

Step 1: We define two (Double) Thresholding values (I.e. Low threshold value and High threshold value)

Step 2: If gradient at a pixel is

- Above high, it consider as edge pixel.
- Below low, it consider as non-edge pixel.
- Between High and Low, consider its neighbors iteratively - it consider as edge pixel if it is connected to an 'edge pixel'.

Below show the final output of this technique. Left side of image is Input image and right side of the image is Canny Edge Detection

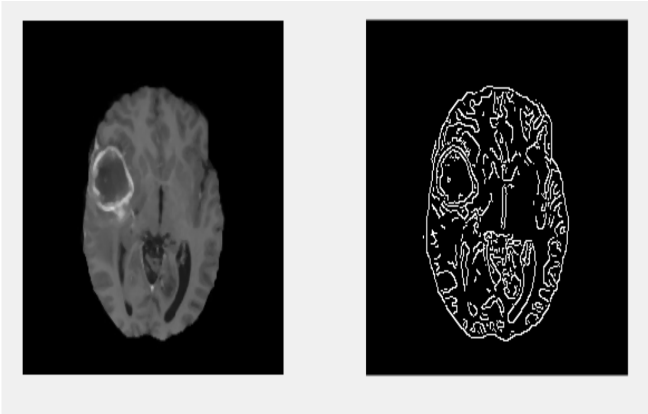

Fig 4. Output of image after applying Canny Edge Detection

ii Fuzzy c-means Clustering

It is the type of image segmentation which region based techniques which used to clubbed together for similar pixel into clusters [9]. It is mostly widely used fuzzy clustering algorithm. This algorithm attempt to partition a finite collection of elements into a collection of "c" fuzzy cluster with respect to some given criterion. This algorithm based on minimization of the following objective function as

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \|x_i - c_j\|^2$$

where "m" is (fuzzy component) any real number greater than 1, "N" is number of data, "C" is number of clusters, u_{ij} is degree of membership of x_i, x_i is i^{th} of d-dimensional data, c_j is D-dimensional centre of cluster.

The following algorithm steps are:

i. Choose random centroid (At least 2)

ii. Computer membership matrix

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

where

$\|x_i - c_j\|$: Distance from point i to current cluster centre j

$\|x_i - c_k\|$: Distance from point i to other cluster centre k

iii. Calculate the new "c" cluster centre

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}.x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

Below Example show clustering (C=3). Left top corner is an Input image and rest are the clusters of input image.

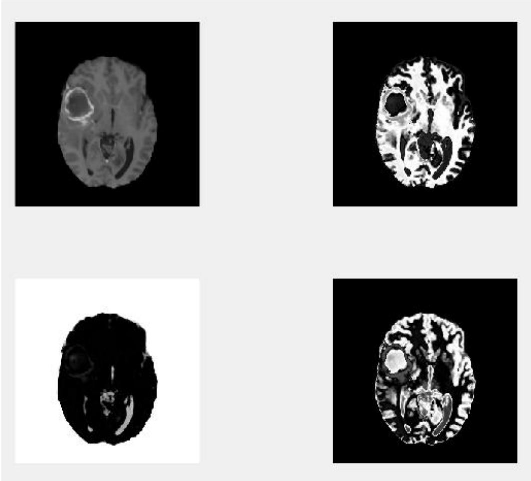

Fig 5. Output of image applying Fuzzy c-mean cluster withnumber of cluster=3

C. Image Feature Extraction

It is the process used to extract the significance feature of the images which are used to comprehend the image easier. The reason to apply this technique is that while extracting the feature like contrast, mean, variance, entropy, etc., it will be very helpful in classification stages. Three techniques apply in this work.

i. Intensity histogram feature

In this method evaluate the intensity histogram feature by different formula

Table 1: Intensity Histogram Features

S.No.	Features	Formulae
1	Mean	$\frac{1}{Size(Image)}\sum_{i=0}^{N-1} i.h(i)$
2	Variance	$\frac{1}{Size(Image)}\sum_{i=0}^{N-1} (i-\mu)^2 .h($
3	Skewness	$\frac{1}{Size(Image)}\sum_{i=0}^{N-1} (i-\mu)^3 .h$
4	Entropy	$-\sum_{g=0}^{1} P(g).\log_2[P(g)]$

In table 1 where h(i) is histogram value of that pixel, u is the mean of an image pixel values, p(g) is the normalized histogram of 'g' intensity value.

***ii.* Graylevel Co-occurence Matrix(GLCM)**

It is based on second order statistics that is relationship between two pixels is considered. It is calculating how often a pixel with the intensity (graylevel) value "i" occurs in a specific spatial relationship to a pixel with the value "j".

$$P(i,j \mid d,\theta)$$

This means that the probability that two pixels "i" and "j" which are placed with a distance "d" and a direction "θ".

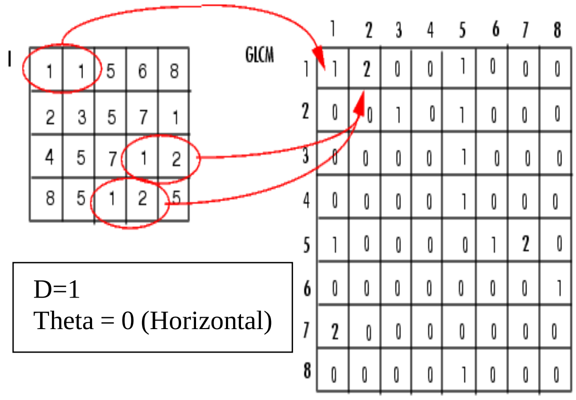

Fig 6. Visualization of GLCM example

Table 2: Feature Extaection formula

S.No	Features	Formula
1	Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$
2	Homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$
3	Energy	$\sum_{i,j=0}^{N-1} (P_{i,j})^2$
4	Correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\frac{(i-\mu)(j-\mu)}{\sigma^2}$

D. *Classification*

i. Back-propagation Neural Network

Back-propagation neural network [10] is a supervised learning algorithm. It used Multi-Layer Perceptron for training the network. While training, it proceed with two phases:

First one is, forward phase, initially random weight is assigned to this network. When the input are given into the input unit, synaptic weights of the network are fixed. So input layer propagated through network, layer by layer until it reached output layer.

Second one is, backward phase, once the its reached to output units, error signal produced by comparing output of the network and desired response. Then these signal are propagated in backward direction of the network. Based on error signal, synaptic weight of the neural network are adjusted.

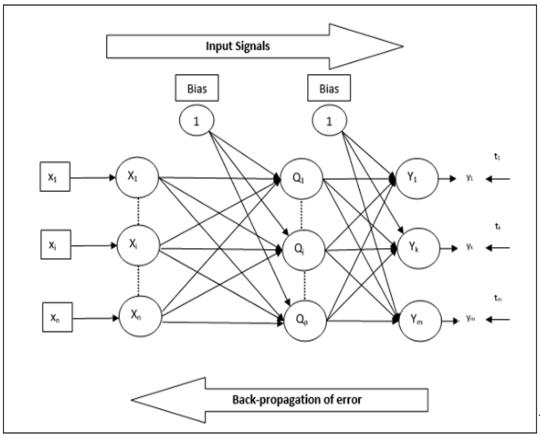

Fig 7. Generalized Backpropogation Neural Network

The following steps are:

1. Assign random value of all input, hidden and output weights and set learning rate between (0,1).

2. Each Input unit receives input signal xi and send to hidden unit (i = 1 to n)

3. Each hidden unit zj (j = 1 to p) sum its weighted input signal to calculate net input

$$z_{inj} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij}$$

4. Apply activation function over zinj and send from hidden unit to the input of output layer units

$$z_j = f\,(z_{inj})$$

5. Each output unit yk (k = 1 to m), calculate net input and apply activation function to net input

$$y_{ink} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$$

$$y_k = f\,(y_{ink})$$

6. Each output unit yk (k = 1 to m) receive target pattern and compute error correction term

$$\delta_k = (t_k - y_k) f'(y_{ink})$$

7. Update the change in weights and bias and send delta(k) to hidden layer

$$\Delta w_{jk} = \alpha \delta_k z_j \Delta w_{0k} = \alpha \delta_k$$

8. Each hidden unit zj (j = 1 to p) sums its delta inputs From the output units

$$\delta_{inj} = \sum_{k=1}^{m} \delta_k w_{jk}$$

9. Calculate error term

$$\delta_j = \delta_{inj} f'(z_{ij})$$

10. Update the change in weight and bias

$$\Delta v_{ij} = \alpha \delta_j x_i \qquad \Delta v_{0j} = \alpha \delta_j$$

VI. SUPPORT VECTOR MACHINE (SVM)

It is a supervised learning algorithm that can be employed for both regression and classification purposes. The idea is to find the hyper-plane that best divide a dataset into two classes.[11]

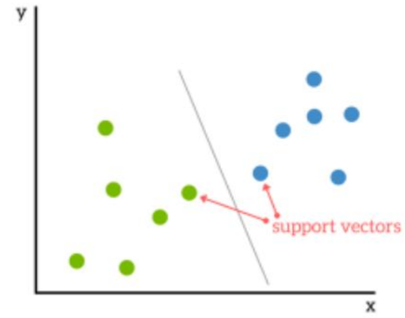

Fig 8. Visualization example of support vector

Support Vector are the data points nearest to the hyper-plane. The points of a dataset that, if removed would alter the position of the dividing hyper-plane. The distance between support vector and hyper-plane is called margin which it should be maximum.

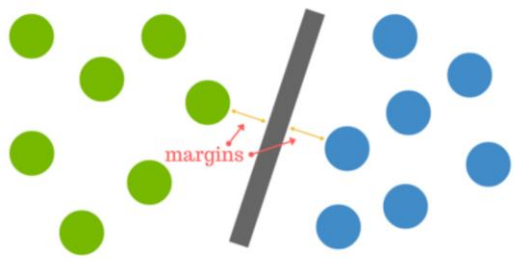

Fig 9. Visualization example of margins

If the data cannot be create a line between classes then we try to move the data into next dimension state of data, so that a hyper plane can be created. (as show below example):-

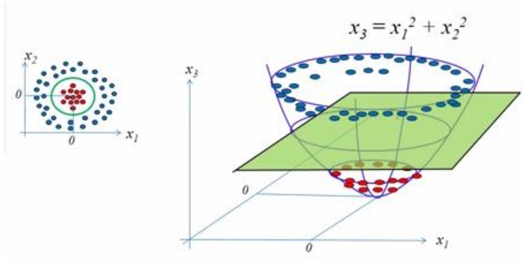

Fig 10. Visualization example on non-linear hyper-plane

VII. CONVOLUTION NEURAL NETWORK (CNN)

Convolution Neural Network are the part of neural network that has proven very effective in areas such as image recognition and classification.[12]

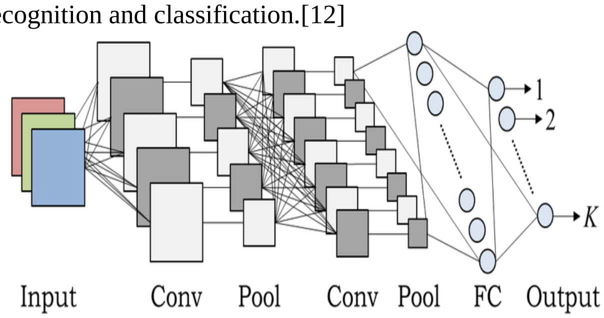

Fig 11. Generalization of Convolution Neural Network

There are four main operation involved in this steps, i.e. convolution, ReLU, pooling, fully connected layer.

Now once its reached in output units, we need to update weights and filter values based on error function.

The following steps are:

1. Assign all filters and weights with random values
2. The network takes a training image as input, process goes through like forward propagation steps (Convolution, Activation(ReLU), Pooling along with forward propagation in fully connected layer) and find the output probabilities from each class
3. Calculate the overall error at output layer
4. Use Back-propagation to calculate gradient of the error with respect to all weights from output layer (to input layer) in the network and use these gradient descent to update all filter values and weights.
5. Repeat steps 2-4 with all images in training set until stopping condition (with number of epochs).

VIII. EXPERIMENT AND RESULT

All images collected from MICCAI BraTS 2015 which contain (.mha) files.I manually converted into images using Fiji (Distribution of ImageJ) and about 124 images which each image consists of 240x240 pixels. Out of 124 images, 99 images belonged to HGG category and 25 images belonged to LGG category of brain tumour.

For the CNN model, train data is further split into 84 training data and 15 validation data. In CNN model, I apply two convolution layer with 25 number of filters and kernel size about 3x3 following with MaxPooling layer with kernel size 2x2 and then Flatten them resultant from 2D (coming from previous layer i.e. MaxPooling) into 1D and apply Dense (hidden layer) about 128 units with activation function of ReLU and the output layer which contain number of classes.

In this work, every images have been extracted, analyzed and classified among them and evaluated each performance measure as shown below table.

Table 3: Comparison accuracy of different Methodology

Methodology	Classification	Accuracy
Intensity Histogram Features+ GLCM	Back-Propagation	73%
Canny edge detection	Back-Propagation	78.38%
Fuzzy c-mean clustering	Back-Propagation	64%
	Convolution Neural Network (CNN)	88%
Intensity Histogram Features+ GLCM	Support Vector Machine (SVM)	88%

The training accuracy and validation accuracy graph of training network using CNN,(on x-axis, it is number of Epoch and on y-axis, it is accuracy)

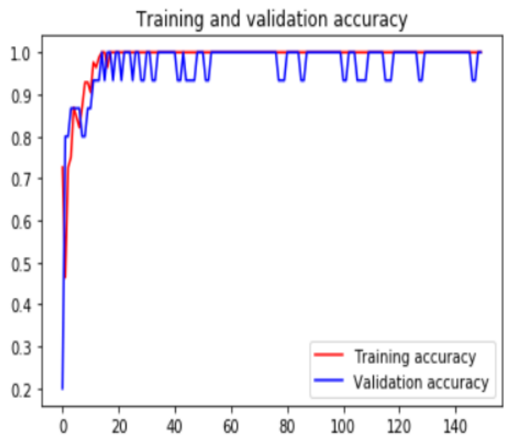

Fig 12. Graph show between training and validation accuracy on CNN

The training loss and validation loss graph of training network using CNN,(on x-axiss, it is number of epoch and on y-axis, it is loss)

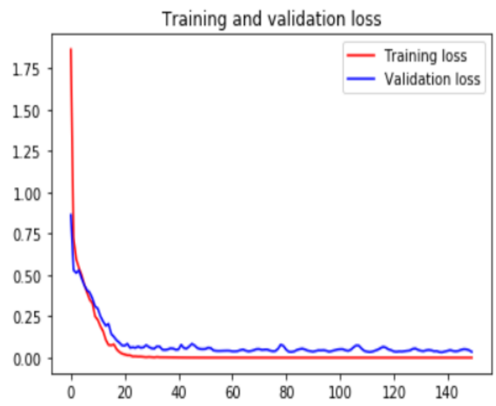

Fig 13. Graph show between training and validation loss on CNN

Table 4: Confusion for testing data after training model

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Actual/Predict	LGG	HGG
LGG	3	1
HGG	2	191

IX. CONCLUSION

Identification and classification on Magnetic Resonance Imaging (MRI) on Brain Tumour is the way by which brain tumour can be identified and classified as earlier as possible with expecting to have achieved high percentage. This proposal architecture in this work didn't outperformed well. So, more relevant segmentation techniques and features extraction can be found out to achieve highly performance. And, we have to perform on other different medical images of different pathological conditions and diseases status also once the performance got highly achieved.

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REFERENCES

1. G N. Varuna Shree, T. N. R. Kumar, "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network",Brain Informatics,March 2018, Volume 5, Issue 1, pp 23–30
2. Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, Har Pal Thethi,"Brain Tumor Classification Using PNN and Clustering", International Journal of Innovative Research in Science, Engineering and Technology, 2017
3. Khalid Usman, Kashif Rajpoot," Brain Tumor classification from multimodality MRI using wavelets and machine learning", International Journal of Pattern Analysis Application (Springer),pp 871-881,2017
4. A.Harishavardhan,Dr. SureshBabu and Dr.T. Venugopal,"Analysis of Feature Extraction Methods for the classification of Brain Tumour Detection", International Journal of Pure and Applied Mathematics,2017,vol. 117 no. 7, pg. 147-155
5. J.selvakumar, A.Lakshmi and T.Arivoli,"Brain Tumor Segmentation and Its Areas Calculation in Brain MR Images using K-mean clustering and Fuzzy c-mean Algorithm", Internation Conference On Advances in Engg., Science and Management, Mar,2012,ISBN-978-81-909042-2-3
6. Hwah-ho Cho and Hyunjin Park,"Classification of Low-grade and High-grade glioma using multi-model image radiomics features", IEEE, 2017, ISBN-978-1-5090-2809/17
7. Mohd Tahir, Anas Iqbal, Abdul Samee Khan," A Review of Various Filters for Noise Removal in MRI Brain Image", International Journal of Innovative Research in Computer and Communication Engineering, Dec, 2016, vol. 4, issue 12.
8. Jamil A. M. Saif,"Tuning of Canny edge detection", International Journals of Computer Science and Information Security (IJCSIS), Vol 15, No. 11, Nov 2017
9. Azzeddine Riahi,"Image Segmentation Techniques Based on Fuzzy C-Means and Otsu, Applied to the Brain MRI in Tumor Detection", International Journal Of Computer Sciences and Engineering, Vol. 03, Issue-12, E-ISSN: 2347-2693 ,Dec 2015
10. Matt Mazur,"A Step by Step Backpropogation Example", https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/
11. Himani Bhavsar, Mahesh H. Panchal,"A Review on Support Vector Machine for Data Classification", Internatinal Journal of Advanced Research in Computer Engineering & Technology (IJARCET), Dec 2012, Vol 1, Issue 10.
12. R. Yamashita, M. Nishio, R. Kinh Gian Do, K. Togashi,"Convolution Neural Network: an overview and application in radiology",Insights into Imaging, Aug 2018, Vol 9, Issue 4, pp 611-629

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