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Brain Tumor MRI Image Segmentation using Deep Learning

P. Suresh Pandiarajan[1], S. Lakshmi[2], K. Karthik[3], P. Vedhanayagi[4], S. Vaitheki[5]

[1,3,4,5] *P.S.R.R College of Engineering, Sivakasi, India*

[2]*Department of ECE JAIN Deemed-to-be University), INDIA*

Abstract:

Throughout the human history, Brain tumor is a well-known deadly disease. Curing of Brain tumor is entirely dependent on early detection of the disease. If a disease can be detected at its earlier stage, it's mortality rate may come south. Due to advancement of various scientific methods, early detection becomes possible. Even though various sophisticated methods are available, early detection suffers a setback due to their structural similarity and sizes. In this article we proposed an automatic early brain tumor detection method. Our proposed approach depends on Extreme learning Machine (ELM). For our experiments, we used MRI image data set. In this work, three models are used to enhance the classifier performance. These models are ELM, CNN-PCA and CLACHE. The backbone of our proposed method is CNN. The CNN architecture leverages both 2D and 3D feature to enhance the exactness of the segmentation. The experimental outcomes of our projected model produce high accuracy in terms of segmentation when compared with its counterparts.

Keywords—*Deep Learning, BraTS, Medical Imaging, CNN, ELM, PCA*

1.INTRODUCTION

In the current society, the people living on the earth are being troubled with several diseases. Based on the statistics, 1/2th of humans are harmed by diseases and have medicines in an unavoidable situation for their survival. The doctors and the hospitals are increasing day by day and each day brings a new disease. To handle these kinds of diseases, doctors need some special automation tools for prediction and to make their tasks easier. To enhance the advanced prediction based on a patient's care, medical innovation is to be enhanced in the form of automated tools. This is essential to improve the efficiency of doctors/technicians and also to minimize the death rate and reduce the suffering of the patient. WHO anticipated that mortality caused by cancer is high. The most cancer-affected people are under70 years of age in the year 2015.

Population growth, ageing, economic development, and change in lifestyle are the reasons for these cancer occurrences. Brain cancer/tumor is the most significant disease that has risen vigorously in recent decades in the world. Malignant is one type of brain tumor that is caused rarelyforadultsin1–2%. Based on the GLOBOCAN2012,the survival rate of brain cancer is minimum and it impacts people's quality of life, mortality rate, and economic costs. The brain tumor is developed by several factors to ionizing radiation, cyclic aromatic hydrocarbons, pesticides, etc. Socio economic and environmental factors are the main reasons behind brain cancer mortality. Brain tumor is rectified around the world by preventing causative factors, improved medical care, and enhanced diagnostic methods in different countries.

2.LITERATURE SURVEY

This inquire about work is utilized to display an progressed digitized programmed strategy for the classification and division of brain tumor infections. This proposed work develops an advanced technique based on Image Processing to predict the brain tumor in the earlier stage and to reduce death rate. Our goal is to confidentially identify brain tumor types to reduce doctor's burden, leaving the most complex diagnoses to them.

N.Moon; presented the Combined picture division grounded on factual classification earlier have been appeared to extend strength and reproducibility. Employing a probability in geometric show and picture enlistment serves for both initialization of likelihood thickness capacities and spatial limitations.

HaochengShen; displayed the Framework conditional irregular areas (CRFs) are broadly connected in both normal and restorative picture division task. It as it were considered the name consistency in locality pixel or locale, which is constrained their capacity to demonstrate long-term associated inside the picture division and by and large comes about in over the top smoothing of tumor boundaries. A modern framework for brain division is displayed in MRI pictures based on fully-connected CRF (FC-CRF) demonstrate that set up pair wise potential on all sets of pixels within the pictures.

M. Usman Akram ; proposed a strategy for programmed brain tumor demonstrative framework from MR pictures. This framework comprises of three stages to identified and division a brain tumor MR image. In the primary arrange, MR picture of brain is procured and preprocessing is done to expel the clamor and to hone the image. In the moment stage, The worldwide edge division was done on the honed picture to division the brain tumor MR picture. Within the third stage, the division picture was post handled by morphological operation and tumor veiling in arrange to evacuate the wrong portioned pixels of MR image.

Zeljkovic ; proposed The MRI and CT filter pictures are utilized as essential demonstrative instruments when a neuro rationale exam shown a plausibility of essential or metastatic brain tumor presence. The tumor tissue is basically showed up in brighter colors than the rest of the districts within the brain

. Patil Abhishek Uday; proposed the issue that as often as possible happen within the down to earth handling of medical pictures comprises within the need of machines for the assessment of images. In this article, the creators portray a classification strategy which would empower the division of MR pictures through an interesting three strategy of manual tumor segmentation, Tumor displaying and DTI Tractography which would not as it were utilized to section tumor but too be a preoperative arranging for picture guided neuro surgery additionally the demonstrating of the Tumor in 3D utilizing the program SLICER 3D.

Ishita Maiti ; proposed a color based brain tumor location calculation utilizing color brain MRI pictures in HSV color space. The RGB picture was changed over into HSV color picture by which the picture is isolated by three locale tint, saturation, and concentrated. After differentiate picture improvement watershed calculation was connected to the picture for each locale. Canny edge locator was connected to the yield picture. After combining the three pictures last brain tumor fragmented picture was obtained.

NidhiSingh; The Brain tumor was identified to be the major misfortune that tallies as the foremost casualty reason for human creatures. Legitimate and opportune determination can avoid the life of a individual. Division picture preparing was one of the imperative procedures to discover the area and measure of tumor within the brain. Programmed tumor discovery in MRI was exceptionally critical in today's world wellbeing scenario which boosts up the specified therapeutic application.

K.Bhima ;A. Jagan: The momentous development in picture preparing for talking about therapeutic imaging is one of the developing field and the prerequisites for progressions in therapeutic imaging is continuously emanant and challenging. MRI based brain restorative imaging are utilized for restorative determination since it shows the internal parcels of the human brain and Brain tumor is the serious life modifying diseases.

TomaszWęgliński;AnnaFabijańska presents t he Brain segmentation is an important part of medical image processing. Most commonly ,It aims at locating various lesions and pathologies inside the human brain. In this paper, a new brain segmentation algorithm is proposed. The method is seeded region growing approach which was developed to segment the area of the brain affected by tumor. The proposed algorithm was described. Results of testing the developed method on real MRI data set are presented and discussed.

3.PROPOSED METHOD

An automatic brain tumor detection framework has been projected by smearing the extraordinary learning machine (ELM)on the brain MRI pictures. Three models: classification utilizing extreme learning machine (ELM), ELM with a crossover convolution neural network-principal component analysis (CNN assisted PCA)

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based include extraction, and CNN with PCA supported ELM with the MRI pictures. This extend has endeavored to accurately recognize brain tumor from MRI pictures by combining the benefits from both the Deep learning and machine learning (ML) algorithms.

3.1 Feature Extraction from Raw Data Using CNN

The foremost critical perspective in classification is include extraction. All imperative highlights of the MRI pictures are to be extricated which decides the execution of the framework. The segregation between the classes moves forward the execution classification. Include extraction converts high dimensional data into low dimensional, non-redundant, and useful information. Information handling and data management is moved forward assist.

A novel profound CNN is created to extricate 512 critical highlights for location in MRI pictures as these pictures are more complicated. The proposed CNN show comprises of Six convolution layers. For each two progressive convolutional layers, a max-pooling layer and batch normalization are utilized. To create the show run speedier and to be steadier, batch normalization is used by re-scaling and re-centering the layer's input.

A pooling layer is put between two consecutive convolution layers. To extricate the foremost critical highlights from the MRI pictures, max-pooling layer with2× 2filters is utilized. This major esteem is selected in cluster's neuron at the convolution layer.

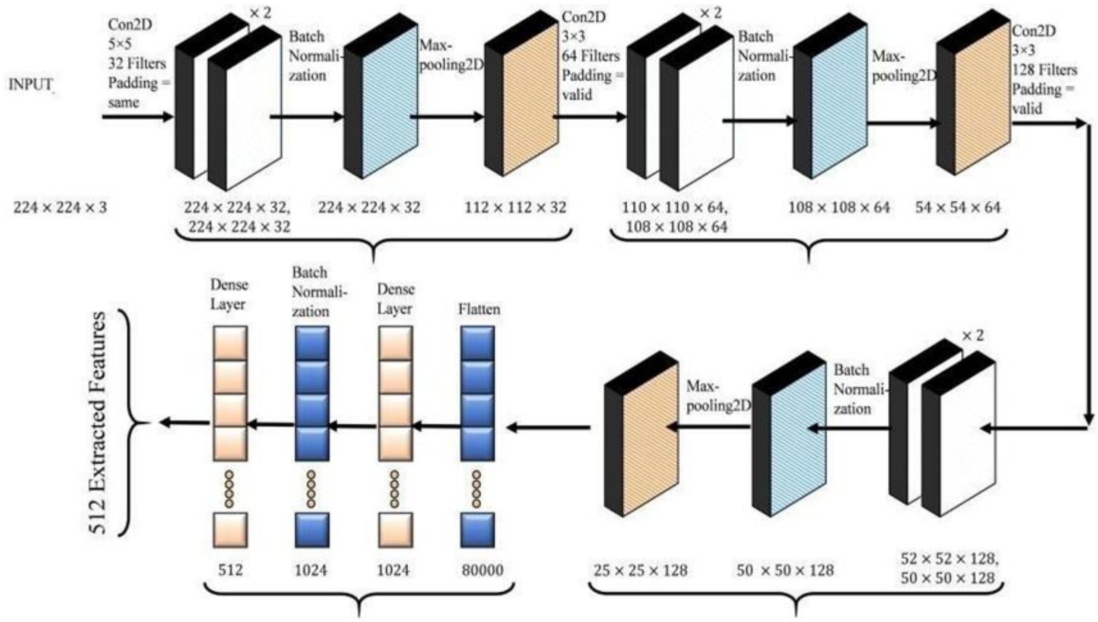


Fig 1: CNN model with batch normalization and max pooling for features extraction.

The primary two convolutions' layers comprises of 'SAME' cushioning. The cushioning is done since the yield is calculated by sifting all picture tuples. By utilizing this strategy all the border components are considered. These border components are calculated with zero padding. The border components overlooked in case of 'VALID' padding. ReLU, function of activation is included to maintain a strategic distance from the slope vanishing issue. One drop out layer with 0.5 likelihood is included in to begin with completely associated layer. Another dropout layer with 0.5 probability is included within the final max-pooling layer, and another is utilized for the primary completely associated layer. To maintain a strategic distance from rehashed preparing of all hubs in each layer drop out layers are executed this will increment the speed of preparing. The preparing with huge sum of information in CNN can deliver tall exactness and great execution with utilization of Adam optimizer. In this paper, CXR pictures dataset is utilized, meager categorical cross-entropy is utilized to calculate the loss. The proposed preparing demonstrate for a bunch measure 32 and 100 ages, the learning rate is 0.001. The thick layer at the final is utilized to extricate 512 highlights in each image.

3.2 Feature Extraction Using PCA

Dimensionality decrease can be done by different methods. The measurable procedure of unsupervised learning for dimensionality lessening is CA. The related highlights are changed into straightly uncorrelated highlights utilizing CA. Each highlight within the datasets are adjusted with zero-mean and unit-variance through highlight standardization. This gives an imperative result on PCA. Scaling influences the covariance network. An element-wise increase is performed to discover the relationship between them. Consequently, both highlights are scaled with the same extend or else the determination of the covariance framework will be varied. On extraction of 512 features by the CNN, standardization, include scaling, is done on the data.

The feature scaling is performed by the equation

$$a' = \frac{a-\bar{a}}{\sigma} \qquad (1)$$

where, a = Original feature vector

$\bar{a}$ = Mean of that feature vector

σ = the standard deviation.

S is the standardized edition of feature matrix A.

The covariance matrix is determined by

$$A=S \cdot S^T. \qquad (2)$$

Eigen value is given by (A−λI) = 0

And Eigen vector is determined in tackling the condition (A− λI) V = 0 for diverse values of lambda. There are 512 Eigen values in this work, and each Eigen vector contains 512 elements. After calculating the Eigen values, sort in slipping order, their comparing eigenvector. In the midst of the 512 Eigen values, top 100 Eigen values are chosen. Presently, the measurement of the Eigen vector lattice, E is given by (512×100).

The included framework, X is increased with the Eigen vector lattice, E. The modern highlight space's measurement is (5856×512) • (512×100) = (5856×100). Thus, the measurement is reduced.

3.3 Extreme Learning Machine

Huang et al projected ELM algorithm. The taken a toll of preparing time is minimized by utilizing the iterative demonstrate parameter tuning prepare. In this work, 100 highlights are bolstered into the input hubs for the parallel classification and 500 hubs are utilized within the covered-up layer and one hub acts as yield hub. The multi-class classification, 3outputnodes are utilized within the ELM, as appeared in Fig. A single hidden layer is utilized in ELM thus there's no mistake back-propagation process. The pseudo-inverse strategy is utilized to calculate Yield weight lattice.

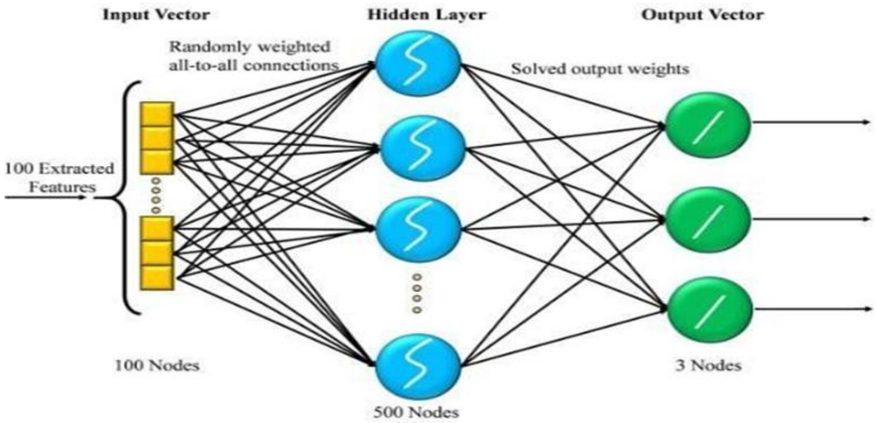


Fig 2: Proposed ELM for Classification

Let train of sample be {X_1, Y_1} = {X $_{(1, m)}$, Y $_{(n, t)}$: mR+, tR+}, where X is the input and Y is the output respectively.

Then sample train is denoted in lattice form.

$$X_{(n,m)} = \begin{bmatrix} x_{(1,1)} & x_{(1,2)} \cdots & x_{(1,N)} \\ \vdots & \ddots & \vdots \\ x_{(n,1)} & x_{(n,2)} \cdots & x_{(n,N)} \end{bmatrix} \quad (3)$$

$$Y_{(n,t)} = \begin{bmatrix} y_{(1,1)} & y_{(1,2)} \cdots & y_{(1,t)} \\ \vdots & \ddots & \vdots \\ y_{(n,1)} & y_{(n,2)} \cdots & y_{(n,t)} \end{bmatrix} \quad (4)$$

Where, n, m and t are instances count, attribute count and output node count respectively. For this work, utilize m = 100 which infers the include space is decreased to 100 and esteem of n will be changed with the measure.

Let hidden nodes count be N and assume its value as 500. The hidden layer output is given by

$$H_{(n,M)} = G(X_{(n,M)}.W_{(n,M)} + B_{(1,N)}) \quad (5)$$

where,G(x)be the activation function.

ReLU is the function of activation.

$$H_{(n,M)} = \begin{bmatrix} h_{(1,1)} & h_{(1,2)} \cdots & h_{(1,N)} \\ \vdots & \ddots & \vdots \\ h_{(n,1)} & h_{(n,2)} \cdots & h_{(n,N)} \end{bmatrix} \quad (6)$$

Finally, the output weight β(N,t) is evaluated by the Moore-Pen rose pseudo-inverse.

$$\beta_{(N,t)} = H_{(n,M)} . T_{(n,t)} \quad (7)$$

T=Output of trained data; t=no. of output.

Confusion Matrix

The Confusion Matrix is a matrix which given as an output and it depicts the depicts the whole execution of a lattice.

Table1: Confusion matrix

N=167	*Estimated: NO*	*Estimated: YES*
real: NO	50	10
real: YES	5	100

There are 4 important terms:

True Positive: Estimated YES & the Real output YES.

True Negative: Estimated NO & the Real output NO.

False Positive: Estimated YES & the Real output NO.

False Negative: Estimated NO & the Real output YES

Accuracy matrix can be calculated by taking average of the values lying across the "main diagonal" i.e

$$\text{Accuracy}= \frac{\text{True Positive + True Negative}}{\text{Total Sample}}$$

$$\text{Accuracy}= \frac{100+50}{165}$$

$$= 0.91$$

Accuracy, Specificity, Recall and Precision rate measurements are calculated for proposed and existing works. The formulae are given by:

$$\text{Specificity}= \frac{\text{True Negative}}{\text{True Negative + False Positive}}$$

$$\text{Recall}= \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\text{Precision}= \frac{\text{True Positive}}{\text{True Positive+ False Positive}}$$

4.SIMULATION AND RESULTS

4.1 Dataset

The2020 Brain Tumor Segmentation Challenge (BraTS) dataset [6] is utilized, with the preparing set representative to prepare the show and the approval set to assess the proposed gathering. 259 Glioma patients of higher grade and 76 glioma patients of lower grade with skillfully clarified data are utilized in preparing sets. The approval set comprises of 125 cases of obscure review [8] – [11].

The multi-institutional datasets are attainedfrom19 diverse supports that contains patient's multi modular MR pictures, named as T1 contrast-enhancement (T_{1ce}), T_2-weighted-contrast enhancement(T_2), and Liquid Constricted Reversal Recuperation (Energy). The brain tumor sub locales are portioned utilizing these datasets. The datasets are utilized to overcome disparity such that they are stripped by skull, anatomical format coordinating and resample information determination of 1mm3. The outside datasets are not utilized in our tests.

The division comes about of the proposed framework on the approval set is detailed. at that point it is compared with the existing method.

4.2Biopsy

Biopsy, a surgical strategy that is used to perform a small tissue sample examination from the tumor which is suspected malignancy in a microscope. The biopsy results are used to collect information about the cancer cell type. It is used to remove a tumor during surgery or isolate the tumor part for diagnosis. Some of the slow-growing cancers occurs inthe optic nerve pathway or midbrain. Hence the patient is observed minutely and if the tumor does not show any growth then the treatment is not processed.

Based on these imaging techniques, medical image processing is performed. Medical image processing is used to segment and classify diseases based on segmentation and classification algorithms. Therefore, in this thesis, the Brain tumor is identified and classified using the brain tumor MRI dataset.

4.3 Lumbar Puncture

A lumbar puncture is a technique that can be used to attain a cerebrospinal fluid sample for a tumor cell examination. The Spinal fluid can be investigated whether certain tumor markers substances are present. Many primary brain tumors, on the other hand, do not use tumor markers to detect tumors. Therefore, before performing this lumbar procedure, the CT and MRI techniques are processed to assure that the lumbar is safe for that patient.

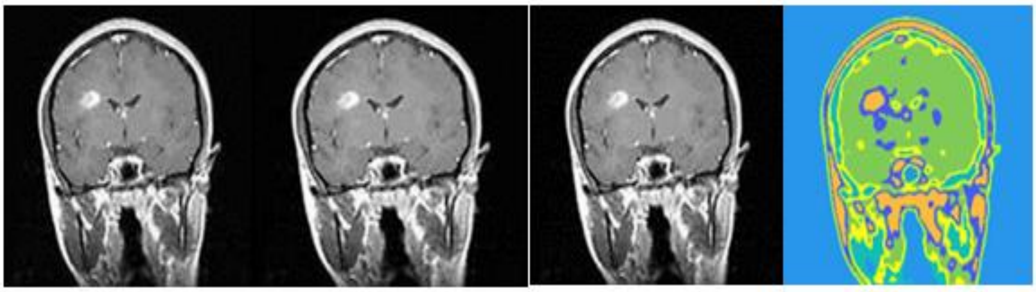


Fig 3. a) Input image b) Preprocessed image c) Filtered Image d) Segmented image

4.4 Histogram Equalization

The image contrast can be improved by using Histogram equalization. Histogram equalization is performed by comparing a number of obtained images on a definite base. The equalization can be modified for the histogram to be identical, smooth and balanced. A few methods are used to handle image contrast, visualization and sharpening in a proper form.

4.5 Pre-Processed Image

The Image pre-processing is the first and initial step of DIP. This process comprises of image re-sizing and RGB to gray scale conversion. The image quality is enhanced in preprocessing and perceptibility is improved by using various software that is also known as image enhancement. This process has an improvement in the subjective and objective, to develop points and local functions. These improvements are distanced into spatial space and change space strategies. The spatial space procedure is straightforwardly handled on the esteem of pixel; the change space procedure is prepared on Fourier strategy and after that to the spatial strategy.

4.6 Filter Image

Median filtered are used to filters the MRI Image. The statistics shows that median filter is the best filter when compare to all other filters. This filter replaces the pixel value with the gray level median value. An excellent noise reduction is provided by median filter.

4.7 Fragmentation Image

Image fragmentation is the next step. Fragmentation separates an image into various parts. Image separation and image partitioning are used for analysis and provide quality protection in the image. The segmentation is mostly used to recognize the border of an object within the image. It also performs pixel labeling by its characteristics and intensity. In the medical field, the segmentation is applied in many sectors namely anatomical, tissue volumes investigation, machine perception, malignant disease investigation, functional analyses, visualization of virtual reality,3D-rendered methodology, anomaly prediction, and detection of an object etc.

The segmentation process is classified into various categories namely global segmentation and local segmentation. The global segmentation considers an overall image as a single unit that has multiple pixels to implement it and utilizes global properties of image such as mean, continuous region boundary. The local segmentation is used to process a single image subdivision specifically. It has minimum number of pixels than global segmentation.

TABLE 2: Comparison of existing system and proposed system

Methods	Existing method	Proposedmethod
F1 score	90.83	91.76
Accuracy	94.5	96.6
Precision	89.06	93.61
Specificity	90.87	92.47

5.RESULTS

Result 1: Malignant stage of transvers image.

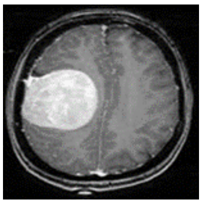
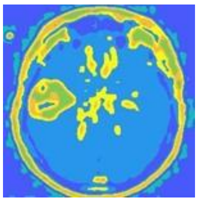


Fig4.a) Flair



b) Prediction

This is the transverse image of flair and prediction. It predicts the output as malignant.

Result2: Benign stage of coronal image.

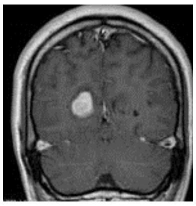
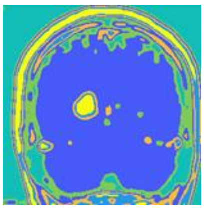


Fig5.a) Flair



b) Prediction

This is the coronal image of flair and prediction. It predicts the output as benign.

6.CONCLUSION

A novel Machine Learning show for programmed location of brain tumor is created with superior execution. The quality of picture is improved by utilizing HE in to begin with arrange, preprocessing. Following, the foremost critical highlights are extricated by a crossover CNN-PCA highlight extractor demonstrate. A novel ELM show is proposed which identifies a few sorts of brain tumor from the include extricated. The CLAHE assisted demonstrate ELM and crossover CNN with PCA works way enhanced than other models. The accuracy, review and exactness for the two-fold lesson categorization were1.0, 1.0 and 99.83%. The accuracy, review and exactness for the multiclass classification 0.99,0.98 and 98.32%. The proposed system attains maximum F1 score, accuracy, precision and specificity of 91.76, 96.6, 93.61 and 92.47. In future scope the optimized ELM will be used to improve the accuracy further.

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