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Brain Tumor Segmentation and Classification using Multiple Feature Extraction and Convolutional Neural Networks

Tasmiya Tazeen, Mrinal Sarvagya

Abstrac: Intracranial tumors are a type of cancer that grows spontaneously inside the skull. Brain tumor is the cause for one in four deaths. Hence early detection of the tumor is important. For this aim, a variety of segmentation techniques are available. The fundamental disadvantage of present approaches is their low segmentation accuracy. With the help of magnetic resonance imaging (MRI), a preventive medical step of early detection and evaluation of brain tumor is done. Magnetic resonance imaging (MRI) offers detailed information on human delicate tissue, which aids in the diagnosis of a brain tumor. The proposed method in this paper is Brain Tumour Detection and Classification based on Ensembled Feature extraction and classification using CNN.

Keywords: Segmentation, Brain Tumor, Convolutional Neural Network, Deep Learning.

I. INTRODUCTION

The term "brain tumor" refers to an abnormal proliferation of cells in the brain. Primary and secondary brain tumors exist. Primary tumors start in the rain, whereas secondary tumors start in diverse regions of the body, such as skin, intestines, and lungs, before spreading to the brain. Tumors are classified into three categories based on the cells that give rise to them: glioma, pituitary, and meningioma. Meningiomas are most common in older people and women, and they usually result in low-grade melingacy. Meningiomas develop in the meninges, which are three membranes that cover and protect brain.

Gliomas are tumors that arise from glial cells. The nerve cells are supported by glial cells.This form of tumour is very prevalent in the elderly. Ependymomas, oligodendrogliomas, and astrocytomas are examples of gliomas. Glioma accounts for over 80% of all deadly brain tumours. Pituitary tumours are benign tumours that arise from the pituitary glands. Early identification can help radiologist, physician, and expert decision-makers make better decisions, as well as increase the survival rate of Tumor patients.

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* Correspondence Author
Tasmiya Tazeen*, School of Electronics and Communication Engineering, Reva University, Bengaluru-560064, India. Email: tasmiyatazeen2298@gmail.com
Mrinal Sarvagya, School of Electronics and Communication Engineering, Reva University, Bengaluru-560064, India. Email: mrinalsarvagya@gmail.com

Magnetic resonance imaging (MRI), ultrasound imaging, and CT scanning are some of the methods used to detect brain tumours. Early detection can improve the decision-making process for radiologist, physician, and expert decision-makers, as well as raise the survival rate of Tumor patients. The most popular and effective method is MRI, which produces more detailed images of the brain tissues. Manual tumour segmentation and categorization would waste time and introduce human error, both of which would have to be reduced. It is suggested that automated segmentation and classification be used to address issue A fresh technique is proposed for the development of an automatic diagnosis system. (a) image capture (b) pre-processing (c) segmentation (d) post-processing (e) feature extraction (f) classification are the simulated steps in the proposed system In the past, various segmentation techniques such as region expansion, thresholding, clustering, and edge detection were used. The suggested approach employs a novel hybrid strategy that combines OTSU and adaptive particle swarm optimization, as well as a convolutional network. The adaptive particle swarm optimization technique is adopted because of its improved and space performance. The optimal threshold value is obtained using the OTSU+APSO technique, which allows for improved segmentation. Anisotropic diffusion filtering is used to smooth and denoise the brain MRI. The GLCM technique, which is utilised for feature extraction, is used to extract all statistical and textural properties. A convolutional network classification is trained and tested using the data gathered during the feature extraction stage. The classification is used to identify whether or not a tumour exists. Deep neural networks take into account network structure, activation function, number of neurons, learning rate, and other factors that are highly dependent on data representation. In medical imaging, convolutional neural networks help with the visualisation, processing, and exploration of large amounts of data. The accuracy of the parameters is used to evaluate the proposed autonomous computer diagnosis system's performance. The accuracy of the proposed method is 98 percent, which is higher than any other system now in use.

II. LITERATURE SURVEY

Brain tumor detection using image processing Saurabh Kumar1 , Iram Abid2 , Shubhi Garg3 , Anand Kumar Singh4 , Vivek Jain5:

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In this paper the work is focused on finding the best and most correct way for detecting neoplasm from brain magnetic resonance imaging scans, and if it confirms the presence of a tumour, it's next focused on determining its stage, i.e., benign or malignant. Image processing is used to automate the diagnosis method for brain tumour detection in this study. Apart from numerous existing brain tumour segmentation and detection methodologies, MRI of the brain imaging has proven to deliver an average of 97 percent accuracy.

Tumor classification based on MRI employing a combination of deep characteristics and machine learning classifiers Jaeyong Kang 1 , Zahid Ullah 1 and Jeonghwan Gwak : They created a method for diagnosing brain cancers that blends pre-trained deep convolutional networks with machine learning classifiers. In their proposed design, they used a number of pre-trained deep convolutional neural networks to extract deep properties from brain MR images. The acquired deep features are subsequently analysed by a number of machine learning classifiers.

Using biologically inspired BWT and SVM, image analysis for MRI-based brain tumour detection and feature extraction Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi : In this study, they looked into Berkely wavelet transformation (BWT) based brain tumour segmentation in order to improve performance and simplify the medical image segmentation procedure.

Automatic segmentation of multimodal brain tumour pictures using super-voxel classification; N. Karimi; H. Mohaghegh; S. M. R. Soroushmehr; K. Ward; A. All; K. Najarían, M. Kadkhodaei; S. Samavi: A preprocessing step in this paper enhances and normalises photos to the same scale. The improved images and then often segmented using 3D super-voxels depending on their intensities. The borders of the original images are aligned to the saliency map using an edge-aware filtering technique, which increases tumor's boundaries. Then, from super-voxels, for tumor classification in brain images, a set of robust texture features is extracted.

BRATS (The Multimodal Brain Tumor Image segmentation Benchmarks) Stefan Bauer, Bjoern H. Menze*, Andras Jakab,: BRATS, whiuch was held in conjuction with the MICCAI 2012 and 2013 conferences, is described in this work. Quantitative assessments found significant discrepancy between ratings by humans in segmentation of various tumor sub-regions (Dice score ranging from 74% to 85%), highlighting the difficulties of the endeavour.

Deep learning used to segment brain tumours using type-specific image sorting., Zahra Sobhaninia, Safiyeh Rezaei, Alireza Noroozi : They provide a technique based on deep learning for brain tumor segmentation in this paper. They looked at several angles of brain MR images and used different networks to segment them in this study. By comparing the findings with a single network, the effect of using distinct networks for MR image segmentation is analysed.

Singular Value Decomposition Classification of Brain Tumors, Nidahl K. El Abbadi, Neamah E. Kadhim:

They proposed a new method for detecting brain tumors based on single value decomposition in this work (SVD). The system was initially trained/ learned with normal brain MR images, and then it was able to classify healthy and unhealthy brain MR images in the second stage (that have a tumor). The algorithm is tested with 50 MR pictures after being trained with 20 normal brain MR images. This approach had a 97% accuracy rate.

III. PROPOSED SYSTEM

Proposed method as shown in figure 4.1 is the Brain Tumour Detection and Classification based on Ensembled Feature extraction and classification using CNN.

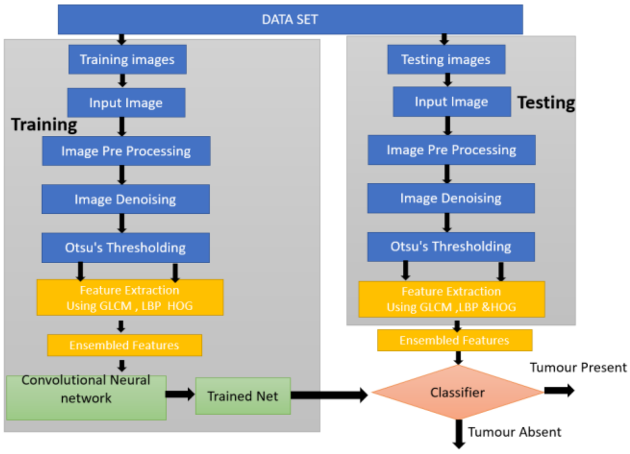

Fig 4.1: Proposed system

Input image: Around 250 MRI images were used in the proposed network 60-70% of the data is used in training, whereas 30-40% in testing.

Image pre-processing: It consists of the two modules: colour conversion (from three dimension to two) and image denoising with NLM.

The non-local means (NLM) approach is a common and successful denoising technique that modifies each pixel value with a weighted average of the image's pixels. The proposed strategy outperforms existing techniques in terms of edge preservation and noise suppression, according to the experimental results.

Image thresholding and morphological operations: The Otsu technique, named after Nobuyuki Otsu, is used in computer vision and image processing to perform automatic image thresholding. The method gives back a threshold of single intensity that divides pixels into two groups, foreground and background, in its most basic form.

Feature Extraction:

LBP: Local Binary Pattern (LBP) is a method for describing surface texture features. The likelihood of the texture patterns can be summarized into a histogram using LBP. All of the image pixels' LBP values must be determined. The distribution form of the LBP histogram can be used to determine texture regularity. The implementation results of LBP on two texture types-synthetic and natural textures –suggest that extracted texture features can be used as a pattern classification input. The texture pattern created via LBP computation is classified using the Euclidean distance approach.

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HOG: The histogram of oriented gradients (HOG) is a feature descriptor for object detection in computer vision and image processing. The technique counts the number of times a gradient orientation appears in a certain area of an image. This method is analogous thereto of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs therein it's computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy Edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts are all comparable methods, but this one differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalisation for enhanced accuracy.

GLCM: Texture features are generated using the statistical distribution of observed combinations of intensities at defined places relative to each other in the image in statistical texture analysis. Statistics are categorized as first-order, second order or higher order based on the number of intensity points (pixels) in each combination. The Gray Level Co-occurrence Matrix (GLCM) method is a technique for obtaining statistical texture features of second order.. Third and higher order textures consider the relationships among there or more pixels, and have been employed in a variety of applications. These are theoretically possible but due to calculation time and interpretation difficulty, they are rarely used. The number of rows and columns in a GLCM matrix equals the number of grey levels, G, in the image P (i, j | Δx, Δy) is the frequency with which two pixels separated by a pixel distance (Δx, Δy) appear inside a particular neighbourhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, ɵ) contains the second order statistical probability values for changes between grey levels I and 'j' at a specified displacement distance d and at a specific angle (ɵ). P (i, j | d, ɵ) is a matrix element. Using a large number of intensity levels G necessities keeping a lot of temporary data, i.e. a G G matrix for each (Δ x, Δ y) or (d, ɵ) combination. The GLCMs are particularly sensitive to the size of the texture samples on which they are estimated because to their enormous dimensionality. As a result, the number of grey levels is frequently decreased.

Classification:

CNN: The classification model for the tumor detection system is a convolutional neural network. In situations when a large amount of data must be processed, the CNN beats other classifiers. Three layers of convolutional neural networks with activation functions are used in the suggested study. Layers 1 and 2 employ the RELu activation function, whereas layer 3 employs the SoftMax activation function. The information split into a 7:3 ratio. From one neuron to the next, the layers are closely linked. The proposed work has a 98% accuracy rate. Fig 4.2 depicts the diagrammatic representation.

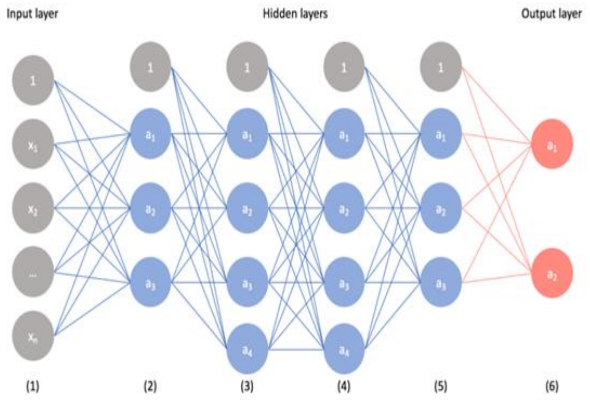

Fig 4.2: diagrammatic representation of CNN

IV. RESULT

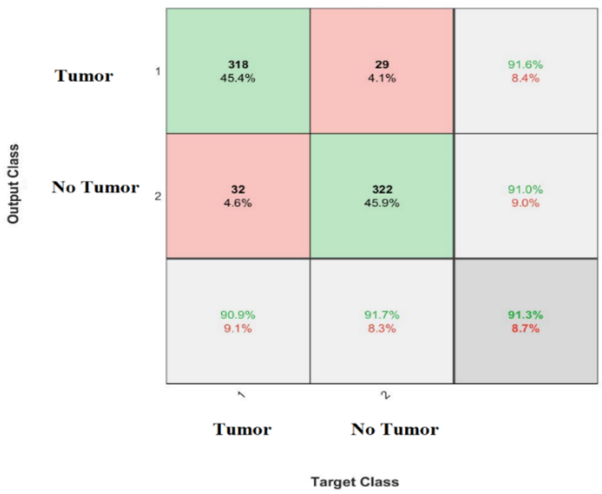

Fig 5.1: Confusion matrix accuracy for only GLCM

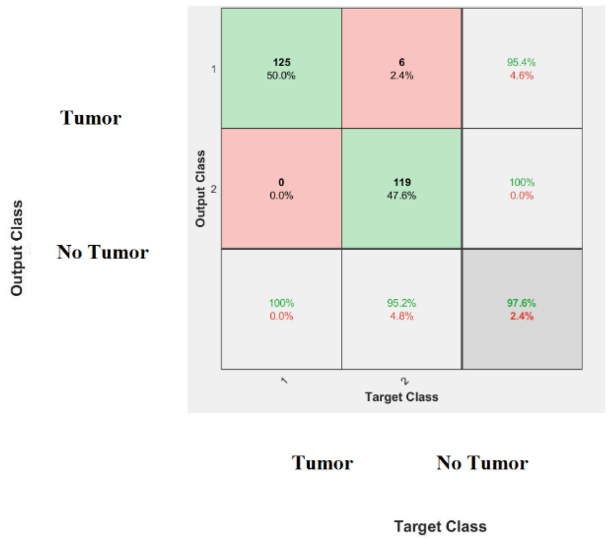

Fig 5.2: Confusion matrix accuracy for Ensembled Features

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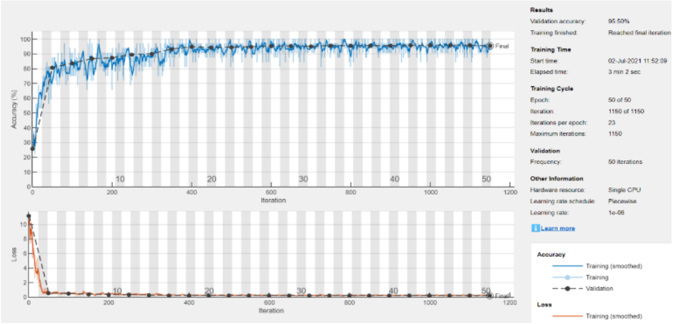

Fig 5.3: Plot for Accuracy and Loss vs Iterations for CNN Training

Image Processing output for Tumor and Non Tumor image is as shown below

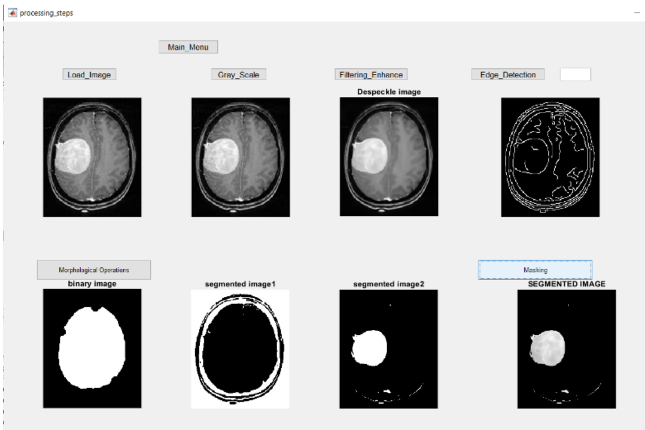

Fig 5.4: Tumour detected

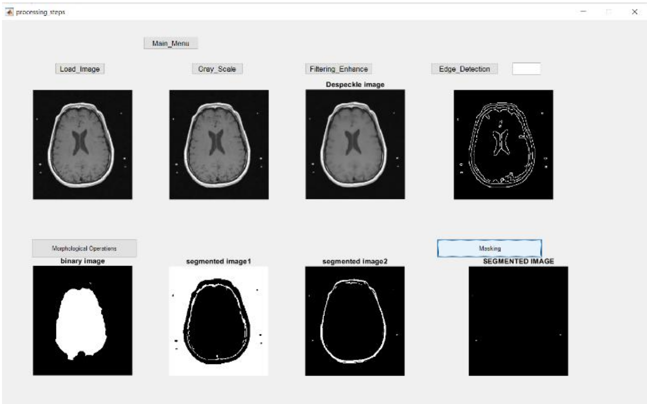

Fig 5.5: Tumor not detected

V. CONCLUSION AND FUTURE SCOPE

This Project mainly deals with Segmentation of Tumour and its classification. Tumour segmentation is done using image processing algorithms, mainly image denoising, edge detection, Otsu's thresholding. Features are extracted using GLCM, LBP and HOG. These features are ensembled and fused. The Convolutional neural Network is trained using these Ensembled Features. It is shown that the validation accuracy for Ensembled Features is around 95.5 and with only 1 features it is around 91.1.This project can be further improved be including ensembled classification also, like use o CNN with various layers configuration , Bilstm and DNN to achieve higher accuracy. Also Nose can be introduced to MRI dataset to check the accuracy of the algorithms with nosy images.

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AUTHOR'S PROFILE

Tasmiya Tazeen, is a Mtech student in the department of Digital communication and Networking from Reva University, Bangalore. She has received her B.E degree in Electronics and Communication from Visvesvaraya Technological University (VTU), Bangalore in the year 2019. Her current research focuses on brain tumor segmentation by cascaded deep neural networks using multiple image scales

Dr. Mrinal Sarvagya, Professor, School of Electronics and Communication Engineering PhD degree in Wireless Communication from IIT Kharagpur, MTech degree in digital Communication, (Course work from IIT kanpur) from DAVV Indore and B.E degree in Electronics and communication Engineering " from Govt Engineering College Ujjain". She received the best thesis award from IIT Kharagpur in the year 2009 for her thesis titled "QoS based packet scheduling and resource allocation schemes for WCDMA UMTS". She is the member of Professional bodies WIE,IEEE. She has 20 years of teaching experience, teaching various subjects like Wireless communication, Advanced Digital Communication, Computer communication and networking, real time Operating Systems, Adhoc wireless networks, Protocol Engineering. Her area of research is Wireless communication, channel equalization in OFDM-IDMA / SCM receivers, Cognitive Radio networks. Principal Investigator , VGST Karnataka " Zero padding OFDM signals for Cognitive radio Networks" (2012 -2014). Principal Investigator, IEEE Hyderabad "Multimedia Communication over Fibre Optical link" (2012) exhibited at Birla science Museum Hyderabad. Currently Principal Investigator for the sponsored Project from Naval research Board, Ministry of defense India (2015). Principle Investigator for the Project titled" Attitude determination of Ship in floating drydock" sponsored By ISRO India 2019. Her name is included in Marquis who is who in the world directory from 2007 onwards. She has received many awards like young research scientist from VGST karnatala in 2013 Bharat Jyoti award from international friendship society of india . She has received Outstanding faculty in engineering Award from Venus International foundation India 2017.

She has more 80 publications in international journals and conferences.

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