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Brain Tumor Detection Based on Watershed Segmentation and Classification Using Deep Learning

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Abstract - The computer-aided diagnostic-based that supports deep learning (DL) algorithms consists of several processing layers, which symbolize data with several stage of construct. In current years, the use of deep learning has increased speedily in almost all areas, especially in the field of medical imaging, medical image investigation or bioinformatics. Therefore, deep learning has effectively untouched or enhanced the methods of recognition, calculation or diagnosis in many medical and health areas such as pathology, brain tumors, lung cancer, stomach, heart or retina. Given wide application of deep learning, the purpose of this paper is to appraise the most important deep learning perception related to tumour analysis detection and classification In recent applications of pre-trained models, normally features are extracted from bottom layers which are different from natural images to medical image. To overcome this difficulty, in the proposed method GLCM feature and Resnet-50 techniques used for feature extraction and watershed based segmentation is used for brain tumour detection and its classification. A significant, practical deep learning model is proposed which uses back propagation neural network feature to predict brain stroke through CT/MRI scan images. The performance and accuracy of the proposed model is evaluated and compared with existing models and it produces high sensitivity, specificity, precision and accuracy.

Index Terms- Deep learning, magnetic character imaging, brain tumor classication, pretrained model,

I. INTRODUCTION

Generally of the tumor is two types namely benign and malignant. Malignant tumour is referred to as cancer. Abnormal growth of cell inside brain is called brain tumor. There are two general groups of brain tumor. Primary brain tumor starts in brain and tends to stay there. Secondary brain tumor starts somewhere else in the body but travels to brain. Secondary tumors are more common than primary tumors. The motive for brain tumor is unknown till now. Those probable reasons of brain tumor can be a number of conditions like neurofibromatosis, exposure to chemical vinyl chloride, Epstein-Barr virus and ionizing radiation. The use of mobile phones is also measured as one of the risk factors but there is still no clear evidence. According to the World Health Organization and American Brain Tumor organization [3][4][10] the for the most part common grading system uses a scale from grade I to grade IV to classify benign and malignant tumor types. On that scale, benign tumors fall under grade I and II glioma and malignant tumors fall under grade III and IV glioma. The grade I and II glioma are also called low-grade tumor type and possess a slow growth, whereas grade III and IV are called high-grade tumor types and have a rapid growth of tumors. If the low-grade brain tumor is left untreated, it is likely to develop into a high-grade brain tumor that is a malignant brain tumor. Patients with grade II gliomas require serial monitoring and observations by magnetic timbre imaging (MRI) or computed tomography (CT) scan every 6 to 12 months. Furthermore, the most malignant form of a strocytoma, which is also the highest grade glioma, is the glioblastoma. The abnormal fast growth of blood vessel and the presence of the necrosis (dead cells) around the tumor are distinguished glioblastoma from all the other grades of the tumor class. Grade IV tumor class that is glioblastoma is always rapidly growing and highly malignant form of tumors as compared to other grades of the tumors. Image processing is a process of analyzing, manipulating an image in order to perform some operation to extract the information from it. check-up imaging seeks to disclose internal structure hidden by skin and bones and also to diagnose and luxury disease. And also it establishes a file of normal anatomy and physiology to make it possible to identify abnormalities. In today's world, one of the reasons in the rise of mortality among the people is brain tumor. [1][5]Abnormal or uncontrolled growth of cell residential surrounded by the individual body is called brain tumor. This group of tumor grows within the skull, due to which normal brain activity is disturbed. Brain tumor is a serious existence frightening disease. Consequently which not detected in earlier stage, can take away person's life. Brain tumors can be mainly three varieties called benign, malignant, and pre-malignant. The malignant tumor leads to cancer. Treatment of brain tumor depends on many factor such as appropriate diagnosis and the different factor like the type of tumor, location, size, and state of development. beforehand stage of tumor is used to be notice bodily with the assist of observation of image by means of doctors and from time to time it takes more time and marks may be inaccurate[8][7]

In last few years, the development of biomedicine and human intelligence technology has overcome many diseases, but due to its unpredictable nature, people still suffer from cancer. This sickness is still a major difficulty for mankind. Brain tumor cancer is one of mainly grave acute diseases. In the United States, nearly 23,000 patients were recognized as brain tumor cancer in 2015 [1].The main origins of such diseases are diseases or illness associated to cancer. Effective treatment of the disease is crucial, which depends on its timely or correct recognition. The specificity of the treatment depends on: size of tumor at time of examination, nature of pathology or type of tumor. The brain is mainly complex and critical part of person anatomy. It enclose tissues or nerve cells to normalize body's key actions, such as breathing, our senses and muscle function. A unit has its capabilities; by virtue of its functions,

The formation of abnormal cell populations in or near the brain leads to initiation of brain tumors. Abnormal cells will intensify brain function and affect patients' health [4]. Brain imaging, diagnosis and conduct using medical imaging method are research focus of researchers, radiologists and clinical experts [5]. The examination of brain imagery is measured a top priority because brain diseases called brain tumors in developed countries are fatal and cause a great amount of deaths. For example, according to data from National Brain Tumor Foundation (NBTF), 29,000 people in United States (USA) are diagnosed with brain tumors, and 13,000 patients die each year [6]. Many superior magnetic resonance imaging system embrace diffusion tensor imaging magnetic resonance spectroscopy (MRS), or perfusion MRI to analyze brain tumors by MRI [7-9]. Brain tumors are roughly separated into two types: cancerous tumors (called malignant tumors) and non-cancerous tumors (called benign tumors). The World Health Organization (WHO) further divides malignant tumors into grade I to IV [10]. The first-class tumor is called malignant astrocytoma, the second-class tumor is low-grade astrocytoma, the third-grade tumor is anaplastic astrocytoma, or fourth-class tumor is glioblastoma. Primary tumors or secondary tumors are less aggressive semi-malignant tumors. Grade III or IV are hateful tumors that have a major impact on patients' health and can lead to death of tumor patients [11].Many ultrasound practice or process have been used to diagnose and treat brain tumors. Dissection is a basic step in the imaging technique used to remove the affected area of brain cells from MRI [12]. The division of the tumor area plays an important role in cancer identification, treatment and evaluation of treatment response. Several semi-automatic or automatic division method and practice are used in tumor division [13].

1) Deep Features of Brain Tumors-Exploration and representation of deep features is an important task in predicting and diagnosing brain tumors through radiological MRI. Extract deep features from MRI images for oncological diagnosis, treatment or prognosis. The radiological assets of images are clearly linked to meaningful biological features and provide qualitative information known to radiologist’s .Once the network is pre-trained as a feature extractor, the deep degradation neural network can achieve the latest prediction and classification. Deep feature extractor technique or practice is more suitable for predicting the overall survival time of patients [8]. The deep convolutional neural network (CNN) establishment technique is used to remove skin texture from ImageNet to train the CNN network for organization or segmentation.

The CNN activation feature technique uses a variety of techniques, including feature selection, function merging, or figures enhancement algorithms [6]To condense varying concentration of different average filters in the image, function selection, function removal, or fusion are execute. Gabor wavelet function technology can be used to attain texture information of image, which includes the tumor's location, direction, and frequency. Core Principal Component Analysis (KPCA) decides on a small portion of the function condenses redundancy by mounting correlation of function. The Gaussian Radial Basic Function (GRBF) provides function differentiation information from many sets of functions to function fusion [7]. Function extraction based on fine tuning is used in pre-trained CNN method.

II. LITERATURE REVIEW

Machine learning methods are widely used in various fields such as clinical diagnostics and preventive medicine. However, limited research has focused on the identification of brain tumors, particularly using magnetic resonance imaging (MRI). In general, machine learning scheme train or test traditional machine learning algorithms with MRI data. More freshly, some methods have used DL to define brain tumors. Rehman et al. [3] proposed a system that uses a space describe a three-dimensional CNN (Convolutional Neural Network). Network) to classify the types of tumors (GoogLeNet, AlexNet and VGGNet).This organization includes the types of pituitary tumors, gliomas and malignant. The algorithm described above cuts the MRI brain to detect the area of interest. The data were also well organized and converted into further classifications. The authors also measured data amplification system to obtain the accuracy of the results. By using the VGG16 model to recover classification and detection, the exactness of this study reached 98.69%.

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Deepak et al. [7] also used thought of deep remove to classify the images or used same source of information discussed there [5]. Remove the functions from the image, and use these functions in the experimental and classification models. At the patient level, using a classification model of 5, the author's accuracy was reached 98%. The research concluded that automatic classification can help in the organization of areas and is better than the classification of urban areas.

Another study by Afshar et al. [8] classifies CapsNets-based brain tumors as a model of Capsule networks. The research improves the degree of accuracy by incorporating CapsNet mapping modifications to certain convolutional layers. The study revealed that 86.50% accuracy can be achieved by using CapsNet on the convolutional layer. This installation is achieved by using 64 maps to improve the accurate metrics.

Another study by Abiwinanda et al. [9] took a CNN-based in-depth study model and applied it to image classification of brain tumors. Although the study uses five classification models, conclusion 2 is the best approach to classify the images. The final building consists of a RELU layer or a topmost pool layer. This site has 64 latent neurons in a covered structure. The lessons revealed that it would achieve 98.5% proficiency in training or 84.19% in certification. The authors in [21] used a two-dimensional contrast pedestal on wavelet and Gabor filters to explore the efficacy of brain MRI. By using the above system with NN backpropagation, the study achieved 91.9% accurate measurements.

Pashaei et al. [11] created a feature mining planning based on CNN. They also calculated a 5-layer architecture, with all layers as learning layers, and with a special 3-layer layout. The revision said it would reach an 81% accuracy rate or further improve the accuracy of CNN's standard classification model based on ELM (Extreme Learning Machine). The revision found that in examining classification, the differences between the pituitary gland and malignant images were limited by the ability to discriminate.
Sajjad et al. [10] planned an arrangement based on neural network organization, which further assisted in providing a clear picture (separating the tumor area from the data). In addition, the research uses noise suppression techniques through the use of concepts of variability and invariance. CNN's analysis can correct the accuracy of the predictions to predict the magnitude of the swelling. For the truth of the prophecy, the data is transmitted to CNN modified. Some experiments were performed on both radioactive and brain tumors. This study uses the innovative data or improved data to determine the accuracy of the system, which is 90.67%. Classifying tumors by different numbers of imaging data can be very useful in clinical perform, as it can also speed up conduct plan of these.

Anaraki et al. [15] projected a CNN or GA (genetic algorithm) -based strategy to organize different types of glioma imagery using MRI data. The proposed system uses a genetic algorithm to automatically select the CNN system. They obtained a 90.9% exactness in predicting images of 3 glioma types. In addition, the accuracy of this study in organization of glioma, malignant or pituitary gland reached 94.2%. Zhou et al. [16] proposed a way to directly use 3D general graphics. First, overall 3D image is then converted into a 2D segment, and then DenseNet is used to extract features from each 2D segment. Subsequently, repetitive neural networks are linked to 2D networks that use both long or short -term memory for classification. They conducted conduct test on public and property data. They also installed a pure convolutional neural complex in DenseNet as a convolutional autoencoder for illustration study. Therefore, they used long- or short-term DenseNet sensing and DenseNet convolutional neural system for tumor detection o classification of tumor types. Their system uses DenseNet-LSTM to achieve 92.13%accuracy.The limitation of the existing method is to remove features from the bottom layer of the pre-designed model, which are unusual from the natural image to the clinical image. To conquer this problem, a multi-feature exploration method is proposed that improves the model's ability to classify brain tumors.

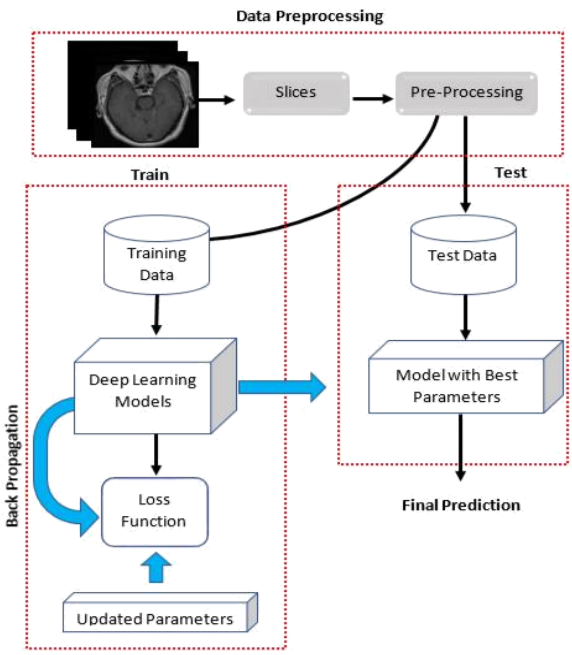

Figure 1. The brain tumor dataset sample for three classes: (a) glioma, (b) meningioma, (c) pituitary.

The rapid development of in-depth learning and practice has provided inspiration for automatic illustration and attribute learning. So, we use ResNet for attribute mining, which is a deep CNN system. CNN feels that learning from the lowest to the highest levels is automatic through

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change and construction. The highlighted images are sent to the neural network for cataloging training. The speed of stochastic neural networks is faster than traditional BPNN because it is based on ramp ancestry. CBA is used to optimize parameters of random neural complex to further recover their organization function.

III. PROBLEM IDENTIFICATION

Traditionally the segmentation and feature extraction of brain tumor MRI images is done manually by Radiologists. It is time consuming as well as can cause unavoidable mistakes. So proper segmentation of tumor region is required to identify tumor location, tumor size and its surrounding structure of brain for the Radiologist.[15] This information is very essential for appropriate treatment. So, the correct assessment of brain tumors by means of imaging modalities is one of the key subjects of radiology departments.Brain tumour can influence persons at any age of a person and it is the main cause of cancer death all-inclusive.

Brain tumour is surrounded in a brain, which results in growth of defect. We have studied and extract different features for classification of tumor type. In this work, we extracted features; features are selected for the classification of the tumor type using optimization technique. To improve the classification accuracy, the Feature extraction and selection are performed for accurate diagnosis analysis. The detection of brain tumor and then deciding the right therapy is a long process, and once it is acquainted then time to time evaluation and its progress is extremely important, The purpose of this research work is to extract relevant information from the deep learning based feature extraction technique and classify healthy and infected tumor tissues for a large database of medical images.

The results of this research are helpful in classifying benign and malignant tumors, fast and accurately and thus, improving the diagnosis of tumor slices[10][13] Traditional human-based imaging methods have been used to diagnose and classify MRI brain tumors, and rely on the radiologist's ability to examine or analyze the imaging elements. For large amounts of data, the operator-assisted classification method is irreversible or inefficient, as manual processing of large amounts of data is a time-consuming procedure. To trounce these troubles, computer-assisted testing tools are needed to effectively procedure great amounts of data. In practice, the classification of brain tumors can be divided into 2 types: 1) MRI is divided into normal or abnormal tumors; 2) abnormal brain tumors are classified as dissimilar nature of tumors. Compared with the categorization of tumors for tumors (normal and abnormal), it is somewhat difficult to automatically classify tumors of the brain into various pathological types.

III. DATASET

The brain data set examined in this revise consists of 233 3064 T1-weighted MRI images with contrast [5].

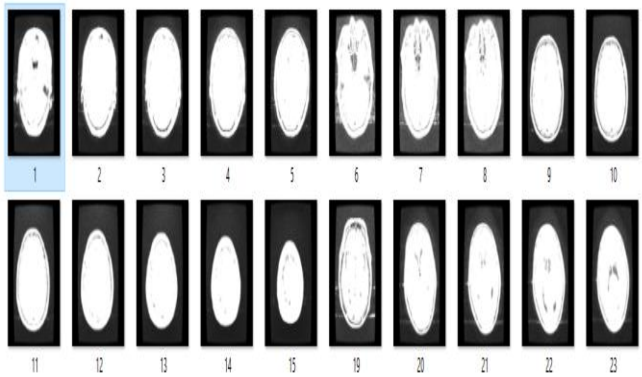

Fig .2 3064 T1-weighted MRI images

There are three diverse types of tumors in this dataset, such as meningiomas, gliomas, and pituitary tumors. An image decision of 512x512 with a voxel spacing size of 0.49 0.49 mm2 has been used in this data set. The image resolution consists of axial (lateral planes), coronal (frontal planes) or sagittal (lateral) planes. The axial planar allotment based on number of categories consists of 708, 1426, and 930 specimens of glioma, meningiomas, or pituitary tumors. The min-max normalization method is used inside the pixel

IV. PROPOSED MODEL

This research proposes a new approach for brain recognition structure based on deep leaning feature extraction. First, use ResNet as a attribute extractor, which is a well-known neurological network construction. Then we used 3 random neural complexes, namely Schmidt neural complex, chance vector function link network, or extreme learning machine. The weights or biases in the three networks are taught by chaotic bat algorithm. The 3 planned techniques attain comparable consequences based on five runs, and they produced comparable presentation compared to latest method.

The proposed models with dissimilar numeral of layers and pre-trained models are described in follow segment. Figure 2 illustrate pretreatment, training, testing or calculation process of brain tumors. The planned model is pretreatment, on deep learning that uses various hyperparameters for training and uses a loss function to optimize these parameters during training process. Machine learning through the loss utility is a way of evaluating how an exacting algorithm models the delivered data. Gradually, loss occupation learns to use some optimization functions to minimize the prediction error. We used pre-trained ResNet-50 model to extract the brain's MRI functions. The results of this study show a new way to recognize the structure of the brain that is based on extracting deep learning features. Figure 2 shows how the steps of pretreatment, training, testing, and calculating are done for brain tumors. The results of this study show a new way to recognize the structure of the brain that is based on extracting deep learning features. The major rationale of the future system is to categorize the MR image into usual and abnormal. Tissue the nonstandard Images are added classified keen on two types low-quality and high-grade gliomas. The MR images are pre-processed such as gray scale conversion, filtering, image enhancement is applied to create the images working for the subsequently steps. A step that we used in our proposed method. For segmentation, we have used k-means clustering to segment the images and find out the tumor area watershed based segmentation algorithm is proposed. Watershed transform is used efficiently in the field of classification, clustering of document categories and is a well suitable technique for retrieving the documents. The segmented images are after that used to extract kind, and classified by the ResNet50, the classification classify the input dataset as normal or abnormal (inferior, high-grade glioma Brain tumor)

2.Architecture of Resnet-50-Now we will discuss building of ResNet50. The architecture of ResNet50 is divided into four phases, as shown in figure below. The network can use height or width of the input image as multiples of 32 and 3 of the channel width. For sake of illustration, we treat the input size as 224 x 224 x3. Each ResNet architecture uses 7 × 7 and 3 × 3 core sizes to perform initial folding and maximum pooling, respectively. Then the first phase of the complex starts. It has 3 residual blocks and each residual block contains 3 layers. The core sizes used to perform folding operations in all 3 layers of the block in step 1 are 64, 64 and 128, correspondingly. The curved arrow refers to individuality association. The dashed projectile indicates that the difficulty process in residual block is executed in step 2. Therefore, the input size is reduced by half in terms of height or width, but channel width is twofold. As we go from one step to another, channel width doubles or input size is condensed by half. For deeper system like ResNet50, ResNet152, etc. Need to use bottleneck design. For each residual utility F, 3 layers are stacked on top of each other. These three layers are 1 × 1, 3 × 3, 1 × 1 folding. The 1 × 1 folding layer is answerable for shrinking and then restoring size. The 3 × 3 layer is still the bottleneck in the smaller input / output size.

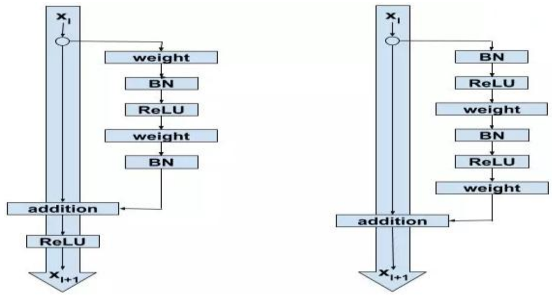

Fig 3 Architecture of Resnet-50

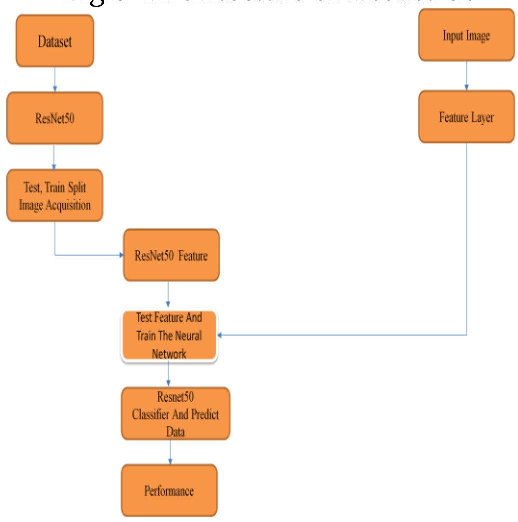

Fig.4 proposed flow diagram.

V. RESULTS AND DISCUSSION

The proposed fingerprint representation will be analyzed based on the performance measures: In terms of segmentation accuracy and similarity metric of performance. In this work, GLCM is used and feature extraction and Resnet-50 is a must due to the abundance of noisy, irrelevant or misleading skin tone. By remove these factors, learning from data techniques can advantage very much. Characteristic assortment is able to be viewed as single of the most primary problems in the field of machine learning. The most effective features a generate - GLCM and Resnet-50 methods used to improve the presentation of the model but also facilitate the examination of the results. Finally, SVM is used to classify the descriptions into normal or abnormal type tumor

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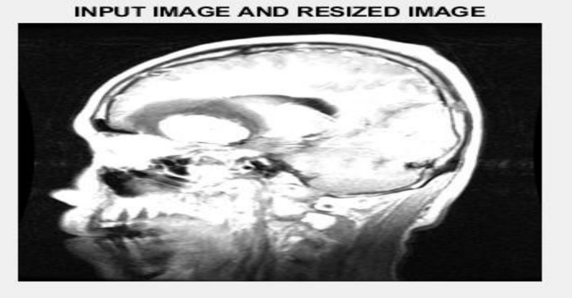

Fig .5 input image

Pre-Processing contains two sub divisions. One is the filtering and other is the image enhancing section. The main objectives of pre-processing are the suppression of redundant and irrelevant data before process into an application [8]. Median filter is used for smoothing and removing the noise from image. The median filter is often using to perform noise reduction in an image. It preserves the edges of the image while removing the noise. Image enhancement is the process of adjusting the images so that it is more suitable for further analysis. In the proposed method adaptive histogram equalization was done to enhance the contrast of the image.

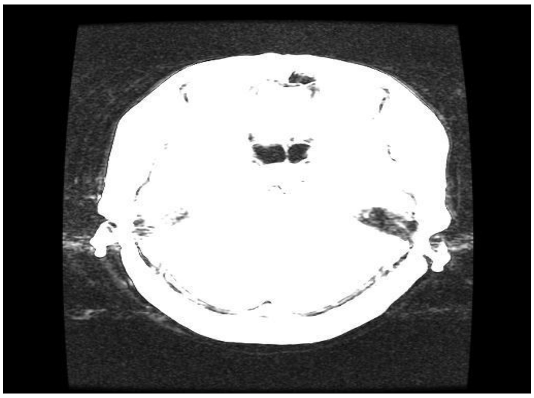

Figure 3: Shows the original image

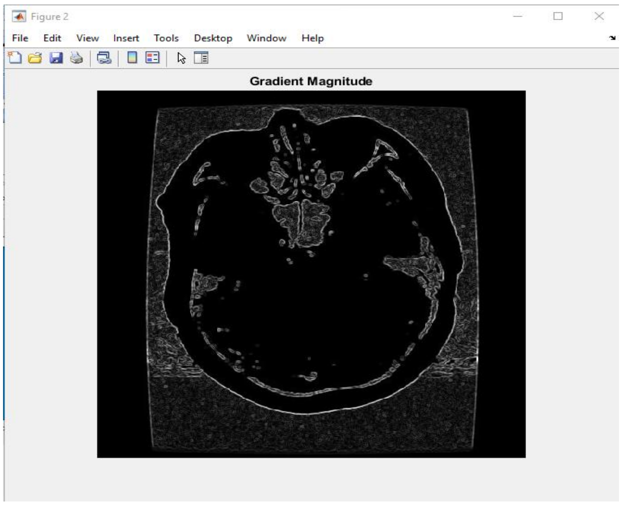

Figure 4.: Gradient Magnitude as the Segmentation Function

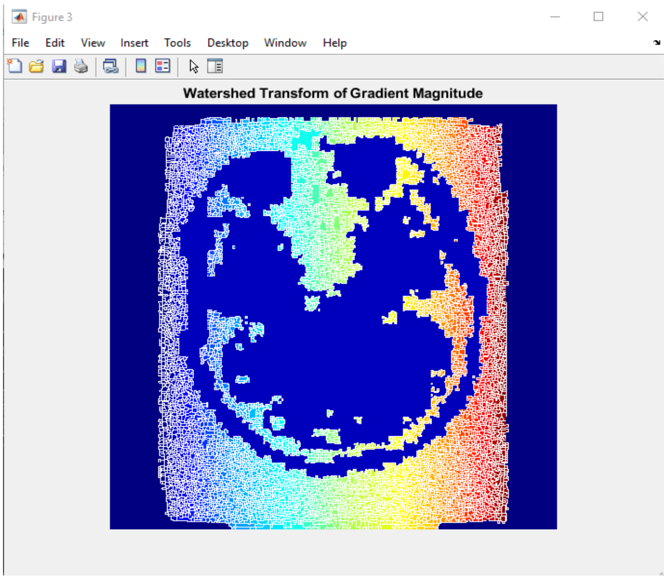

Figure 5: the watershed transform

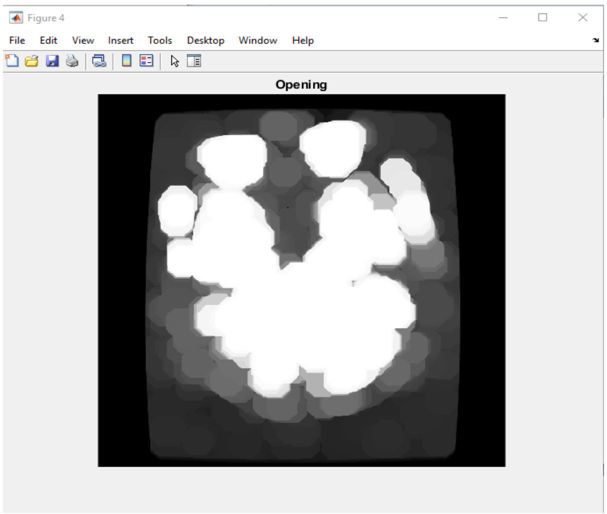

Figure 6: The Opening-by-reconstruction algorithm

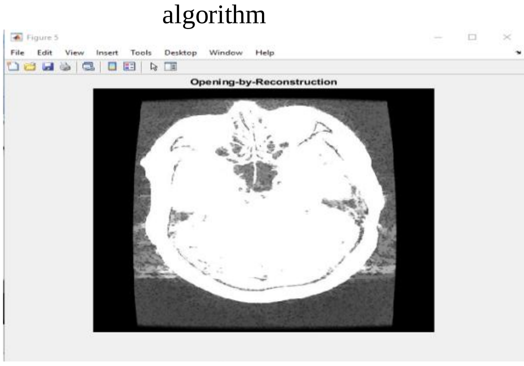

Figure 7: The opening-by-reconstruction

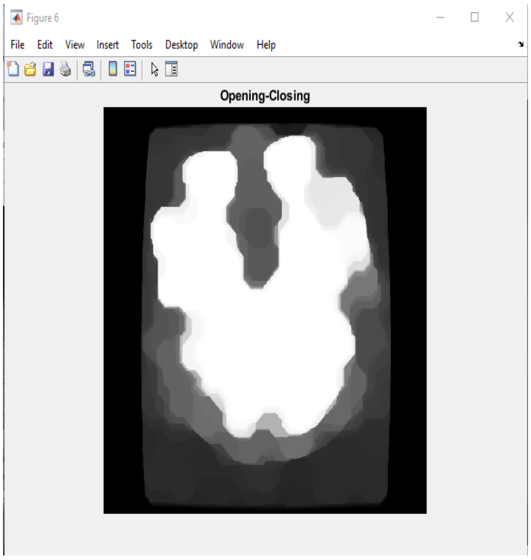

Figure 8: The 'Opening-closing algorithm

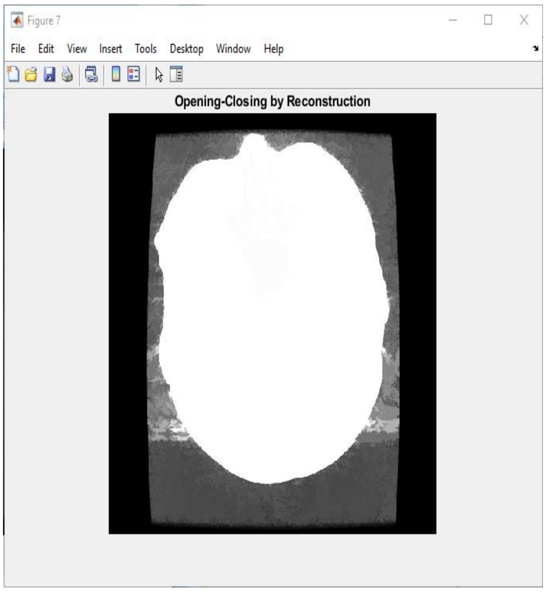

Figure 9: Opening-closing by reconstruction algorithm

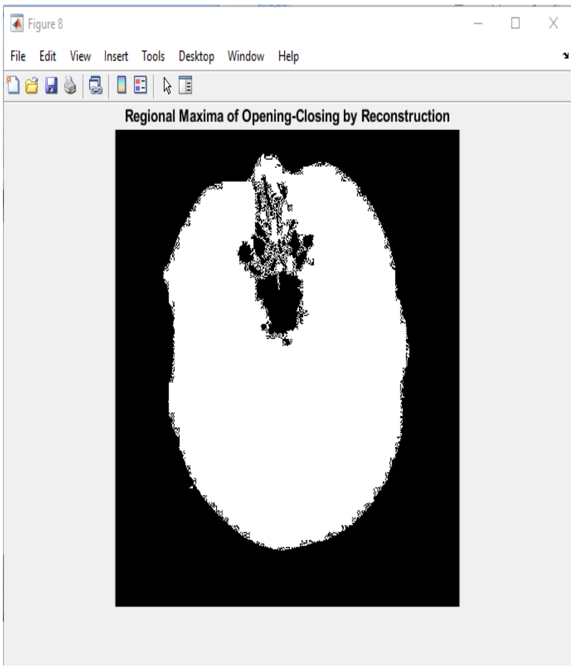

Figure 10: Regional maxima of opening-closing

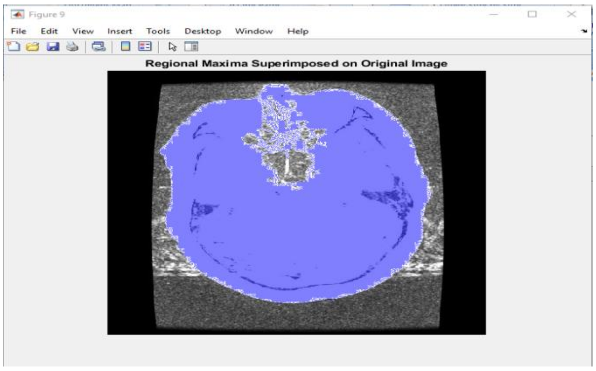

Figure 11: Regional maxima superimposed technique on original image

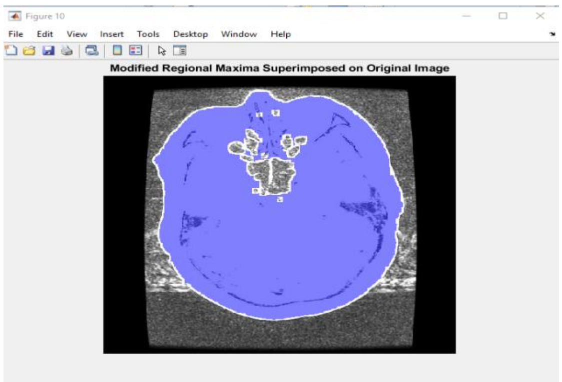

Figure 12: Modified regional maxima superimposed on original image.

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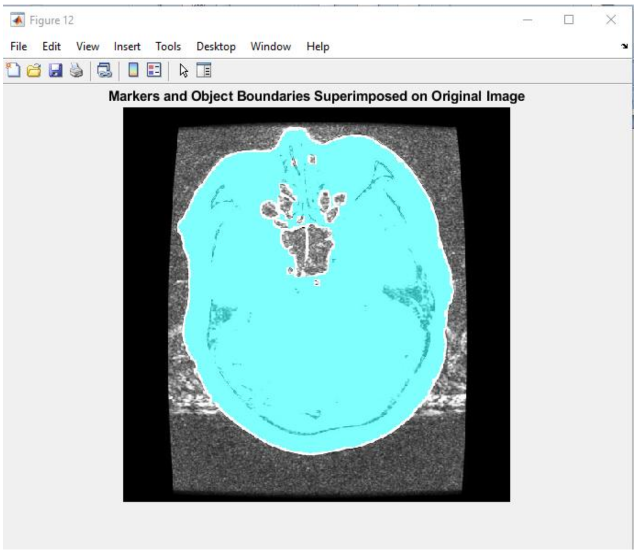

Figure 13: Markers and object boundaries superimposed on original image.

Table 1 showing the Comparison result with existing work and proposed

	Techniques	Accuracy (%)	Precision (%)	Recall (%)	Sensitivity (%)
Existing system [1]	VGG16	82.00	95.12	94.25	91.42
Proposed system	ResNet 50	93.93	94.00	92.00	92.12

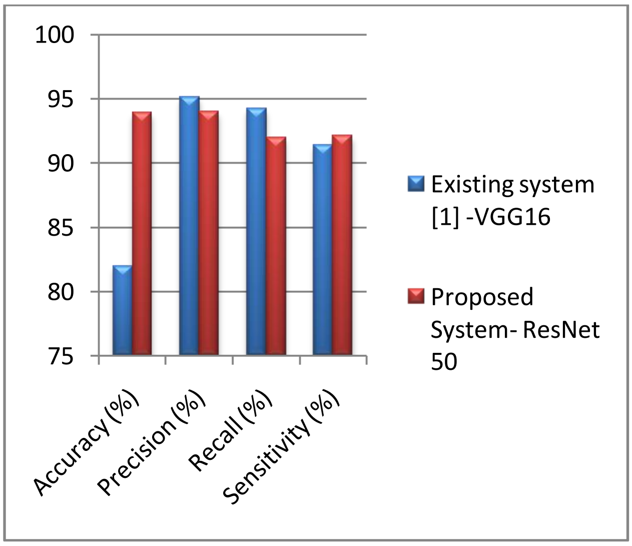

Fig 13 Comparison graph with existing work and proposed work

VII. CONCLUSION

This paper converse functions of deep learning modelsfor the identication of brain tumor. First, use the qualified resnet50 deep learning model and remove functions from different resnet50 blocks. These attribute are then linked and transferred to the softmax category to organize brain tumors. Connect them and then transfer them to softmax for the liver tumor category. Algorithm can greatly reduce the computational load. and increase classification accuracy this work is driven by the motive to provide our clinicians or a radiologist is an efficient and cost effective tool for a classifying the benign and malignant tumors. Brain tumor is any mass that results from abnormal growth of cells in the brain. It may affect any person almost in any age (age between 5 to 80). Brain tumors can have a variety of shapes and sizes; it can appear at any location in different image intensities. Brain tumors can be benign or malignant. Low grade Gliomas and Malignant are benign tumors which represent the most common type of tumor In this paper, two dissimilar scenarios were charge. First, use the qualified resnet50 deep learning model and remove functions from different resnet50 blocks. These attribute are then linked and transferred to the softmax category to organize brain tumors. Connect them and then transfer them to softmax for the liver tumor category. -head.

Both cases were evaluated using three brain tumor data sets. Therefore, evaluate to existing explore technique for organization of brain tumors, effectiveness of the cascade block-based ensemble method using the DensNet201 pre-training model is much better. The proposed method yielded 93.93% of the test example or realizes highest increase in the detection of brain tumors. In the future, we will discover or pertain ne-tune technology to over-trained models, and may classify hair-based models and data-enhancing method to classify brain tumors. We will also examine the company methods (fusion of output classifier) based on ne-tune or floor-based operations derived from the in-depth learning model. In future, we will assemble more brain MRIs to expand the data. We will also try to use the transmission of studies to accurately model the deep network of the brain MRI.Visualization of neural complex is another explore course which can help human to comprehend how complex works in a through way. We shall apply our technique to notice other ailment like Alzheimer's disease, hearing loss, etc.

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