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Machine Learning And Deep Learning Based Tumor Detection

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Abstract:The controller of human system was the brain. The abnormal growth as well different levels of cells in the brain lead to a brain tumor, increase in level leads to brain cancer. In the area of human health, Computer Vision plays a significant role like CT scans, X-Ray, and MRI scans are the common imaging methods among magnetic resonance imaging (MRI) that are the most reliable and secure. .My work aims to focus on the use of different techniques for the discovery of brain cancer using brain MRI. In this study, we performed pre-processing using the bilateral filter (BF) for removal of the noises that are present in an MR image. This was followed by the binary thresholding and Convolution Neural for reliable detection of the tumor region using training, testing, and validation datasets based on our machine, we will predict whether the subject has a brain tumor or not. The resultant outcomes will be examined through various performance metrics includes accuracy, sensitivity, and specificity. It is desired that the proposed work would exhibit a more exceptional performance over its counterparts.
Index Terms: Brain tumor, Magnetic resonance imaging, Adaptive Bilateral Filter, Convolution Neural Network.

1.1 Introduction:

Brain tumors are life-threatening conditions that require early and accurate diagnosis for effective treatment. Traditional diagnostic methods like MRI interpretation by radiologists can be time-consuming, subjective, and prone to human error. This creates a need for automated systems that can assist in the early detection and classification of brain tumors from MRI images.

This work aims to develop an intelligent and automated brain tumor detection system using Machine Learning (ML) technique. The goal is to classify brain MRI scans into tumor and non-tumor categories and further categorize tumor types (e.g., glioma, meningioma, pituitary tumor) using image processing and classification models.

By leveraging convolutional neural networks (CNNs), transfer learning models (like VGG16, Mobile Net, ResNet, etc.), and traditional ML algorithms (like SVM, Random Forest), the system will provide accurate predictions and support radiologists in clinical decision-making.

1.2 Literature Review:

Monica Subashini.M, Sarat Kumar Sahoo, "Brain MR Image Segmentation for Tumor Detection using Artificial Neural Networks," International Journal of Engineering and Technology (IJET), Vol.5, No 2, Apr-May 2012.

Literal report that edge detection, image segmentation, and matching are not easy to achieve in optical lenses that have long focal lengths. Previously, researchers have proposed many techniques for this mechanism, one of which is wavelet-based image fusion. The wavelet function can be improved by applying a discrete wavelet frame transform (DWFT)

S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," in IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240-1251, May 2016.

S.Pereiraetal presented that magnetic resonance prevents physical segmentation time in the medical areas. So, an automatic and reliable segmentation technique for identifying abnormal tissues by using Convolutional Neural Network (CNN) had been proposed in the research work. The massive three-dimensional and underlying roughness amongst brain images makes the process of segmenting the image a severe issue, so a robust methodology such as CNN is used.

S. Roy And S. K. Bandyopadhyay, "Detection and Qualification Of Brain Tumor From MRI Of Brain And Symmetric Analysis," International Journal Of Information And Communication Technology Research, Volume 2 No.6, June 2012, Pp584-588

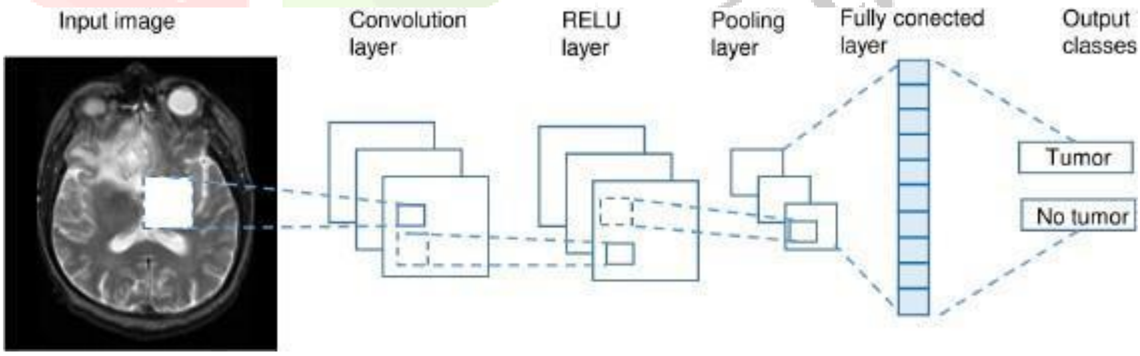
Royetal (2012) [18] calculated the tumor affected area for proportioned analysis. They showed that their algorithm could robotically hit upon and phase the brain tumor from the given photo. Image pre-processing consists of fleeting that pictures to the filtering technique to remove distractors found in given pictures. They first detect the tumor, segment it.

Sankari Ali, and S. Vigneshwari. "Automatic tumor segmentation using convolutional neural networks." 2017 Third International Conference on Science Technology Engineering & Management (ICONSTEM) (2017): 268-272.

Sankari and S. Vigneshwari [19] has proposed a Convolutional Neural Network (CNN) segmentation, which principally based on the brain tumor classification method. The proposed work used the non-linearity activation feature that's a leaky rectified linear unit (LReLU). They primarily focused on necessary capabilities, which include mean and entropy of the image and analyzed that the CNN algorithm is working higher for representing the complicated and minute capabilities of brain tumor tissues present in the MR Images.

1.3 Proposed System:

Currently, CNNs are the most researched machine learning algorithms in medical image analysis. The reason for this is that CNNs preserve spatial relationships when ltering input images. As mentioned, spatial relationships are of crucial importance in radiology, for example, in how the edge of a bone joins with muscle, or where normal lung tissue interfaces. with cancerous tissue. As shown in Fig(a), a CNN takes an input image of raw pixels, and transforms it via Convolutional Layers, Rectified Linear Unit Layers (RELU) and Pooling Layers. This feeds into annual Fully Connected Layer which assigns class scores or probabilities, thus classifying the input into the class with the highest probability.



Fig(a) Layer classification model of CNN

Detection, sometimes known as Computer-Aided Detection (CAD) is a keen area of study as missing a lesion on a scan can have drastic consequences for both the patient and the clinician. The task for the Kaggle Data Science Bowl of 2017 involved the detection of cancerous lung nodules on CT lung scans. Approximately 2000 CT scans were released for the competition and the winner Fang Zhou achieved a logarithmic loss score of 0.399.

Their solution used a 3-D CNN inspired by U-Net architecture to isolate local pitchers for nodule detection. Then this output was fed into a second stage consisting of 2 fully connected layers for classification of cancer probability. Shan*tel* evaluated have well-known CNN architectures in detecting thoracic abdominal lymph nodes and interstitial lung disease on CT scans. Detecting lymph nodes is important as they can be a marker of infection or cancer. They achieved a mediastina lymph node detection AUC score of 0.95 with a sensitivity of 85% using Google Net, which was state of the art.

They also documented the benefits of transfer learning, and the use of deep learning architectures of up to 22 layers, as opposed to fewer layers which was the norm in medical image analysis. Over feat was a CNN pre-trained on natural images that won the ILSVRC 2013 localization task. Ciompi*etal.* Applied over feat to 2-dimensional slices of CT lung scans oriented in the coronal, axial and sagittal planes, to predict the presence of nodules within and around longspurs. They combined this approach with simple SVM and RF binary classifiers, as well as a Bag of Frequencies, a novel 3-dimensional descriptor of their own invention.

1.4 System Requirements:

1.4.1 Hardware Requirements:

Processor: Intel core i5 or above.
64-bit, quad-core, 2.5 GHz minimum per core
Ram: 4 GB or more
Hard disk: 10 GB of available space or more.
Display: Dual XGA (1024 x 768) or higher resolution monitors
Operating system: Windows.

1.4.2 Functional Requirements:

These define what the system **should do** — the core functionalities:

1. **Image Upload**
   - Users (doctors, technicians) can upload MRI/CT scan images via the user interface.
2. **Preprocessing**
   - The system should preprocess input images (e.g., resizing, normalization, grayscale conversion).
3. **Model Prediction**
   - The system uses ML/DL models (e.g., CNN) to detect and classify brain tumors.
4. **Tumor Classification**
   - It should identify whether a tumor is present and classify it into types (e.g., glioma, meningioma, pituitary).
5. **Display Results**
   - The predicted result along with class probability/confidence score should be displayed.
6. **Model Training Module** *(optional for GUI)*
   - Admin users can train or retrain models with updated datasets (if this feature is enabled).
7. **Visualization of Model Output**
   - Display Grad-CAM or SHAP-based heatmaps to explain model decisions (for explainable AI support).
8. **Export/Save Results**
   - Users can export the result as a report (PDF/CSV).
9. **GUI Interaction**
   - Intuitive and easy-to-use interface using Tkinter or Flask-based frontend.

Results and Discussion:

Table 1.1 Six statistical parameters that are used in the present model.

Contrast	Measure of the local variations in the intensity	$= \sum_{i=1}^{A}\sum_{j=1}^{A}(i-j)^2\, p(i,j)$
Correlation	Measure of the correlation of a pixel with its neighbour	$= \sum_{i=1}^{A}\sum_{j=1}^{A}(i-m1)(j-m2)\frac{p(i,j)}{\sigma_1\sigma_2}$
Energy	Measure of uniformity	$= \sum_{i=1}^{A}\sum_{j=1}^{A}\left(p(i,j)\right)^2$
Homogeneity	Measure of spatial closeness	$= \sum_{i=1}^{A}\sum_{j=1}^{A}\frac{p(i,j)}{1+\lvert i-j\rvert}$
Entropy	Measure of randomness of intensity of the pixels in the image	$= -\sum_{i=1}^{A}\sum_{j=1}^{A}p(i,j)log\left(p(i,j)\right)$
Maximum probability	Largest entry in the intensity matrix	$= MAX_{i,j}\,p(i,j)$

Table 1.2 List of parameters for calculating performance criteria

Accuracy (%)	$\frac{N_{TP}+N_{TN}}{N_{FP}+N_{FN}+N_{TP}+N_{TN}}$
Sensitivity (%)	$\frac{N_{TP}}{N_{FN}+N_{TP}}$
Specificity (%)	$\frac{N_{TN}}{N_{FP}+N_{TN}}$

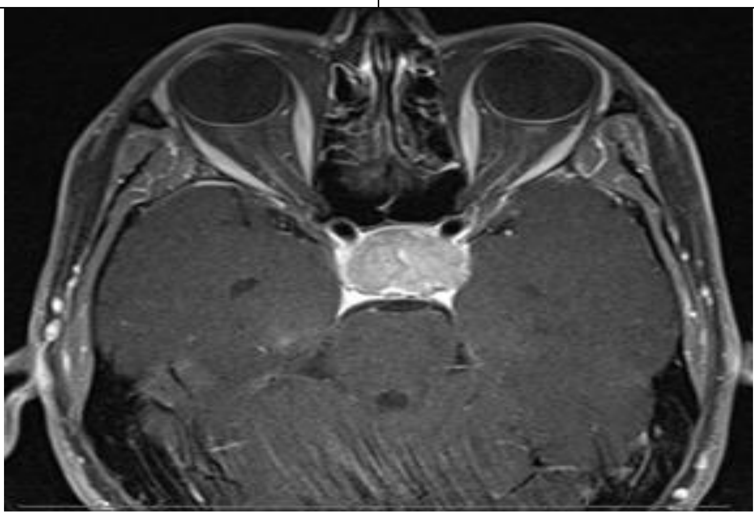


Figure (b) MR image with pituitary tumor (courtesy: https://www. kaggle. com/awsaf49/brain-tumor).

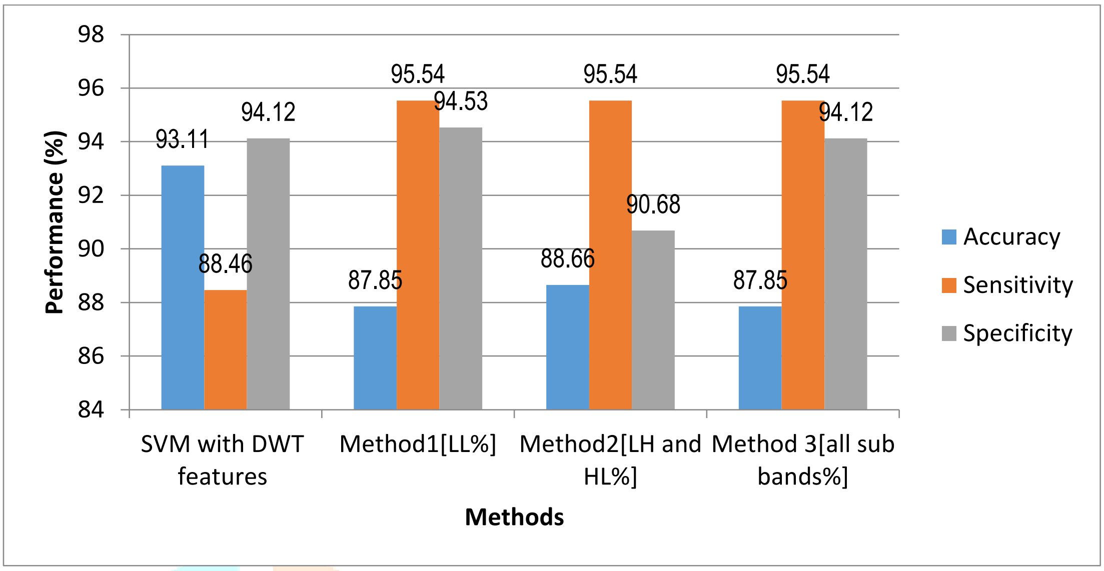


Figure (c) Plot showing the performance of the four selected methods.

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