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Brain Tumor Detection Using VGG-16

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ABSTRACT: Medical science has incredibly grown and become successful in modern years. Technology is altering the world of medicine. The main objective of our project is to detect the brain tumor by using Convolutional Neural Network (CNN) and VGG16. A Convolutional Neural Network is a classification of deep neural networks. CNN is mainly used for Image Processing, by which we will capture the image and compress it. VGG is the simple yet easy model in the CNN. VGG-16 incorporates sixteen nineteen deep layers, a crucial CNN model comes to the notion if one wishes to use an off-the-shelf model for a task. Our paper intends to locate out the brain tumor with the utilization of VGG-16, by using Convolutional Neural Network model.

I. INTRODUCTION

Artificial Intelligence (AI) has revolutionized machine learning (ML) by enabling machines to learn from experience without human intervention. Deep learning algorithms, such as Multi-layer Perceptron, Convolutional Neural Networks (CNN), and Recurrent Neural Networks, help machines solve complex problems like image classification and self-driving cars. CNN, especially models like VGG-16, play a key role in processing images by using multiple layers like convolutional, pooling, and fully connected layers to extract features and reduce dimensions, preventing overfitting.

In medical applications, AI is used for brain tumor detection through MRI scans. Brain tumors, including primary and metastatic types, can be identified and segmented using techniques like GLCM (Gray-Level Co-Occurrence Matrix), which extracts texture features from MRI images. While human-based diagnosis can lead to errors, machine-based methods improve accuracy in identifying and analyzing brain tumors.

II. LITERATURE SURVEY

Qurat-Ul-Ain(2010)Brain tumor diagnosis is a very crucial task. This system provides an efficient and fast way for diagnosis of the brain tumor. Proposed system consists of multiple phases. First phase consists of texture feature extraction from brain MR images. Second phase classify brain images on the bases of these texture feature using ensemble base classifier. After classification tumor region is extracted from those images which are classified as malignant using two stage segmentation process. Segmentation consists of skull removal and tumor extraction phases. Quantitative results show that our proposed system performed very efficiently and accurately. We achieved accuracy of classification beyond 99%. Segmentation results also show that brain tumor region is extracted quite accurately.

Khalid (2020)Segmentation of medical imagery remains as a challenging task due to complexity of medical images. This study proposes a method of k-Nearest Neighbor (k-NN) in abnormalities segmentation of Magnetic Resonance Imaging (MRI) brain images. A preliminary data analysis is performed to analyze the characteristics for each brain component of “membrane”, “ventricles”, “light abnormality” and “dark abnormality” by extracting the minimum, maximum and mean grey level pixel values. The segmentation is done by executing five steps of k-NN which are determination of k value, calculation of Euclidian distances objective function, sortation of minimum distance, assignment of majority class, and determination of class based on majority ranking. The k-NN segmentation performances is tested to hundred and fifty controlled testing data which designed by cutting various shapes and size of various abnormalities and pasting it onto normal brain tissues. The tissues are divided into three categories of “low”, “medium” and “high” based on the grey level pixel value intensities. The overall experimental result returns good and promising segmentation outcomes for both light and dark abnormalities.

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Aslam et. al(2013)This paper presents a new approach to image segmentation using Pillar K-means algorithm. This segmentation method includes a new mechanism for grouping the elements of high resolution images in order to improve accuracy and reduce the computation time. The system uses K-means for image segmentation optimized by the algorithm after Pillar. The Pillar algorithm considers the placement of pillars should be located as far from each other to resist the pressure distribution of a roof, as same as the number of centroids between the data distribution. This algorithm is able to optimize the K-means clustering for image segmentation in the aspects of accuracy and computation time. This algorithm distributes all initial centroids according to the maximum cumulative distance metric. This paper evaluates the proposed approach for image segmentation by comparing with K-means clustering algorithm and Gaussian mixture model and the participation of RGB, HSV, HSL and CIELAB color spaces. Experimental results clarify the effectiveness of our approach to improve the segmentation quality and accuracy aspects of computing time.

III. METHODOLOGIES

Modules Name:
1. DWT based feature extraction
2. Two-tier classifier-training phase
3. Self-organizing map (SOM) based initial training
4. K-nearest neighbor

Modules Explanation
1. **DWT based feature extraction**

DWT extracts key features from brain MRI images by analyzing time-varying signals, identifying discontinuities and abrupt changes in spatial data, which improves results compared to Fourier analysis.

2. **Two-tier classifier-training phase**

A two-tier classification method reduces feature space dimensionality, with the SOM neural network first training the features and then using the KNN classifier for improved efficiency and reproducibility.

3. **Self-organizing map(SOM)based initial training**

SOM is an unsupervised learning method that iteratively trains features by clustering data based on similarity measures, requiring no human intervention or prior class knowledge.

4. **VGG16**

VGG-16 is a powerful CNN-based algorithm used for image classification, achieving 92.7% accuracy in classifying 1000 categories, and is known for its deep architecture with small convolution filters.

Existing System Disadvantages
- It does not execute very well when the data set has more sound i.e. target classes are overlapping.
- It doesn't perform well when we have large data set because the required training time is higher.
- It has three serious disadvantages: shift sensitivity, poor directionality, and lack of phase information.

Proposed System

Intracranial tumor also known as a brain tumor is an unwanted, abnormal mass of tissue in which large numbers of cells grow and multiply in an uncontrollable fashion. Tumors can be of different types and can have different features and thus have different treatment processes too. In a ground level, tumors basically are of two types i.e. Metastatic tumor and Primary tumor. Primary brain tumor occurs in the brain and stays there while the metastatic leads to cancer in later stages. Segmentation [3] of Brain tumor is very popular and common for the treatment of the tumor.This study aimed to critically analyze the proposed literature solutions, use the Visual Geometry Group (VGG 16) for discovering brain tumors, implement a convolutional neural network (CNN) model framework, and set parameters to train the model for this challenge.

Proposed System Advantages
- It is one of the popular algorithms for image classification and is easy to use with transfer learning.
- It is an innovative object-recognition model that supports up to 19 layers.
- It is also out performs baselines on many tasks and datasets outside of ImageNet.

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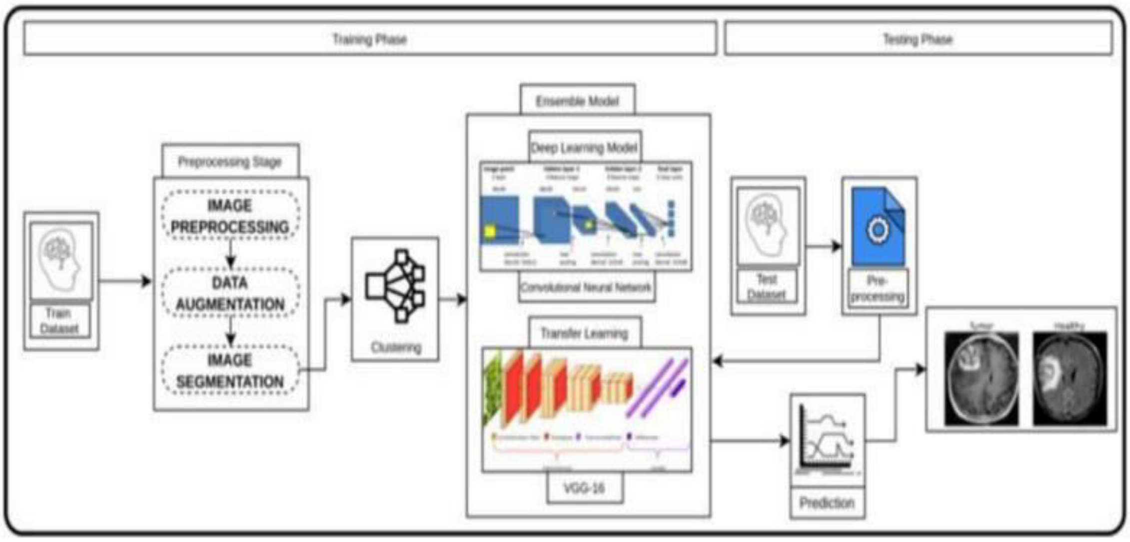
System Architecture



Explanation

The "System Architecture" for brain tumor detection using machine learning and medical image analysis involves two key phases: Training Phase and Testing Phase.

Training Phase:

The process begins with a training dataset of brain images. These images undergo a Preprocessing Stage, which includes steps such as Image Preprocessing to enhance quality, Data Augmentation to increase dataset size artificially, and Image Segmentation to isolate regions of interest. After preprocessing, the images are subjected to Clustering to group similar data for better feature extraction. An Ensemble Model is then utilized, integrating a Convolutional Neural Network (CNN) for deep feature learning and Transfer Learning with a pre-trained VGG-16 model to leverage existing knowledge for improved accuracy.

Testing Phase:

A separate test dataset is preprocessed similarly to the training phase. The preprocessed images are input into the trained model, which performs predictions. The output classifies brain scans into two categories: "Tumor" and "Healthy".

Implementation

Input Data:

- Images of brain MRIs or CT scans.
- These images serve as input for detecting brain tumors using a VGG16 model.

Processing:

Image Preprocessing:

- Resize and Normalize: Convert the images into a fixed size of 224x224 pixels (as required by VGG16) andnormalize pixel values to the range [0, 1].
- Grayscale Conversion: Convert input images to grayscale if the detection focuses on intensity patterns (though for deep learning, the color channels are generally kept).
- Data Augmentation: Use techniques like random rotations, flips, and zooms to augment the dataset, increasing variability and helping prevent overfitting.
- Image Scaling: Scale images according to the input requirements of VGG16.

.Feature Detection:

- VGG16 Feature Extraction: The pre-trained VGG16 model is used to extract features from MRI/CT images.
- The model is loaded with weights pre-trained on the ImageNet dataset, and its top (classification) layer is replaced to fine-tune it for binary classification (tumor vs. non-tumor).
- Fine-Tuning: The last few layers of VGG16 are retrained on labeled brain tumor images to adapt the model for the new task.

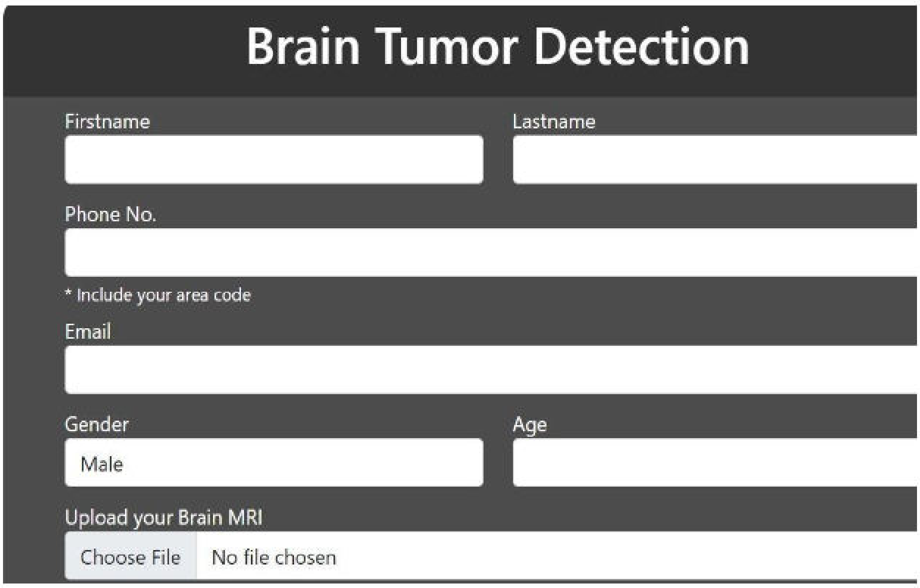
Model (VGG16) Architecture:
- Load VGG16 Model: Utilize Keras' VGG16 with ImageNet weights.
- Customization: Remove the fully connected layers and replace them with a new classifier suited for the tumor detection task (binary classification: tumor vs. non-tumor).
- Compile and Train: Compile the model with a loss function like binary cross-entropy, using an optimizer like Adam. Train the model using labeled brain MRI data.

Homography (Optional):
- In case the input MRI images have multiple perspectives (e.g., multiple scan angles), homography can be used to align images to a common reference plane.
- This step could involve detecting keypoints or aligning with a fixed template, though typically, VGG16 does not require this for tumor detection.

Augmentation:
- Data Augmentation: Increase the variety of the dataset by applying random transformations during the training process (e.g., rotating, flipping, and zooming into the images).
-Model Augmentation: As part of training, the augmented input images are fed into the VGG16 model to enhance its ability to generalize.

Output:
Real-Time Visualization:
- Display the predictions on the images (tumor or non-tumor) in real time after each frame is processed.
- Visualization: The model outputs probabilities for the tumor presence. Based on the threshold, the result (either 'Tumor' or 'No Tumor') is displayed on the image.

Experimental Results



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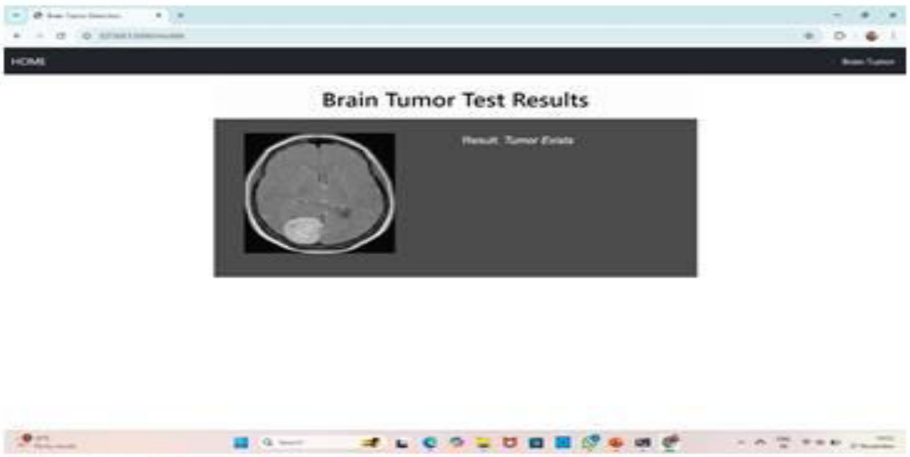

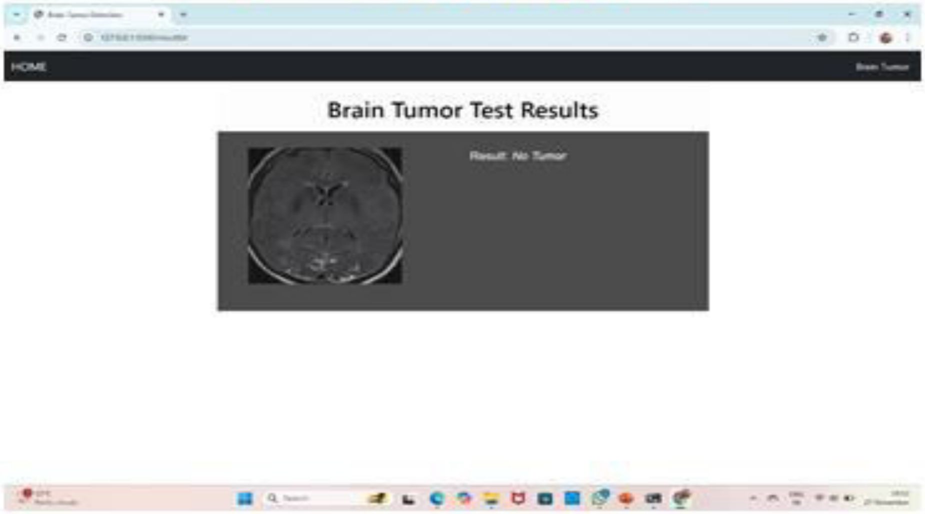

IV. CONCLUSION

The proposed two-tier classification system with the efficient segmentation technique classifies the normal and abnormal MRI brain. The performance of the two-tier classifier system in terms of statistical measures such as sensitivity, specificity and classification accuracy isanalyzed. The results indicated that the proposed system yielded superior performance when compared with SVM based classification technique. It further suggests that the proposed two-tier classifier is a promising technique for image classification in a medical imaging application and it can be used in computer aided intelligent health care systems. This automated analysis system could be further used for the classification of images with different pathological condition, types and disease status.

V. FUTURE ENHANCEMENTS

This automated analysis system could be further used for the classification of images with different pathological condition, types and disease status.

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