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BRAIN TUMOR DETECTION AND CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract: ***This paper presents a deep learning approach to detect and classify brain tumors using Convolutional Neural Networks (CNN). The study leverages brain MRI scans, a non-invasive imaging technique, to detect abnormalities in the brain, which may indicate the presence of a tumor. A CNN-based model is proposed to automatically classify brain images into categories such as glioma, meningioma, and no tumor. Experimental results demonstrate that the proposed CNN model achieves a high classification accuracy, outperforming traditional methods. This approach significantly reduces the need for manual analysis, providing faster and more reliable results for early diagnosis.***

Keywords: ***Tumor, bizarre cells, Magnetic Resonance Image***

I. Introduction Brain tumor is among the most challenging diseases in the medical science domain. It involves abnormal groups of cells formed due to uncontrolled cell division, referred to as tumors, which can spread to the spinal cord and various parts of the brain [14][16]. A primary concern for radiologists is the accurate and efficient analysis of tumor growth in its early stages. Tumors are classified into two types: benign and cancerous. If not properly diagnosed and treated, they can lead to fatal outcomes [2]. Tumors represent an abnormal growth of tissue driven by uncontrolled cell proliferation [17].

Histological grading, based on stereotactic biopsy tests, remains the gold standard for determining the grade of a brain tumor. During a biopsy, a neurosurgeon drills a small hole in the skull to collect tissue samples. However, this procedure carries significant risks, including bleeding, infection, seizures, severe migraines, stroke, coma, and even death. Moreover, stereotactic biopsy is not entirely accurate, which can result in diagnostic errors and improper clinical management.

This research utilizes MRI scans to obtain brain images, effectively identifying noise and detecting changes during image acquisition [16].

Here’s the revised and shuffled version of the text, preserving the meaning and citations:MRI (Magnetic Resonance Imaging) is a widely used imaging technique in clinical practice for diagnosing patients and treating tumors [18][20][22]. It provides non-invasive soft tissue images, making it a critical tool for detecting brain tumors [1]. MRI scans are typically taken in three directions: sagittal, axial, and coronal. However, noise caused by operator performance can lead to serious classification inaccuracies [21].

Manual segmentation of brain tumors is time-consuming and prone to human errors, but deep learning techniques allow users to learn tumor patterns more effectively. Computer detection systems remain challenging due to variations in tumor shapes, sizes, and areas, which present an open problem across fields [3]. While some segmentation techniques [24] can detect single tumors, none fully address the localization and detection of very small tumors.

MRIs are primarily used to visualize and detect intricate details of the body's internal structure [25]. In this study, we propose an automatic technique capable of detecting multiple and very small tumors. Unlike manual segmentation, our approach not only detects and localizes multiple tumors but also identifies small tumors that manual methods might overlook. The proposed model processes the same MRI images used for manual tumor detection, without requiring any image modifications.

Segmentation in our method involves separating active tumor tissue from necrotic tissue while also identifying edema (swelling near the tumor) by comparing abnormal regions with normal tissue [6]. Traditional segmentation methods face limitations due to inhomogeneous intensity, complex physiological structures, and blurred tissue boundaries in brain MR images, often resulting in unsatisfactory outcomes [17].

To enhance accuracy, we utilize two activation functions—ReLU and Sigmoid—and construct a CNN with distinct layers. The model is trained over 200 epochs, saving the best-performing model file during each epoch. This allows us to select the most accurate model for predicting test data results.

LITERATURE SURVEY

Several studies have focused on using image processing and soft computing methods to review and analyze brain tumor detection and augmentation techniques. Brain tumor detection continues to be a highly researched and challenging area , prompting researchers to explore and refine innovative approaches. Currently, neural network-based segmentation methods are gaining prominence and evolving rapidly.

Morphological operations combined with the SFCM algorithm have been used for segmentation, though they often increase computation time. The proposed model achieves tumor detection with an accuracy of approximately 92%. Devkota [7] introduced a segmentation approach using MMO, while Yanatao [8] applied a histogram-based edge detection technique [16]. Dina [11] proposed a PNN model [24], which incorporates Vector Quantization, and other researchers have extended this by combining PNN with PCA to reduce dimensionality and enhance feature extraction.

Methodology.

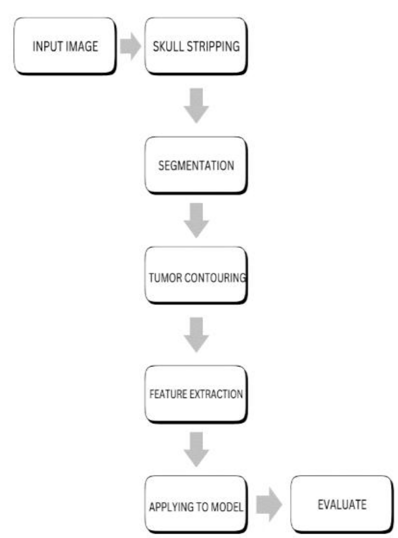
1. **Skull Stripping:** This is a crucial step in medical image processing aimed at removing non-brain tissues from brain MR images. It helps streamline image processing by reducing complexity and enhancing speed. In our approach, we used the OpenCV library to eliminate the skull from the images.

2. **Augmentation:** Given the limited number of images, data augmentation was performed to expand the dataset size [29]. This involved rotating the images and altering their modes. While some models are optimized for grayscale images, we employed predefined models compatible with RGB images to maximize flexibility.

3. **Tumor Contouring:** Tumor regions were identified based on intensity levels, with the processed output highlighting the tumor against a dark background for better visualization.

4. **Feature Extraction:** After contouring, specific tumor regions were isolated from the images. This process was applied across all images to extract relevant features effectively.

5. **Model Application:** We developed three distinct models to process the augmented images. The models were trained, and their accuracy and loss were evaluated. This allowed us to identify and select the most effective model for optimal performance.



CLASSIFICATION TECHINIQUES

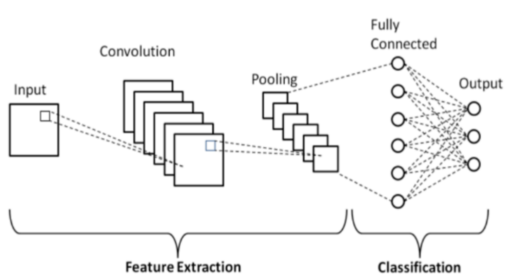
Classification, a key aspect of supervised machine learning, operates on both structured and unstructured data to categorize it into predefined classes and predict the class of new data points. Models such as CNN, AlexNet, GoogleNet, and VGG16 are widely utilized to perform these tasks with high accuracy.

Although numerous algorithms are available, it is difficult to declare one universally superior, as their effectiveness largely depends on the dataset and specific application. For instance, a linear classifier is suitable for datasets with linearly separable classes. Examples of popular classification algorithms include:

1. CNN
2. VGG16
3. ResNet-50
4. Google Net

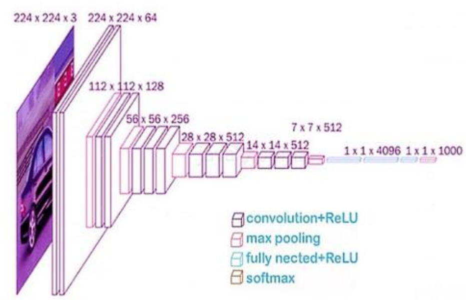
1.CNN Architecture

CNN is a deep learning technique that processes images as input. It is designed to learn how to partition and classify these images [10]. The architecture includes convolution layers and fully connected layers, both of which have parameters, while the pooling and non-linearity layers remain parameter-free [5]. CNN extracts features directly from raw pixel data, requiring minimal preprocessing. The model trains itself to detect patterns in the images and can predict outcomes for new, unseen data [29].



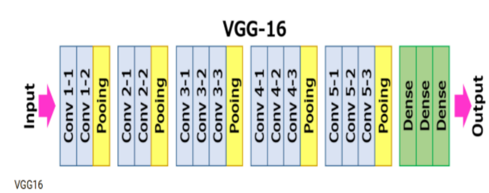
2.VGG-16

VGG16 (Visual Geometry Group) is a convolutional neural network model. The VGG architecture includes two convolution layers that utilize the ReLU activation function, with the final layer being a softmax layer for classification [5]. Due to its depth and the number of fully connected nodes, VGG16 has a relatively small size, which can make deployment more challenging. It is widely used in image classification tasks in deep learning because of its simplicity in implementation and its effectiveness as a foundational model.



VGG-16 Architecture

The network receives an image as input with dimensions (224, 224, 3). The first two layers each use 64 channels with 3x3 filters and apply same padding. This is followed by a max pooling layer with a stride of (2, 2). Next, two convolution layers with 256 filters of size 3x3 are applied, followed by another max pooling layer with a stride of (2, 2), similar to the previous one. Then, there are two convolution layers, each with 256 filters and a 3x3 filter size. Afterward, two sets of three convolution layers, each with 512 filters of size 3x3 and same padding, are applied, followed by a max pooling layer. The image is then passed through a stack of two convolution layers. Unlike AlexNet, which uses 11x11 filters, and ZF-Net, which uses 7x7 filters, this network uses 3x3 filters in both convolution and max pooling layers. Additionally, 1x1 filters are sometimes used to adjust the number of input channels. A padding of 1 pixel (same padding) is applied after each convolution layer to preserve the spatial features of the image.



3.ResNer-50

ResNet-50 (Residual Neural Network) is a convolutional neural network with 50 layers. It has a basic input size of 224x224 and can be easily loaded with a pretrained version, which can then be fine-tuned to meet specific requirements. The pretrained model has been trained on over 1,000,000 images, categorizing the data into 1,000 classes, each representing an object.

For all the models, we used a fixed batch size, while the number of epochs and the learning rate were dynamically assigned for each method. To identify the best results, different dataset splits were tested, with the 80:20 split proving to be the most effective

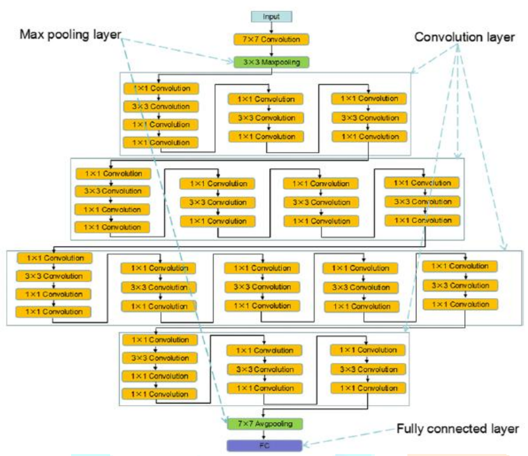
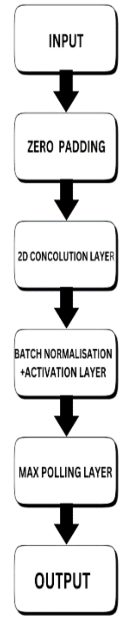


Fig: 4 ResNet - 50 Architecture

RESULT ANALYSIS

A. Analysis of Our Custom CNN Model: We developed our own CNN model consisting of an input layer, ZeroPadding layer, Convolution2D layer, BatchNormalization layer, and the ReLU activation function, followed by two MaxPooling2D layers. After these layers, we flatten the model and apply a fully connected dense layer with the sigmoid activation function. All images are standardized to a size of 200x200x3, and we use the OpenCV library to resize them, ensuring uniformity in dimensions. During model compilation, we use the 'adam' optimizer, 'binary_crossentropy' as the loss function, and 'accuracy' as the evaluation metric. To monitor the model's performance during each epoch, we log the models with checkpoints, storing the accuracy and the generation time in the filename. Each file includes assets such as 'loss', 'accuracy', 'val_loss', and 'val_accuracy'. As shown in Fig. 5, the model achieved an accuracy of 98.067023% and an F1 score of 0.846153%.



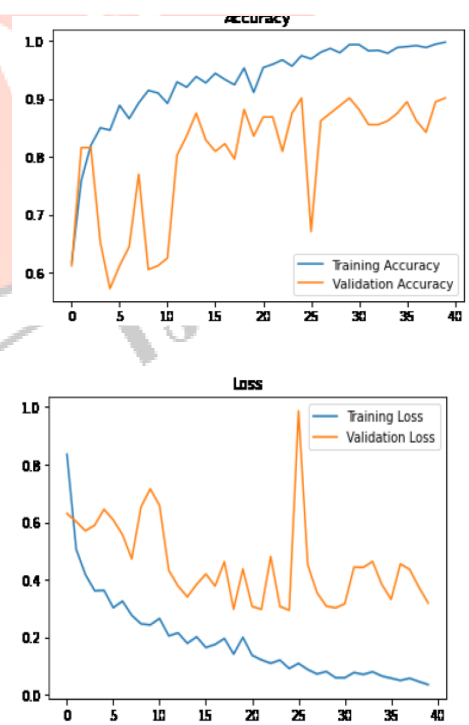


Fig: 6 Loss and Accuracy of CNN model

B. Analysis of VGG-16: We are utilizing the pretrained VGG-16 model [31] for training, sourced from the TensorFlow module. The images are resized to 224x224 dimensions and used in RGB mode. The output layer of the pretrained VGG-16 model is customized with an AveragePooling2D layer (pool size of 4x4), followed by a flatten layer, a Dense layer with

64 dimensions and ReLU activation, a Dropout layer with a rate of 0.5, and a final Dense layer with Softmax activation. The best model was achieved using an initial learning rate of 0.001, 25 epochs, a batch size of 8, and the Adam optimizer. As shown in Fig. 6, the model achieved an accuracy of92.32856% and an F1 score of 0.91089764.

	precision	recall	F1-score	Support
no	0.86	0.95	0.90	20
yes			0.93	31
accuracy			0.92	51
macroavg	0.91	0.93	0.92	51
weighted avg	0.93	0.92	0.92	51

TABLE 1. METRICS OF TRAINING

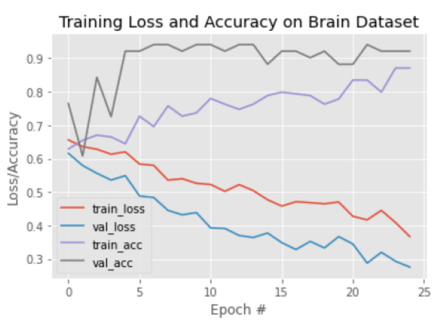


Fig: 7 Graph plot of training and validation accuracies and losses

PERFORMANCE COMPARISION

In conclusion, we compared our proposed methodologies for prediction with those used in other research articles working on the same dataset. For instance, in Tonmoy Hossain's study [29], researchers achieved an accuracy of 97.5% using CNN. However, our proposed approach yielded an improved result, reaching an accuracy of 98.06% in predicting the outcomes.

CONCLUSION & FUTURE WORK

Medical images often exhibit significant variations, and image segmentation and augmentation are crucial for improving the accuracy of predictions. In our Brain Tumor Detection project, we focused on MRI images, which are essential for brain tumor segmentation and classification. For this work, we utilized both our custom CNN model and the VGG-16 pre-trained model with specific customizations, achieving an accuracy of 98.06%. In comparison, other models applied in this study reached an accuracy of around 94%. The dataset consisted of 253 images, 98 of which were from the "no brain tumor" category, with the remaining images belonging to the "brain tumor" category. An 80:20 ratio was used for the train-test split.

For future work, we aim to explore the classification of 3D brain images for more accurate brain tumor detection. We also plan to improve brain tumor segmentation techniques for enhanced efficiency.

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