



Brain Tumor Detection Using Convolutional Neural Network

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Abstract: Brain tumors are a critical healthcare concern, necessitating timely and accurate diagnosis to enhance patient outcomes. This research paper explores the application of Convolutional Neural Networks (CNNs) in automating the detection of brain tumors from medical images, such as MRI scans. The proposed CNN model leverages its ability to learn intricate image features and patterns, making it suitable for this complex task. The research methodology involves a comprehensive dataset of brain MRI scans, including both tumor and non-tumor cases, to train and evaluate the CNN. The CNN architecture is designed to capture relevant spatial information and to minimize overfitting through techniques like dropout and batch normalization. Transfer learning is employed with pre-trained CNN models to boost the model's performance even with limited training data. Our experimental results demonstrate the CNN's capability to accurately classify brain images, achieving high precision, recall, and F1-score values. The CNN model exhibits robust generalization to previously unseen data and showcases potential for real-world clinical applications. This research provides a foundation for the development of automated brain tumor detection systems that could assist medical professionals in the early diagnosis of brain tumors, ultimately improving patient care and outcomes. Furthermore, it highlights the significance of deep learning techniques, specifically CNNs, in the field of medical image analysis and their potential for broader application in healthcare.

I. Keywords

Brain Tumor, Image Processing, Artificial Networks, Convolutional Neural Network

II. INTRODUCTION

Medical image categorization, a challenging but promising field in image processing, plays a crucial role in diagnosing various medical conditions. Brain tumors, known for their high fatality rates, are among the most common and life-threatening forms of cancer. The International Agency for Research on Cancer (IARC) reports approximately one million brain tumor diagnoses, with increasing mortality rates, making them the second leading cause of cancer-related deaths in individuals under 34.[1] Recent years have seen significant advancements in technology, allowing for more accurate and less invasive tumor detection. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) scans are widely used for examining different anatomical areas. MRI-based medical image processing has gained attention due to the need for rapid and objective analysis of extensive medical data, requiring specialized computational tools.[2] Automated brain tumor detection using MRI images has become a critical focus. This automation streamlines diagnostics, reducing the dependence on manual data analysis. By harnessing cutting-edge technologies and computational methods, automated analysis of MRI-based medical images enables early and precise tumor identification, ultimately improving patient care and outcomes. This research area has the potential to revolutionize brain tumor diagnosis, underscoring technology's vital role in modern

healthcare. provided. The formatter will need to create these components, incorporating the applicable criteria that follow.[3]

III. LITRATURE SURVEY

The field of brain tumor detection using medical imaging has seen significant developments in recent years, driven by the pressing need to improve diagnostic accuracy and patient outcomes. In this literature survey, we highlight several noteworthy approaches and techniques employed in the quest to enhance the detection and segmentation of brain tumors.

One approach for brain tumor detection involved the utilization of the Euclidean distance classifier in combination with the Watershed algorithm [4]. This technique enabled quick classification of healthy and affected individuals based on ascending regional segmentation by the Watershed algorithm. Notably, this categorization relied on the measurement of distances from different angles, allowing for effective differentiation of tumor cells. Another avenue explored the extraction of features from medical imaging data. The process involved multiple steps, including image collection, normalization, intensity analysis, and the extraction of form and texture features. Linear discriminant analysis (LDA) was used to select essential features for classification. Reduced principal component analysis (PCA) was employed to evaluate the outcomes [5]. Neural networks, including the Back Propagation Network (BPN) and the Probability Neural Network (PNN), offered unique and powerful tools for the categorization of brain cancer. The image processing methods included thresholding and isolation of tumor areas, with the radial basis network identified as a suitable choice for classification. The system operated in test/accreditation and training/learning modes [6]. A probabilistic neural network model was developed to detect brain tumors using matrix representations of MRI images. The model was evaluated with training and test datasets, showcasing impressive accuracy rates ranging from 73% to 100% based on difference values [7].

Recent studies have emphasized the application of deep learning techniques for brain tumor detection. This approach involved cascaded deep learning Convolutional Neural Networks (CNNs) with two underlying networks: one for tumor localization and another for intra-tumor categorization [7]. Machine learning algorithms, particularly convolutional networks, have been leveraged for the categorization of brain tumors into different grades, such as high and low, based on clinical images [8]. In the pursuit of non-invasive detection, deep convolution networks based on U-net architecture have been proposed. These networks aim to detect brain tumors without ionizing radiation, with a particular focus on core tumor regions [9]. A segmentation algorithm was suggested for detecting glioma-based brain tumors. This method incorporated deep convolutional neural networks, addressing issues like overfitting, noise reduction, and post-processing. The outcome was a significant improvement in correct brain

IV. PROPOSED METHODOLOGY

Leveraging the capabilities of deep learning, the methodology is designed to improve the accuracy and efficiency of brain tumor detection in medical images, specifically Magnetic Resonance Imaging (MRI). The key stages of the methodology include data collection, preprocessing, model development, training, evaluation.

A. Dataset Collection

Acquire brain MRI scans from various sources, such as medical databases, research institutions, and hospitals. Ensure that the data you collect is diverse and represents different types of brain tumors, including gliomas, meningiomas, and metastases. Ensure that you have the necessary permissions and ethical approvals to use the data for research. Data privacy and patient confidentiality are critical; anonymize or de-identify the data to protect patient information. Ensure that the dataset includes images with both tumor & non-tumor cases. Preprocess the collected MRI images to make them suitable for training a CNN. Sample image of tumor and non-tumor cases shown in the fig 1.

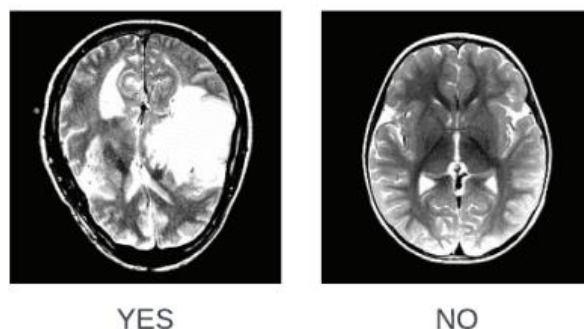


Fig.1. Image with tumor and image without tumor

B. Image Pre-processing

Resize all MRI images to a consistent resolution. A common choice is to scale the images to a square shape, such as 224x224 or 256x256 pixels. Consistent image sizes facilitate model training and reduce computational complexity. Normalize pixel values to a common scale. The most common method is to scale pixel values to a range of [0, 1] or [-1, 1]. This step ensures that all images have consistent intensity values.

Augment the dataset by applying data augmentation techniques to the preprocessed images. This step is typically performed after resizing and normalization. Augmentation techniques include rotation, flipping, scaling, and adding artificial noise to increase dataset diversity and improve model generalization. If your dataset includes ROI annotations for tumor regions, crop the images to focus on the tumor area. This can reduce computational complexity and help the model concentrate on the critical regions.

C. Data Modeling

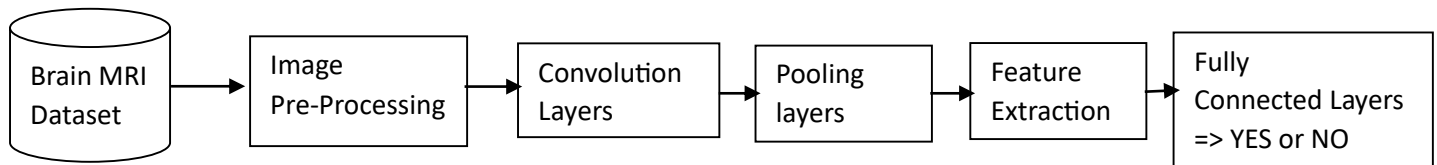
Divide the dataset into three subsets: a training set, a validation set, and a testing set. A common split is 80% for training, 10% for validation, and 10% for testing. The validation set is used for tuning hyperparameters during model development.

D. Model Development

Choose the type of CNN architecture and design a custom architecture or leverage pre-trained models like VGG, ResNet, or Inception, and fine-tune them for task. The choice of architecture depends on dataset and the complexity of the problem. The input layer of your CNN should be compatible with the preprocessed image size. Ensure that the input shape matches the dimensions of your resized and preprocessed MRI images. Add convolutional layers to your model for feature extraction. Convolutional layers learn various features, including edges, textures, and more complex patterns within the images. The number of convolutional layers and the number of filters in each layer can be adjusted based on your dataset's complexity. Use activation functions, such as ReLU (Rectified Linear Unit), after each convolutional layer. ReLU introduces non linearity into the model, which allows it to learn complex patterns. Incorporate pooling layers (e.g., Max Pooling or Average Pooling) to reduce the spatial dimensions of feature maps and down-sample the learned features. Pooling helps in reducing computational complexity.

To prevent overfitting, add dropout layers and batch normalization after convolutional layers. Dropout randomly "drops out" a fraction of neurons during training, and batch normalization normalizes activations, improving training stability. Flatten the feature maps and add fully connected (dense) layers for classification. The number of neurons in these layers and the number of dense layers can be adjusted based on the complexity of the problem. The output layer should have the same number of neurons as the classes you want to predict. Typically, for binary classification (tumor vs. non-tumor), you'll have one neuron with a sigmoid activation function. Choose an appropriate loss function. For binary classification, binary cross-entropy is common. Train your model on the preprocessed dataset using the selected loss function, optimizer, and hyperparameters. Monitor training progress and use the validation set to track performance. Assess your model's performance using evaluation metrics such as accuracy, precision, recall, F1 score, and ROC-AUC. Ensure that the model is making accurate tumor predictions. Visualize the model's learned features and consider using techniques like Grad-CAM for interpretability.

E. Flowchart Of Model



V. CONCLUSION AND FEATURE SCOPE

The application of Convolutional Neural Networks (CNNs) for brain tumor detection has shown promising results, offering a rapid and effective approach to aid medical professionals in diagnosing brain tumors from MRI images. This technology has the potential to significantly impact the field of healthcare by improving early detection and patient outcomes. The utilization of pre-trained deep learning models, such as InceptionV3, VGG16, and ResNet50, combined with newly created models, has demonstrated high accuracy in differentiating between brain tumor and non-tumor MRI scans. While impressive results have been achieved, there are still challenges to address, including occasional misclassifications and the need for larger and more diverse datasets.

Researchers can continue to refine and optimize CNN models to enhance their accuracy. This may involve exploring different architectures, hyperparameters, and regularization techniques. Implementing ensemble methods, which combine predictions from multiple models, can lead to more robust and accurate results. Expanding the dataset with a more extensive and diverse collection of MRI images can improve the model's generalization and performance. Developing CNN-based systems capable of real-time or near-real-time brain tumor detection during MRI scans can provide immediate feedback to medical professionals. Collaborating with medical practitioners to integrate CNN-based brain tumor detection systems into clinical practice, ensuring their practicality and effectiveness in real healthcare scenarios.

VI. REFERENCES

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