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Brain Tumor Detection using Deep Learning

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ABSTRACT—

The scientific community defines a brain tumor as the development of aberrant cells in the brain, it may develop into cancer. Nuclear Magnetic Resonance is the conventional technique for detecting brain tumors. (MRI). The information on the unchecked growth of tissue in the brain is identified using the MRI scans. Brain tumor identification is carried out using machine learning and deep learning algorithms in a number of research articles. Brain tumor prediction using these methods on MRI data is completed extremely rapidly, and more accuracy aids in patient treatment. Using 2D MRI scan images, Convolutional Neural Networks (CNNs) have demonstrated considerable potential in the detection of brain tumors. By examining these images, CNNs can automatically spot patterns and characteristics, such as changes in tissue density or aberrant growths, that are suggestive of brain tumors. Using CNN algorithm this paper defines about the detection of brain tumor using Brain Tumor Epocho datasets.

Keywords—Brain, Brain tumor Classification, Magnetic resonance image, Preprocessing, Medical image analysis.

INTRODUCTION

A brain tumor is a mass or growth of abnormal cells in the brain. Many different types of brain tumors exist. Some brain tumors are noncancerous (benign), and some brain tumors are cancerous (malignant). Brain tumors can begin in the brain (primary brain tumors), or cancer can begin in other parts of the body and spread to the brain as secondary (metastatic) brain tumors. The signs and symptoms of a brain tumor vary greatly and depend on the brain tumor's size, location and rate of growth. General signs and symptoms caused by brain tumors may include New onset or change in pattern of headaches, Headaches that gradually become more frequent and more severe, Unexplained nausea or vomiting, Vision problems, such as blurred vision, double vision or loss of peripheral vision, Gradual loss of sensation or movement in an arm or a leg, Difficulty with balance. Among the various problems to the brain, the most common and the life-threatening problem these days is that of the brain tumor. Every year, about 11,000 persons are being diagnosed of the brain tumor [2]. Brain tumor is an anomalous lump of flesh comprising of uncontrolled growth and multiplication of cells. Depending upon the cell type the brain tumor originates from or where they are positioned inside the brain or their rapidness for growth and expansion, their exists around 130 different types of brain tumors.

CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNNs) have shown promising results in brain tumor detection. CNNs are deep learning models that can learn and extract features from input images automatically. The architecture of a CNN consists of several layers, including convolutional layers, pooling layers, and fully connected layers. In the case of brain tumor detection, CNNs can be trained on a large dataset of brain MRI or CT scans, where each image is labeled as either having a tumor or not. The CNN can learn to identify patterns and features in the images that are indicative of the presence of a tumor. During training, the CNN optimizes the weights of its layers to minimize the difference between its predicted output and the true output labels of the training data. This process is called back propagation, and it allows the network to learn the most relevant features for the task at hand. Once trained, the CNN can be used to predict the presence of a tumor in new brain images. The input image is passed through the network, and the output layer produces a prediction of the probability of the image belonging to the tumor or non-tumor class. The threshold for this prediction can be adjusted depending on the specific use case and the level of accuracy desired. CNNs have several advantages over traditional machine learning algorithms for brain tumor detection. They can learn complex and non-linear relationships between input features, and they can extract relevant features automatically without the need for manual feature engineering. Additionally, CNNs can be trained on large datasets, allowing them to generalize well to new and unseen data.

A. ***Input Layer***

The input layer takes the input image of the brain (MRI or CT scan). The input layer can be designed to accept images of a certain size and type. For example, it may require images to be in grayscale or RGB format, and have a specific number of pixels in the x and y dimensions.

B. Convolutional Layer

The convolutional layer applies filters to extract local features at different spatial scales. Each filter detects a specific feature, such as edges, corners, or textures. The output of the convolutional layer is a set of feature maps, which are matrices that represent the presence of different features at different locations in the image. For brain tumor detection, additional 3D filters may be used to account for the depth of the brain.

C. Activation function

The activation function applies an activation function to introduce non-linearity. The activation function is applied element-wise to the output of the convolutional layer. It is used to introduce non-linearities in the network, which can improve the network's ability to model complex features.

D. Pooling layer

The pooling layer down samples the feature maps to reduce spatial dimensions. This can help the network to be less sensitive to small shifts in the input image, and to reduce the number of parameters in the network. The most common pooling operation is max pooling, where the maximum value in each pool is retained.

E. Output layer

This layer derives the final prediction of the network, such as the probability of the input image belonging to the tumor or non-tumor class. The output layer can be designed to have one or more neurons, depending on the specific problem being addressed. In the case of brain tumor detection, it might have two neurons that output the probability of the input image belonging to the tumor or non-tumor class.

RELATED WORK

During the past decades, a wide range of machine learning and deep learning models for detecting brain tumors have been proposed. In this section, a summary of such models is presented.

A. Brain tumor detection with segmentation

As a large volume of medical MRI imaging data is gathered through image acquisition, the researchers are now proposing different machine learning methods to identify brain tumors. These methods are based on feature extraction, feature selection, dimensionality reduction, and classification techniques. Most of those suggested machine learning models are focused on the binary identification of brain tumors. For example, Kharrat et al. proposed a binary classification of brain images using a support vector machine (SVM) and a genetic algorithm (GA). In this study, the features are extracted using Spatial Gray Level Dependency (SGLDM) method. In a different study, Bahadure et al., used Berkeley wavelet transformation (BWT) and SVM to segment and categorized normal and abnormal brain tissues . They were able to achieve 96.5% prediction accuracy on 135 images. In a related study, Rehman et al., used a Random Forest (RF) classifier to the 2012 BRATS dataset .They compared their model to other classifiers and found that the RF classifier achieve better results in terms of precision and specificity. Later, for the purpose of identifying brain tumors, Chaplot et al. used a discrete wavelet transform (DWT) as a feature extractor and SVM as a classifier. On 52 images, they achieved 98% prediction accuracy. The K-nearest neighbor (KNN) classifier was then applied by El-Dahshan et al. to 70 images, and the results showed 98.6% prediction accuracy. For feature extraction and feature reduction, they employed.

DWT and the principle component analysis (PCA), respectively. They also used Particle Swarm Optimization (PSO) and SVM to select and classify textural features. To detect different grading of glioma tumors, Chen et al., used a 3D convolution network to segment the tumor region . The segmented tumors are then classified using the SVM classifier. They also used the recursive function exclusion (RFE) method to extract features with significant discriminatory information. More recently, Ranjan et al., proposed a new model using 2D Stationary Wavelet Transform (SWT) as a feature extractor, and AdaBoost and SVM classifiers to detect brain abnormalities. Although those techniques significantly enhanced brain tumor detection accuracy, they still have several limitations, Since all these methods are based on binary classification (normal and abnormal), it is not sufficient for the radiologist to decide the patient's treatment concerning tumor grading. Those methods are based on different hand-crafted feature extraction techniques, which are time-consuming, complex, and in many cases not effective. Techniques that were used in those studies performed well with a small amount of data. However, working with a large volume of data required advanced classifiers.

B. Brain tumor detection through transfer learning

Transfer learning does well when the volume of data is limited since such a model is previously trained on a large dataset (e.g., the ImageNet database), containing millions of images. In this approach, the pre-trained model with adjusted weights is adopted for the classification tasks. Another benefit is that it does not require a massive amount of computational resources since only the model's fully connected layers need to be trained. Due to such advantages, different transfer learning models have been used for diagnosing brain tumors. For instance, Talo et al., used a pre-trained ResNet34 model to detect normal and abnormal brain MRI images. A large-scale of data augmentation is also carried out to reach high prediction accuracy . Furthermore, for detecting multiclass brain tumors, Swati et al., proposed a fine-tuned VGG19 model . Later on Lu et al., suggested a fine-tuned AlexNet structure to diagnose brain abnormalities. In this study, just 291 images were used. In a similar study, Sajjad et al., used a fine-tuned VGG19 model for multiclass brain tumor detection and conducted it on 121 images .They achieved an overall prediction accuracy of 87.4% before the data augmentation. Finally, by applying the data augmentation technique, they increased the accuracy to 90.7%. Despite all the benefits, there are several shortcomings associated with transfer learning which are Pre-trained models fail to obtain satisfactory results when training on imbalance datasets. They are more biased towards classes with a larger number of samples. Proper fine-tuning is required in pre-trained models. Otherwise, the model will fail to achieve satisfactory results.

Although previous studies achieved significant improvement in brain tumor diagnosis, there is still room for improvement. This research mainly concentrated on overcoming those shortcomings by fine-tuning the deep learning models and improving forecast accuracy.

RESULTS AND DISCUSSIONS

The model is being trained with the epoch value as 25. Training for a higher epoch value allows the model to adjust its weights and biases to detect more subtle features of brain tumors. This increases the sensitivity of the model and enables it to detect tumors that may have gone unnoticed in earlier models. It can lead to improved patient outcomes, by providing earlier detection of brain tumors and enabling earlier interventions, leading to better prognosis and survival rates for patients as shown in Fig.1 and Fig.2.

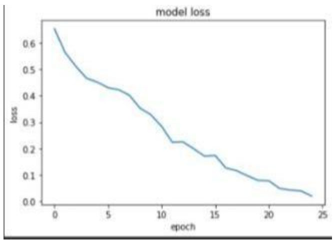


Fig.1 Model loss graph (Epoch value 25)

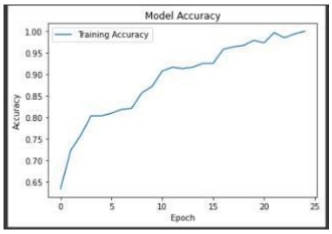


Fig.2 Accuracy graph (Epoch value 25)

The model is being trained with the epoch value as 50. longer training time allows the model to learn and analyze from a larger set of brain images, which improves its accuracy and sensitivity in detecting tumors. raining a brain tumor model with an epoch value of 50 provides a more reliable and accurate tool for diagnosing and treating brain tumors, thereby improving patient outcomes.

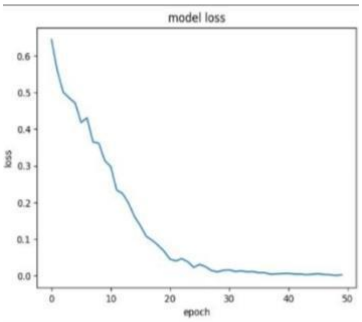


Fig.3 Model loss graph (Epoch value 50)

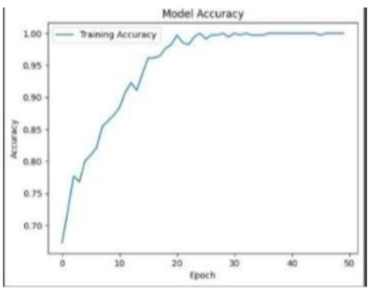


Fig.4 Accuracy graph (Epoch value 50)

The model is being trained with the epoch value as 100 helps the model to capture more complex features and patterns of brain tumors, which can be missed in models with lower epoch values. The use of an epoch value of 100 can help in identifying rare and hard-to-detect tumor subtypes that might go unnoticed in models with lower epoch values. So the increased accuracy and sensitivity of the model can lead to earlier diagnosis and treatment of brain tumors.

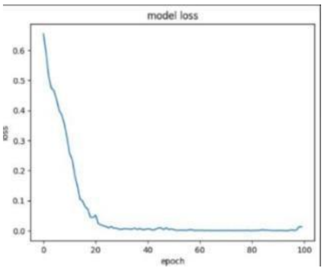


Fig.5 Model loss graph (Epoch value 100)

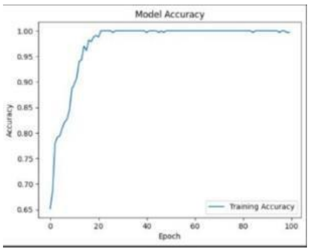
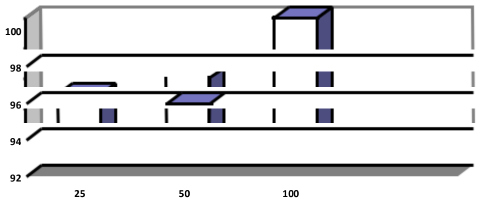


Fig.6 Accuracy graph (Epoch value 100)

The models are being trained with different epoch values to provide the better accuracy for the datasets. Here’s a bar chart representation of the epoch values 25,50,100.



CONCLUSION

This paper defines about the brain tumor detection using convolutional neural network algorithm with the BrainTumorEpocho dataset and the models are being trained with different epoch values to know in which epoch value the model gives better accuracy for the outcomes.

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